ERASMUS UNIVERSITEIT ROTTERDAM

THE WAGE RETURN TO EDUCATION DURING THE RECENT ECONOMIC CRISIS – AN APPLICATION TO THE NETHERLANDS

MASTER THESIS

ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Department of Economics

April 13, 2016

Abstract

This paper examines the wage return to education in the Netherlands over the recent economic crisis (2008 – 2009). The data is based on the LISS-dataset and covers the years 2008 – 2015. The primary focus is male individuals, working full time, aged 30 – 55 years, but is extended to include young (20 – 29 years), old (56 – 65 years), part time and female workers. The wage return to education is estimated using the Mincer and wage differential model. Based on the interaction results of year dummies, unemployment rate and GDP growth rate with the level of education, it can be obtained that there is a significant decrease in the wage return to education in the years 2010 and 2013 for all individuals. However, the higher the educational level of the individual, the lower the decrease in the wage return to education. Furthermore, in line with the related literature, the wage return to education based on the instrumental variable approach is significantly higher. Also, the Heckman procedure suggests a negative sample selection due to non-response and some minor degree of positive sample selection due to non-employment.

Supervisor: Associate Prof. Dr. Anne Gielen
Name: Kevin van Trigt
Exam number: 343999
E-mail address: kevin.van.trigt@gmail.com

SECTION 1: INTRODUCTION

For almost a decade, the Netherlands experienced the detrimental effects of the recent global economic crisis. The first blow to the Dutch financial system was by the end of 2008 and the Netherlands is still recuperating from its impact. Especially in the years 2008 and 2009, the Netherlands has seen stark periods of economic contraction. Moreover, from the start of the economic crisis, unemployment rates have increased steadily. In 2014, the Netherlands started to grow at a more stable path again and prospects became more positive (FD, 2015b, 2015d, 2015f; Hinrichs, 2014). Although the unemployment rate started to decline (modestly) since 2014 (FD, 2015a, 2015c), in some periods the decline is interrupted due to a starker increase in the labour supply than the number of created jobs (FD, 2015e).

One of the well-established facts of Becker's (1962, 1964) Human Capital Theory is that the unemployment rate is inversely related to the level of education. As investments in education improve the productivity of workers, it raises the monetary incomes of the workers[1]. Given the benefits of education, several researchers have examined the returns to education, both in the Netherlands as well as other countries around the world.

There are essentially two types of return to education. The first type of return to education is related to the probability of having a job. As explained in the job loss literature, especially lower educated workers experience a strong cyclical pattern as compared to more educated workers. As a result, the job loss rate is much higher for the lower educated individuals as compared to higher educated individuals. This is in accordance with the data from Statistics Netherlands (CBS, 2015) and van der Meer (2015), as the unemployment rate increased more for lower educated workers than for higher educated workers during the recent economic crisis. Over 2008 to 2014, the male unemployment rate increased 6.7 percentage points for the lower educated workers and only 2.1 percentage points for the higher educated workers. Moreover, both in absolute and relative terms, the increase in unemployment is larger for lower educated than for higher educated workers.

The second type of return to education is, conditional on having a job, the wage return to education. This type of return to education is higher, the higher educated an individual is (Becker, 1964). Although the wage return to education is examined and discussed extensively

[1] The literature has established that there are also non-monetary (i.e. non-pecuniary) benefits to the investment in education (e.g. a better health and more job satisfaction). See for example Oreopoulos & Salvanes (2011). Although the non-monetary benefits are examined more often nowadays, it is not of particular interest for this paper. In the rest of this paper, the return to education will refer to the "monetary" return to education.

by many researchers, there remains to be a large gap in the literature. To my knowledge, no researcher has examined whether this type of return to education changed during business cycles in the Netherlands. Only a few papers have examined this for other countries.

Research question: did the wage return to education change in the Netherlands over the recent economic business cycle (2008 – 2015)?

In light of this research question, one of the interesting factors to examine is the role of tenure. Workers who started working with their current employer before the economic crisis may had a stronger bargaining position as compared to workers who started working during (or after) the economic crisis. The economic crisis most likely impacted the workers relative bargaining position and as a result there may be a difference in wages between these two groups of workers.

The data used in this paper is based on the LISS-dataset (Longitudinal Internet Studies for the Social Sciences) and covers the years 2008 – 2015. Although the economic crisis hit the Netherlands by the end of 2008, this paper is still able to estimate a pre-crisis return to education as the (core) questionnaire was already conducted in April 2008. Therefore, this paper is able to examine the wage return to education over the entire business cycle in the Netherlands.

The results of the wage return to education are in line with the related literature. The Mincer models suggest that the effect of education on wages is around 7.2 to 8.4 percent for each additional year of education and around half of this effect is due to career components. Also the wage differential model suggest that the wage premium is higher the higher educated the individual is. Focusing on the economic crisis, especially the years 2010 and 2013 showed a significant drop in the wage premium. However, the higher educated the individual, the lower the decrease in the wage premium. These results are confirmed by all crisis indicators (i.e. the level of education interacted with respectively year dummies, unemployment rate and GDP growth rate). Based on the instrumental variable approach and the Heckman procedure, the baseline results can be argued to be a lower bound of the true effect of education on wages. However, some caution in this interpretation is necessary. Moreover, the results are generalizable to male full time workers aged 20 – 65 years.

Section 2 discusses the related literature. Section 3 discusses the methodology to examine the wage return to education during the recent economic crisis. Section 4 discusses the data used for the analysis and presents the main summary statistics. Section 5 discusses the various results and robustness checks. Section 6 is used to discuss this research paper. Section 7 concludes.

SECTION 2: LITERATURE REVIEW

In order to examine if the recent economic crisis affected the returns to education in the Netherlands, it is useful to first review the related literature. Moreover, if the recent economic crisis indeed affected the returns to education in the Netherlands, it is also important to examine how the returns to education have been affected. The generally applied framework to examine the wage return to education is based on the Human Capital Theory of Becker (1962, 1964) and the Human Capital Earnings Function of Mincer (1974).

Section 2.1: Human Capital

Many economists contributed to the theory on human capital. However, especially Becker shaped it. The Human Capital Theory assumes that human capital raises earnings and productivity mainly by providing workers with knowledge, skills and a way of analyzing problems. According to the evidence, human capital is very important. Becker (1964) states that probably the most impressive evidence is that more highly educated and skilled individuals almost always tend to earn more than others.

Although all investments in human capital contribute to an increase in the workers' productivity, the two most important and often mentioned investments in human capital are (formal) education and on-the-job training. However, not all of the workers' productivity is acquired via investments in human capital. Part of the workers' productivity is innate (e.g. ability and motivation) and represents the individuals' initial level of human capital.

Becker (1962, 1964) treats human capital as an investment process in which the individual invests more or less in human capital to maximize its (expected) net present value of income (minus cost of education) over their life span. The individual will only make the investment if the expected stream of future benefits exceeds the short-term costs of the investment. At the optimum, the marginal benefit (i.e. rate of return) to an additional investment in human capital is equal to the marginal cost of this additional investment. The relationship between the costs and benefits of an additional investment in human capital can be derived by defining the internal rate of return. The internal rate of return is the discount rate that equates the present value of benefits to the present value of costs. More specifically, if the internal rate of return is larger than the market rate of interest (assuming perfect capital markets), more investments in human capital are worthwhile for the individual.

In the Human Capital Theory, Becker (1962, 1964) distinguishes between general and specific human capital. General human capital is acquired via (formal) education and specific human capital is acquired via on-the-job training or tenure. As a result, general human capital increases productivity in all jobs, while specific human capital only raises productivity in the firm providing it. According to Becker (1962, 1964), the worker pays the costs of acquiring general human capital as firms are unable to collect the returns from general human capital training. On the other hand, firms and workers will share the costs of acquiring specific human capital due to the fact that both are able to collect returns from specific human capital training. As a result, workers with specific human capital have less incentive to quit their job and firms have less incentive to lay them off.

Based on Becker's treatment of human capital, one can draw important implications for this study. As the optimal level of human capital investment differs for each individual, especially lower-skilled individuals will invest (none to) little in human capital due to the fact that the benefits are smaller or the costs are larger as compared to higher-skilled individuals.

Given the increased importance of technologies, this paper also introduces a related view to Becker (1964), namely the human capital view of Schultz (1975). The human capital view of Schultz (1975) is mostly related to the individuals' ability to deal with situations in which there is a disequilibrium (i.e. in situations in which there is a changing environment). High-skilled individuals, are better able to deal with these situations as opposed to low-skilled individuals. More specifically, in economies where technologies are becoming more important and require the capacity to adapt to these technologies, higher educated individuals are better able to adapt to these situations and are therefore more attractive for firms to hold on to as compared to lower educated individuals. According to Becker (1964) studies show that rapidly progressing industries do attract better-educated individuals and provide better on-the-job training.

Moreover, related is the general notion of job polarization by Acemoglu & Autor (2012). Job polarization is the simultaneous growth of high-skilled jobs (i.e. high wage occupations) and low-skilled jobs (i.e. low wage occupations), while the number of middle-skilled jobs decreases. Due to the fact that routine type work is often performed by middle-skilled workers, machines primarily replace these workers. As a result, there is a loss in the share of employment that requires this level of skills. Van den Berge & ter Weel (2015) specifically examined the job polarization in the Netherlands. They concluded that job polarization is also visible in the Netherlands, however, the trend is less strong as compared to many other OECD countries.

According to van den Berge & ter Weel (2015), a potential reason could be that Dutch middle-skilled individuals have, by international standard, a relatively high-skilled level.

Although the general view of human capital is that education increases earnings and productivity by providing knowledge, skills, and a way of analyzing problems, an alternative view is "credentialism" (i.e. "signaling"). This alternative view states that education does not improve the productivity of workers, but rather conveys information about the underlying abilities, motivation, and other valuable characteristics of individuals. More specifically, this view states that more productive individuals undertake more education to signal their skills and therefore earn more. Becker (1964) also discussed this alternative view and acknowledges its existence (e.g. 'sheepskin' effects discussed in Section 2.2). However, it cannot fully explain the positive association between earnings and education. Therefore, credentialism or signaling does not replace the Human Capital Theory of Becker (1964), but rather complements it.

Section 2.2: Estimating the return to education

While Becker (1964) primarily focused on establishing a theoretical view on human capital, Mincer (1974) focused more on the empirical part. Based on the Human Capital Earnings Function, Mincer (1974) is able to estimate the wage return to education. This paper will only focus on (formal) education as an investment in human capital. Other forms of investment in human capital will therefore not be discussed.

There are essentially two types of return to education:

i. The probability of having a job
ii. (Conditional on having a job) the wage return to education

To start with the first type. The probability of having a job represents the extensive margin as the individual either has a job or does not have a job. The Human Capital Theory does not explain why some individuals have a higher probability of having a job. There is no (apparent) direct link between the initial level of education and the probability of having a job. It is, however, able to explain why tenure differences among workers can affect the probability of having a job. The longer an individual works for its current employer, the more specific human capital the individual acquired. As a result, both the employee and the employer will lose valuable skills when the employee quits or gets laid off. Therefore, the probability of having a job is higher for individuals who have more tenure (i.e. more specific human capital). As the Human Capital Theory can be used to explain the impact of education on wages, but is not able to explain the probability of having a job, one needs to resort to a different strand of literature. This is discussed in detail in Section 2.3.

To continue with the second type. The wage return to education represents the intensive margin of work and indicates that, conditional on having a job, wages are higher for higher educated individuals. Although the wage return to education is often examined, research papers examining the return to education during business cycles are very scarce.

The conventional framework to measure the wage return to education is the Human Capital Earnings Function of Mincer (1974). In this framework, the log of wages (generally gross hourly wages) is determined by years of schooling and work experience. However, this framework is only able to examine the intensive margin of work.

$$ln\, Y_i = \alpha + \beta_1 S_i + \beta_2 T_i + \beta_3 T_i^2 + \varepsilon_i \tag{1}$$

This is the traditional specification and will be extended in the methodology section. In this specification, $\ln Y_i$ is the log of (gross hourly) individual earnings, S_i is the years of (completed) schooling, T_i is the number of years an individual has worked since completing schooling and ε_i is the error term. The main interest is to estimate β_1, the so called Mincer coefficient. The Mincer coefficient represents the wage return to education or in other words, the percentage change in wages for each additional year of education.

As the traditional Mincer-framework is based on linear years of schooling, an alternative is to adopt credentials (i.e. level of education). Although this approach should in principle lead to an equivalent outcome, this is generally not the case due to 'sheepskin' effects (Card, 1999; Harmon, Oosterbeek, & Walker, 2003; Heckman, Lochner, & Todd, 2008). As there may be a wage premium over the average return to education for fulfilling a particular year of education (e.g. the final year in college or high school to obtain a degree), there can be non-linearities at different years of education. In order to capture this effect, researchers can allow each educational level to have a different impact on the wage level (Blundell, Dearden, & Sianesi, 2001; Vilerts, Krasnopjorovs, & Brēķis, 2015).

Furthermore, as any other research method, the Mincer-equation can potentially be biased. The most often mentioned bias is the endogeneity bias, which is generally the result of an omitted variable (e.g. ability) and causes the error term to be correlated with the explanatory variables (Doran & Fingleton, 2015; Harmon et al., 2003; Leigh & Ryan, 2008; Levin & Plug, 1999; E. J. S. Plug, 2001; Strauss & De La Maisonneuve, 2009; Trostel, Walker, & Woolley, 2002;

Vilerts et al., 2015). The endogeneity bias and the various approaches discussed by researchers to circumvent (or at least strongly reduce) the endogeneity bias, are discussed in more detail in Section 3.

<u>Section 2.3: Studies examining the probability of having a job</u>

Researchers examining the probability of having a job, generally do not focus directly on this probability, but rather focus on the job loss rate (i.e. displacement rate) and/or the job finding rate (i.e. the re-employment rate). The general literature results are shortly discussed below.

The empirical evidence is able to indicate which demographic groups of workers have, on average, the highest job loss rates (see for example Farber (2011), OECD (2013) and Shimer (2012))[2]. The results suggest that the job loss rate is much higher for less educated workers than for more educated workers. Although there is also a cyclical pattern for more educated workers, the cyclical pattern in job loss rates is much stronger for less educated workers (Farber, 2005). Moreover, job loss rates are highest for the youngest workers. Over time, however, the job loss rates by age have converged, with the job loss rates of older workers increasing relative to those of younger workers (Farber, 2011). According to the OECD (2013), older workers have a higher job loss rate than prime-age workers in most countries. This is, however, less evident from the raw data on job loss rates. Older workers have, on average, longer tenure (i.e. more specific skills) in their jobs and as a result have more protection against the probability of being displaced (OECD, 2013). Therefore, a longer tenure reduces the job loss rate (OECD, 2013). The cross-country trends in job loss rate in the paper of the OECD (2013) suggests workers in smaller firms (10 – 49 workers) are more likely to be displaced than those working in large firms (500 workers or more). These results are statistically significant in most countries even after controlling for other personal, firm and job characteristics (OECD, 2013). Although the job loss rates are, on average, higher for men than for women in most countries, this is generally the result due to the overrepresentation of men in some type of industries and occupations (OECD, 2013).

According to Shimer (2012), who studies the job loss and job finding probability in the U.S. from 1948 to 2010, the job finding probability accounts for three-quarter of the volatility of the unemployment rate and thereby contradicts the conventional wisdom stating the job loss rate is

[2] When mentioning young workers, research papers generally focus on workers aged 20 – 29 years. Moreover, although there are sometimes small differences, for prime-aged and older worker this is generally around 30 – 54 years and 55 – 64 years, respectively.

the key to understanding business cycles. It is therefore also important to focus on the job finding rate and to examine which demographic groups are more strongly attached to the labour force. Research showed that prime-age workers have the strongest attachment to the labour force, as they have the highest fraction employed and the lowest fraction out of the labour force (Farber, 2005). However, after a job displacement, especially older workers and workers with a low level of education take longer (and suffer more) to get back into employment (OECD, 2013). Given the low job finding rate for older workers, it is not surprising that many will move out of the labour force into long-term unemployment or retire subsequent to a job loss (Farber, 2005). Although the job loss rate is also high for young workers, young workers have the highest mobility and are therefore able to recover more quickly during an economic upturn. The job loss is therefore less harmful for this group (Gielen & van Ours, 2006). Generally, young workers find work relatively quickly and often in jobs with greater skills requirement than their previous job (OECD, 2013). Moreover, while women are not more likely to be displacement than men, they are more likely to disconnect from the labour force and experience longer periods of inactivity after a job displacement (OECD, 2013). This is presumably the result of women having a richer set of alternative activities on which to spend time (e.g. bearing and raising children) (Farber, 2005). Overall, especially women, older individuals and individuals with lower education are more likely to move out of the labour force after a job loss.

Section 2.4: Studies examining the wage return to education

Meghir & Palme (2005) exploited a Swedish education reform in 1948 to examine its impact on the educational attainment and earnings of individuals. They used data from the 1948 and 1953 cohorts of the Individual Statistics project of the Institute for Education at the University of Gothenburg. The reform was evaluated based on a difference-in-difference methodology as in most cases the 1948 cohort was assigned to the old system and the 1953 cohort to the new system. However, in some municipalities, both cohorts were assigned to the old system, while in other municipalities, both cohorts were assigned to the new system. There is no evidence that mobility of individuals biased the results. On average, the educational attainment increased by 0.298 years of education. However, the entire effect is due to the increase in the educational attainment of individuals with unskilled fathers. The effect on earnings was small and not significant. However, this conceals substantial heterogeneity. For those individuals with unskilled fathers, the reform increased earnings by 3.4 percent. This effect is stronger for women than for men, especially for high-skilled women.

Park (2011) tested formally for non-linearity in the wage returns to education using data from the National Longitudinal Survey of Youth. This dataset contains information on the initial educational investment of young workers, who started working, but changed job with an intervening period of educational reinvestment (i.e. additional education). The initial level of education is 13.4 years and the average years of educational reinvestment is 1.4. Given the reinvestment, Park (2011) is able to control for unobserved individual fixed-effects and provides an ability-free estimate. This estimate is slightly larger than its standard OLS counterpart which does not correct for individual fixed-effects. The conventional assumption of linearity is rejected. A typical reinvestment for the 1980 – 1993 period is associated with a rise of 3.5 percentage point in the return to an additional year of education. The estimated return generally increased in the initial level of education, reaches its maximum at 15 years of initial level of education and declines afterwards. At the maximum, an additional year of educational investment is associated with a rise in real hourly wage of approximately 20 percent. The results are robust to sample selectivity corrections, as well as other robustness tests (e.g. sheepskin effects, year effects and the Ashenfelter's dip).

Heckman, Lochner, & Todd (2008) estimated a nonparametric model of earnings to estimate the internal rate of return to education (i.e. the discount rate that equates the present value of benefits and costs of education). The estimates accounted for tuition costs, income taxes, and nonlinearities in the earnings-education-experience relationship as these factors may be important to describe the labour earnings for U.S. workers. Using data from the U.S. decennial census and the Current Population Survey, they followed cohorts of individuals over time to estimate cohort internal rates of return to high school and college education. The results indicated significant differences between the estimated schooling coefficient from the Mincer earnings function and the general method adopted in Heckman et al. (2008). More specifically, they found relatively larger returns to graduating from high school than to graduating from college, however, both have increased over time.

Henderson, Polachek, & Wang (2011) employed a nonparametric kernel regression to relax the assumption of homogenous wage returns to education. They are able to examine the differences in rates of return to education both across and within groups. Nonparametric models have the advantage that they (i) do not require the functional form to be specified a priori and (ii) the estimation techniques do not rely on panel data which is frequently unavailable. However, the results should be seen as raw estimates as they are likely impacted by omitted variables, measurement errors and other (econometric or economic) problems. The results indicated that on average blacks have a higher return to education than whites, and this gap is larger than previously thought. Natives have a higher return to education than immigrants, this gap is, however, smaller than previously thought. Moreover, Henderson et al. (2011) also tried to uncover the characteristics common among those with the highest and lowest returns. Individuals with the highest returns are generally the youngest individuals (aged 20 – 29), while especially immigrants aged 50 – 59 have the lowest returns.

Section 2.5: Examining the wage returns to education in the Netherlands

Levin & Plug (1999) estimated the wage return to education in the Netherlands using two Dutch datasets and adopted different IV approaches. The first dataset is the Brabant survey in 1952 on sixth-grade pupils (around 12 years old). These individuals are also surveyed in 1957 and 1983. The second dataset is the OSA panel survey in 1994 and includes information on individual schooling durations, labour market status and earnings. Not controlling for endogeneity results in a wage return of 2.4 – 3.6 percent, while using instruments the wage return is 4.5 – 5 percent. Based on the instrument quality, validity and relevance criteria, Levin & Plug (1999) concluded that family background variables related to parental education and job level performed the best.

Kalwij (2000) estimated the wage return to education for men in the Netherlands. As the unobserved ability has both an effect on the schooling outcome as well as the earnings of the individuals, the IV approach is adopted to estimate a panel data model with random individual effects. Kalwij (2000) took advantage of the fact that older individuals have relatively less education than younger individuals and also controlled for birth-cohort effects by including the GNP per worker at the time the individual turned 16. With the inclusion of GNP per worker, Kalwij (2000) is able to control for differences in starting wages. Controlling for endogeneity and birth-cohort effects, the wage return to education is around 15 percent. Not controlling for endogeneity leads to a return around 6.9 percent. Also, not controlling for birth-cohort effects leads to a downward bias in the estimated wage return to education.

Plug (2001) estimated the wage return to education in the Netherlands by taking into account endogeneity issues. He used three different instruments. First, the relative age effect as elder children have a developmental advantage over younger children in the same age group. Second, parental education and occupation to exploit differences in social background characteristics. Third, Mammoth's Law (a reform introduced in 1968) to encourage schooling. The results are based on the 1994 wave of the OSA-labourmarket survey. The sample consist of people aged 26 – 57. Controlling for education to be endogenous, the return to education is between 3 and

5 percent for both genders. The relative age effect is present and robust for both males and females, although stronger for females. The relative age effect points to learning effects only and presents higher earnings for individuals born in the autumn compared to those born in the summer (for males and females this effect is 4.7 and 5.8 percent, respectively).

Trostel, Walker, & Woolley (2002) estimated the wage return to education in 28 countries in the period 1985 – 1995 using data from the International Survey Program. The sample consist of employed individuals aged 21 – 59 and excluded students, self-employed and retired workers. The results indicate heterogeneity among the returns across countries. They controlled for the endogeneity of education by either spouse education, father's education or mother's education as instrument. The IV results are 20 percent higher than the OLS results. However, not in all cases the instruments satisfy the necessary conditions. Specific to the Netherlands, the OLS results indicate that for men and women the wage return to education is respectively 3.1 and 1.9 percent. The IV results indicate that for men and women the wage return to education is respectively 4.8 and 5.3 percent (the instrument is based on spouse education).

Harmon, Oosterbeek, & Walker (2003) focused on education as a private investment in human capital and explored the internal rate of return to that private investment. A multivariate (OLS) regression method is used to estimate the wage effect of an additional year of education. Harmon et al. (2003) used results from a pan-EU network of researchers (known as PURE). On the basis of the standard error, the education coefficient of each country is combined to provide a pooled-estimate. The results indicate that on average, the return is around 6.5 percent. Depending on the instrument, the return to education varies between 7 percent (instruments based on family controls) and 14 percent (instruments based on educational reforms). A concern of the use of instruments is that they may only affect a subgroup of the population which has a higher marginal rate of return to education.

Webbink (2007) exploited an institutional reform in 1985 reducing the duration of university education from five to four years. The reform is used to assess the causal impact on wages in 1997. To identify the effect, wages of those enrolled five years before the reform were compared to those enrolled five years after the reform. A difference-in-difference method was applied, where the control group are graduates from higher professional education. Data is obtained from Statistics Netherlands. Due to the fact that Webbink (2007) does not obtain whether a graduate has been assigned to the five- or the four-year program, an alternative approach is adopted. Webbink (2007) either used that younger graduates could only enroll in the four-year program, or used information on the year of graduation. In both cases, a clear discontinuity is found for the university graduates which is not found for the graduates of higher professional education. Three confounding factors are considered: ability bias, a stark increase in the supply of graduates after the reform of 1982, and trends in the return to education. However, none of these factors appeared to be of significant importance. The results suggest that an extra year of university leads to a 7 to 9 percent increase in the wage of the university graduate. Moreover, the wage difference is robust for different specifications and years around the reform.

Strauss & De La Maisonneuve (2009) examined the gross wage premium for tertiary education in 21 OECD countries. The Mincer-equation is based on the level of education and is augmented by a number of labour market-related control variables (e.g. tenure). The countries cover the years 1994 – 2001, but the main focus is the year 2001 due to data availability. The tertiary wage premium is, however, fairly stable over time. The results suggest a tertiary wage premium of 55 percent in 2001. Transformed to a single year, the tertiary wage premium is around 11 percent. However, there is much heterogeneity across countries. Focusing on the Netherlands, the tertiary wage premium is around 42 percent. Despite the rapid increase in tertiary graduates, the wage premium did not fall. Furthermore, the effect of job tenure is positive and significant for the Netherlands. This indicates that the longer an individual works with its current employer, the higher its wage. However, the origin of this increase is unclear (e.g. increasing productivity or mandatory wage increases).

In comparison with the related literature, Hanushek, Schwerdt, Wiederhold, & Woessmann (2015) did not follow the traditional Mincer-framework. Using data of the Program for the International Assessment of Adult Competencies (PIAAC), Hanushek et al. (2015) is able to estimate the wage return to cognitive skills instead of years of education. The PIAAC dataset contains cognitive skills in the following three domains: (i) literacy, (ii) numeracy, and (iii) problem solving in technology-rich environment. They focused on the numeracy skills, which they deem most comparable across countries. However, the results do not depend on the chosen measure of cognitive skills. To obtain the best long-run estimates, only prime-age workers aged 35 – 54 are used. Self-employed workers are excluded. The results indicate that a one-standard-deviation increase in numeracy skills is associated with increased hourly wages averaging around 18 percent across countries. Similar to Trostel et al. (2002), Strauss & De La Maisonneuve (2009) and Hanushek et al. (2015), there is substantial heterogeneity in wage returns across countries. Focusing on the Netherlands, a one-standard-deviation increase in numeracy skills is associated with increased hourly wages of around 18.3 percent. Moreover, Hanushek et al. (2015) tried to control for measurement errors, reverse causality, and omitted variable bias. In general, the results indicate that the obtained OLS estimates are a lower bound for the true causal effect of skills on wages.

Section 2.6: Examining the returns to education during business cycles

Although it is hard to argue how (precisely) the extensive margin has changed during the recent business cycle in the Netherlands, the following papers can give an indication of this change. These research papers discusses the changes in the job loss rate and the job finding rate during the 2008 – 2009 economic crisis. Although the job loss rate can be higher and the job finding rate can be lower during an economic downturn, it remains to be significant even in good times as it is part of an efficient labour allocation process in which firms adjust to structural and technological changes (Farber, 2011; OECD, 2013).

Farber (2011) based its research on the Displaced Worker Survey from 1984 – 2010 to investigate the incidence and consequences of job loss from 1981 – 2009 in the U.S with focus on the year 2010 capturing the job loss in the period 2007 – 2009. The results show the job loss rate is positively related to the unemployment rate. However, the job loss rate was much higher in the recent economic crisis as compared to previous crises. While generally more educated workers are less vulnerable to job loss, their vulnerability appeared to have increased over time. Although job losers are not disproportionately discouraged in the recent economic crisis, their re-employment experience is substantially worse as compared to earlier crises. Overall, the recent economic crisis has been hard on workers in all education groups (Farber, 2011).

The results of the OECD (2013) are (largely) in line with the results of Farber (2011). The results suggest that the job displacement rate for the youngest workers (aged 20 – 24 years) was around 20 – 70 percent higher than for prime-aged workers and this gap increased in most countries during the recent economic crisis. Moreover, workers with less than secondary education are more likely to be displaced than workers with post-secondary qualifications. Also this effect was more pronounced during the recent economic crisis.

Hoynes, Miller, & Schaller (2012) examined the job loss rate and the re-employment rate in the U.S. over the recent economic crisis. They adopted a state panel approach where the effects of the business cycles are identified by variation in the timing and severity of cycles across states (i.e. the regression are adjusted to account for the sensitivity of the business cycles). The results suggest that the economic crisis hit especially hard the youth (aged 16 – 19 years) with a responsiveness twice as high as individuals in their mid-20s. Moreover, the coefficient declines at a more modest rate until individuals in their mid-50s. Overall, the results confirm the simple over-time patterns: men, nonwhites, youth and individuals with lower education are the most responsive to business cycles. Although the Great Recession was deeper than previous recession and especially hit the older workers, for each education category, the recession is otherwise affecting groups more or less similarly. Moreover, workers with a high job tenure were able to reduce their job loss rate, but workers without a job may be hit hardest due to the large drop in the job finding rate.

Motellón & López-Bazo (2015) focused on the Spanish economy which experienced a high influx of immigrants from the mid-90s till the start of the recent economic crisis. Given the significant job losses and the sharp increase in the unemployment rate, they examined whether native and immigrant workers with otherwise similar characteristics showed the same chances of losing their job during the economic crisis. Simple comparisons suggested that immigrants are generally less experienced, lower educated and are predominantly employed in lower-skilled occupations which, overall, tend to make them less productive and therefore more likely to be affected by an economic crisis. However, a more thorough analysis, examining the differences in the probability of job loss between natives and immigrants conditional on the observed endowment of human capital and job characteristics (e.g. occupations, sectors and regions), suggest that these factors account for a large share of the gap in the job loss rate, but for males there remains a large unexplained part. The results of the decomposition suggest that the penalty suffered by male immigrants (either attributable to discrimination or unobservable characteristics) increased during the recent crisis relative to male natives. Overall, the results of Motellón & López-Bazo (2015) suggest that the asymmetric effect of the economic crisis on natives and immigrants caused a widening of the gap for males and a reduction for females.

The general notion is that the recent economic crisis had a severe impact on the job loss rate and the job finding rate in many countries. With some exceptions (e.g. young and old workers), the impact had a similar, although stronger, impact than previous crisis. One can now turn to the intensive margin of work (i.e. the wage return to education) during various business cycles.

Hawley (2004) examined the wage premium to education in 1985, 1995, and 1998 in Thailand. He focused on the relationship between educational attainment and earnings among workers aged 24 to 35. Data is obtained from Thailand's National Labour Force Survey. The average educational attainment increased considerably due to government programs to improve the enrollment in primary and lower secondary education. Between 1985 and 1995, Thailand experienced high growth rates, while between 1995 and 1998 Thailand experienced large negative growth rates. Over the entire period, the average wage return to education (measured by years of education) remained fairly stable. When focusing on educational credentials and gender, the returns widely fluctuate. This is (at least partly) related to the stark increase in the supply of some type of workers. Based on the results, a cautious statement would be that the wage penalty for a low level of education (over lower secondary education) decreased over the entire period (between 1985 – 1995 and 1995 – 1998) for both men and women. For workers with a high level of education the story is somewhat more complicated. For men, with some exceptions, the wage premium decreased over the period 1985 – 1995, but increased again over the period 1995 – 1998. Over the entire period, the wage premium remained stable. For women, the change in the wage premium is mixed over the period 1985 – 1995, but increased in almost all cases over the period 1995 – 1998. Over the entire period, the wage premium increased.

Vilerts, Krasnopjorovs, & Brēķis (2015) examined how the wage return to education changed over the recent economic business cycle in Latvia using EU-SILC micro data over the period 2006 – 2012. The returns are measured by Mincer and wage differential models. In order to reduce the endogeneity, Vilerts et al. (2015) used parental and spouse education as instrument. The models indicate that the wage returns to education moved counter-cyclically (i.e. the return increased significantly during the economic crisis and decreased slightly during the subsequent period of economic recovery) and was particularly strong for males. Moreover, it was evident in a majority of sectors, for all age groups (except for individuals younger than 25), and all regions of the country (especially outside the capital city region). Furthermore, the graphical results seem to indicate that the counter-cyclical return to education is mostly pronounced for higher educated individuals. Vilerts et al. (2015) is able to present robust evidence indicating that higher education in Latvia is associated with higher wages and that the return to education even rose during the economic crisis in 2008 – 2009. Their results also indicate that about half of the impact came via career components (i.e. their educational level provides them with better access to higher paid occupations, sectors and positions).

López Bóo (2010) exploited several exogenous shocks and reforms in Argentina over the period 1992 – 2003 to examine its impact on the earnings-education profile over time. The data is obtained from the Argentina Permanent Household Survey. Four periods can be observed. The first period (1992 – 1995) refers to a period of economic reform with positive growth rates. The second period (1995 – 1998) is the first supply shock and led to a short recession in 1995, but continued positive growth until 1998. The third period (1999 – 2002) is characterized by a crisis in 1999 and a second supply shock in 2001-2002 that led to a downturn of the economy. The fourth and last period (2003) is the start of the economic recovery. López Bóo (2010) focused on the wage premium of educational levels and interacts time and education dummies to capture the time-varying returns to the different levels of education. There are potentially two problems in the estimation: (1) sample selectivity and (2) endogeneity. The first problem is resolved by adopting the Heckman maximum likelihood procedure. For the second problem, López Bóo (2010) resorted to within family observations as they are more likely to have a similar ability and family background as compared to randomly selected individuals. López Bóo (2010) is able to draw four conclusions. First, until the 2001 crisis, the returns to college educated workers were increasing or stable and the returns to less educated workers were decreasing from 1995 onwards. After the 2001 crisis, the wage premium fell faster for the less educated workers than for college graduates. Second, during both shocks (1995 and 2001), the higher the level of education, the lower the impact on the wage level. Third, both shocks had an equal impact across skill levels, but had non-neutral effects across occupations (e.g. the self-employed and informal workers were affected more). Fourth, (i) GDP had a particularly positive effect on college completers as compared to primary completers; (ii) (lagged) unemployment had a negative effect on wages, especially for the less educated, and (iii) after controlling for macroeconomic variables, there remains a downward trend in the wages of all workers.

In contrast to Vilerts et al. (2015) and López Bóo (2010), McGuinness, McGinnity, & O'Connell (2009) focused on the wage return to education in times of economic boom in Ireland. Data is obtained from the Living in Ireland Survey in 1994, 1997, and 2001. Both years of education as well as the level of education are used and the models are estimated separately for men and women. For men, the wage return to education remained stable around 8 percent over the period 1994 – 1997. However, by 2001 it had fallen to 5.6 percent. The decline between 1997 and 2001 related exclusively to a decrease in the incremental returns of intermediate-level qualifications. This is partly explained by the growth in demand for both high- and low-skilled men. For women, the wage return to education dropped substantially over the period 1994 – 2001, namely from 10.5 to 7.5 percent. The results suggest that relative to the base of no qualification, especially women of lower secondary qualification experienced a drop in the wage return to education. The incremental returns also indicated that women with a degree over a post-secondary diploma had fallen considerably. Overall, in the period of economic transition, the relative position of unqualified women improved while the relative position of graduates simultaneously deteriorated. This is likely the result of rising female participation rates. Although the increased demand was relatively skewed towards the more educated, the supply was larger resulting in a lower premium to a university degree.

Doran & Fingleton (2015) examined the resilience of individual wages to the 2008 economic crisis in the U.S. The standard Mincer-equation is used, but with the inclusion of market potential and employment density. The dataset combines individual-level data from the American Community Survey 2005 – 2011 with aggregate-level data for small areas in the U.S. A no-crisis counterfactual wage series and independent variables were created for the year 2011 and is compared to the observed wages in order to examine if wages had been depressed by the crisis to a level below their counterfactual level or whether they proved to be resilient. Although it is not possible to obtain whether the factors affecting the individuals' resilience changed over the business cycle, Doran & Fingleton (2015) do provide a pooled estimate. The results suggest that wages fell relative to the no-crisis counterfactual. However, the extent of the fall depends on individual's characteristics (e.g. age, education, industry and weeks worked), but appears also to be related to the market potential and employment density. Individuals living in areas with a higher level of market potential prove to be more resilient. However, individuals living in areas with higher levels of employment density are less resilient to the 2008 economic crisis.

Based on existing studies, this paper expects to find a strong positive effect of education on wages in the Netherlands. Moreover, during the economic crisis, higher educated individuals are likely to be affected only marginally, while lower educated individuals are affected to a much larger extend. Also, instrumenting education by father's (and mother's) education will likely result in a larger effect of education on wages.

SECTION 3: METHODOLOGY

Section 3.1: Estimating the wage return to education

To examine the wage return to education in the Netherlands, the Mincer model is used. Researchers have extended the standard Mincer framework to include more explanatory variables. In the applied Mincer framework, the log of wages (generally gross hourly wages) is determined by years of schooling, work experience and other explanatory variables.

$$ln\, Y_i = \alpha_0 + \beta_1 S_i + \delta_1 T_i + \delta_2 T_i^2 + \gamma \boldsymbol{X_i'} + \varepsilon_i \quad (2)$$

In this specification, $\ln Y_i$ is the log of (gross hourly) wage of individual i, S_i is the years of (completed) schooling, T_i is the number of years an individual has worked since completing schooling, $\boldsymbol{X_i'}$ is a vector of other explanatory variables, and ε_i is the error term. Due to the fact that work experience is generally not measured, researchers have instead used age to proxy work experience. Also Mincer proposed an alternative measure, namely potential work experience (Card, 1999). Potential work experience is the number of years the individual could have worked and is calculated by taking the age of an individual, subtract the years of (completed) schooling and subtract the school starting age (assumed to be six in Mincer (1974)). Both age and potential work experience will be used in this paper. As stated in the literature review, the main interest is to estimate β_1. The Mincer coefficient represents the wage return to education (i.e. the percentage change in wages for each additional year of education).

The standard Mincer framework assumes that the wage return to each additional year of education is equal and therefore perfectly linear. However, this might not be the case as credentials do have some significance and therefore sheepskin effects can be present. As a result, there may be a wage premium over the average return to education for fulfilling a particular year of education. An alternative is therefore to use a wage differential model which relaxes the assumption of linearity by using the level of education, instead of years of education. The following wage differential model relaxes the linearity assumption by allowing each educational level to have a different impact on wages.

$$ln\, Y_i = \alpha_0 + \beta_1 S_{1i} + \beta_2 S_{2i} + \ldots + \beta_j S_{ji} + \delta_1 T_i + \delta_2 T_i^2 + \gamma \boldsymbol{X_i'} + \varepsilon_i \qquad (3)$$

In this specification, $\ln Y_i$ is again the log of (gross hourly) wage of individual *i*, S_{ji} is a binary variable equal to 1 if the highest level of education for individual *i* is *j*, T_i is the number of years an individual has worked since completing schooling, $\boldsymbol{X_i'}$ is a vector of other explanatory variables, and ε_i is the error term. Regarding the binary variable for the level of education, the wage premium for education level *j* (e.g. university degree), ceteris paribus, reflects the relative differences in wages for people with a university degree to people in the reference group (e.g. no education).

However, in semi-logarithmic regressions, where the dependent variable is in logs and the independent variable is a (zero-one) dummy variable, the interpretation of the coefficient is not similar to the interpretation of a continuous or discrete variable (see for example Strauss & De La Maisonneuve (2009) and Vilerts et al. (2015)). Both continuous and discrete variables can be changed in very small increments (e.g. the variable years of schooling) and therefore result in a small coefficient in the regression (Strauss & De La Maisonneuve, 2009). It is namely the case that $\ln(1 + x) \approx x$ only if x is small, which is the case for continuous and discrete variables. However, this is not the case for a binary variable, indicating whether a certain educational attainment is completed. As the change from 0 to 1 represents a major step, the coefficient in the regression is generally also much larger. The larger the coefficient, the further away the approximation will be from the exact effect. In order to calculate the wage premium for education level j relative to the reference group correctly, the following formula is used:

$$\text{Wage premium of educational level } j = (e^{\beta_j} - 1) * 100 \qquad (4)$$

There are in principle two ways to examine whether the wage return to education has changed during the recent economic crisis. The first way is to estimate the return separately for each single year over the recent economic business cycle and examine whether this has significantly changed. As a result, the (previous) equations do not contain a time subscript. The second way is to pool the data and include year dummies. However, the year dummies would not only be related to the wage return to education. Therefore, the year dummies need to be interacted with the education variable(s). In this case, the interaction term captures the education-and-time variant effect (López Bóo, 2010). An alternative to the interaction of year dummies and the education variable(s) is to use the unemployment rate or GDP growth rate instead of year dummies. These type of variables also capture the severity (e.g. cycle) of the economic crisis. Both approaches are applied to examine the wage return to education during the recent economic crisis in the Netherlands.

However, an important notion should be made. The Mincer-equation and the wage differential model allow the inclusion of additional explanatory variables, these additional explanatory variables can be both exogenous as well as endogenous to education. If all additional explanatory variables are exogenous to education (e.g. gender), the interpretation of the education coefficient remains the same. However, if (some or all of) the additional explanatory variables are endogenous to education (e.g. employment type, sector and occupation), the education coefficient may get smaller as it reflects the direct impact of education on wages (i.e. for people working in the same employment type, occupation and sector). The difference between these two coefficients is the indirect effect of education on the wage level (i.e. the career components). Better education not only increases the wage level, but also promotes employment in higher paid employment types, occupations and sectors (Vilerts et al., 2015).

As any other research method, the estimated wage return to education may be biased and prevent the researchers from estimating the true causal wage return to education. These are generally related to the (i) measurement error bias and the (ii) endogeneity bias.

The measurement error bias can be the result of many issues. Researchers are generally not able to accurately measure the years of education. For example, individuals might not precisely recall their years of schooling or had to redo a year of schooling due to poor results. Generally, this problem can be argued to be limited when using the level of education instead of years of education. However, some problems of the measurement error may still remain. More specifically, education is truncated. Individuals with a low level of education are more likely to overstate it, while individuals with a high level of education are more likely to understate it (Card, 1999, 2001; Vilerts et al., 2015). Therefore, the observed variance in years or level of education may be smaller than in reality. This will result in a downward bias (towards zero) of the wage return to education (Angrist & Krueger, 2001; Hanushek et al., 2015; Harmon et al., 2003; Leigh & Ryan, 2008; Trostel et al., 2002).

The endogeneity bias is generally the result of omitted variables (causing the error term to be correlated with the explanatory variables (Doran & Fingleton, 2015)) or sample selection (only the most able individuals work and are therefore part of the sample). Generally, the endogeneity bias arises as the ability of the individual is unavailable or not observed and therefore excluded from the estimation model. If individuals with a higher ability choose to obtain a higher level of education, and if ability also influences the wage of the individual, the wage return to education will be biased (Doran & Fingleton, 2015; Harmon et al., 2003; Leigh & Ryan, 2008; Levin & Plug, 1999; E. J. S. Plug, 2001; Strauss & De La Maisonneuve, 2009; Trostel et al., 2002; Vilerts et al., 2015). It is, however, not possible to implement a Fixed Effects (or first difference) approach that captures all time invariant characteristics of the individuals (including ability) as the level of education generally does not change once it is obtained. Therefore, the ability bias remains. It is beforehand not definite whether the ability bias (or more generally the endogeneity bias) causes the wage return to education to be biased upwards or downwards. It may be biased upwards when high-ability individuals choose to obtain more education as they find it easier to undertake education or they may choose to obtain more education to signal their skills to potential employers. On the other hand, it may be biased downwards when low-ability individuals compensate by completing more education or take more education due to compulsory schooling laws (Leigh & Ryan, 2008). Moreover, it is not clear whether the ability bias fluctuates with business cycles. It may be that individuals start to undertake more education (instead of entering the labour market) in times of an economic crisis due to a poor labour market conditions. However, if this is the case, it may also be that both low- as well as high-ability individuals will undertake more education.

The endogeneity bias may also arise due to differences in the wage return to education among individuals (i.e. endogeneity by heterogeneity). As individuals with a higher wage return to education, choose to undertake more education, the error term of the Mincer-equation or the wage differential model is correlated with the years or level of education (Vilerts et al., 2015).

Section 3.2: Dealing with the endogeneity bias

Researchers have discussed various approaches to solve (or at least strongly reduce) the endogeneity bias. The most commonly discussed approaches are (i) explicit measures that proxy for the unobserved ability (e.g. individuals' test scores before starting formal education), (ii) estimates based on either directly controlling for family background or using family background as an instrument for education (e.g. parental education), and (iii) via natural experiments[3]. Within natural experiments, there are three commonly used experiments: (a) twin studies (fixed-effects estimator on a sample of identical twins) or sometimes also sibling studies, (b) instrumental variables based on institutional features of the school system (e.g. to instrument schooling by using month/quarter of birth as it has a discontinuous effect on schooling in the presence of compulsory schooling laws; or discontinuities in class size), and (c) instrument schooling using changes in compulsory schooling laws. Other, less common, approaches are also discussed by Leigh & Ryan (2008) and Angrist & Krueger (2001).

Due to the fact that the data does not allow to conduct a natural experiment neither does allow the inclusion of the individuals' test scores, the only alternative is to instrument the individuals' level of education by parental education (as the level of education of siblings is not available).

The used instrument must be both relevant and valid to deal successfully with the endogeneity bias. For the instrument to be relevant, the instrument should be correlated with the endogenous explanatory variable (i.e. the instrument should be strong). For the instrument to be valid (i.e. exogenous), the instrument should be uncorrelated with the error term and should only affect the dependent variable via the endogenous variable (Z must only affect Y via X). Generally, it is hard to find an instrument that satisfies both conditions at the same time. Moreover, whereas the relevance condition can easily be tested, the validity of the instrument cannot be tested. However, if the instrument used is both relevant and valid, the obtained coefficient is the true causal effect of the explanatory variable on the dependent variable.

Focusing on parental education, researchers generally agree that the first condition is satisfied (i.e. parental education is strongly correlated with the respondent's level of education), however, the second condition is discussed intensively (Hoogerheide, Block, & Thurik, 2012).

[3] These approaches are most extensively discussed by Angrist & Krueger (2001), Ashenfelter, Harmon, & Oosterbeek (1999), Card (1999, 2001), Harmon et al. (2003) and Leigh & Ryan (2008).

This is (partly) related to the discussion of nature vs. nurture. Parental ability is an important factor in explaining the educational attainment of children and, according to Plug & Vijverberg (2003), the largest part of ability relevant for education is inherited (i.e. via nature). However, some argue that the validity condition is not satisfied as parental education can have a direct effect on the respondent's income level. It can be argued that parental education is correlated with the household income and wealth. Moreover, it can also be argued that parents with a higher level of education may use their professional relations to help or steer their children into better paid jobs. Overall, parental education may have a direct influence on the respondent's income level and this may violate the validity condition.

However, the study of Hoogerheide, Block, & Thurik (2012) analyzes to what degree the violation of the validity condition in the case of parental education affect the IV results. Their research shows that, relative to the case of perfect validity of the instrument's exclusion restriction, the results do not deviate much when there is a moderate direct effect of the instrument on the dependent variable. Although a sizeable direct effect of parental education on the respondent's level of income leads to a change in the coefficient of the IV model, a violation of the strict validity condition does not necessarily lead to results which are strongly different from the strict validity case. Therefore, depending on the required precision of the estimated wage return to education and the strength of the assumed indirect effect, the use of parental education for the respondent's level of education is a very much viable option. Moreover, according to Hoogerheide et al. (2012), the bias from using parental education as instrument is comparable to the problems generated by alternative instrumentation strategies (e.g. educational reforms) which are rarely available. Therefore, Hoogerheide et al. (2012) states the criticism of using parental education as instrument is not justified.

Overall, various tests are conducted to assess the validity and relevance of the instrument(s) used. These tests are based on the paper of Baum, Schaffer, & Stillman (2010). The results of the tests can be obtained in Table A. 16 and Table A. 17 in the appendix. Both the standard F-test and the Sanderson-Windmeijer F-statistic are used to test for weak identification of each single endogenous regressor. The Sanderson-Windmeijer chi-square test is used to test for underidentification of a single endogenous regressor. The Kleibergen-Paap rk LM statistic is used to test for the underidentification of any of the endogenous regressors. If any of the endogenous regressor is unidentified, the null hypothesis will not be rejected. The Anderson-Rubin Wald test and the Stock-Wright LM S statistic are robust to the presence of weak instruments and test the null hypothesis that the coefficients of the endogenous regressors in the structural equation are jointly equal to zero, and, in addition, that the overidentifying restrictions are valid. The Hansen J statistic for overidentification tests the joint null hypothesis that the instruments are valid. Also the endogeneity of education is tested.

Section 3.3: (Potential) sample selectivity

Sample selectivity can arise due to two (separate) issues. The first is related to the propensity to work (i.e. non-employment or non-participation in the labour force) and the second is related to the propensity to reveal their wage (i.e. non-response).

Starting with non-employment, individuals who do not participate in the labour force, can never report their wage. This may bias the marginal effect of education on earnings especially if the probability of having a paid job depends on the educational attainment of the individual. It may be that individuals with a higher earnings potential are more likely to choose to be employed and participate in the labour market or that lower educated individuals may choose not to work as the wage offered by employers is below the wage for which they are willing to work (i.e. their reservation wage). Moreover, it may also be the case that individuals (especially lower educated individuals) cannot find work or got laid off due to the economic crisis. As a result, sample selectivity due to non-employment may bias the estimated wage return to education either upward or downward if the sample is non-random.

Conditional on having a job, some individuals do not want to reveal their wage to the interviewer. This non-response does not bias the marginal effect of education on earnings if the sample of individuals who do not reveal their wage is random. Both individuals with a high- and low-wage may be equally unwilling to reveal their wage to the interviewer. Although one can imagine that especially individuals with a high wage are less likely to report their wage, individuals with a low wage may also do some undeclared work which they would like to hide. However, if the non-response is non-random, there can be (some) sample selectivity which may bias the results either upward or downward. The estimated wage return to education is namely based on the sub-sample of individuals who have revealed their wage to the interviewer.

Both issues can be reduced by adopting the Heckman selection correction approach (Fersterer & Winter-Ebmer, 2003; Hanushek et al., 2015; Harmon et al., 2003; López Bóo, 2010). In the this approach, the first-stage estimates the selection model (i.e. the non-response or the non-employment sample selectivity) and the second-stage estimates the wage equation (i.e. the response equation). The dependent variable in the selection model is a binary variable either indicating whether the individuals has a job or whether the individual reported their wage level to the interviewer. The identification is based on variables that have a strong impact in the selection equation, but could be credibly excluded from the wage equation (Harmon et al., 2003). The estimated selection term (i.e. the inverse Mills ratio) is then included in the wage equation. As a result, the estimated wage return to education is corrected for sample selectivity. Although it is also possible to run the selection model without identifying variables, the selection model will in this case be solely based on the nonlinearity of the functional form which arises due to the assumption of normality in the selection equation (Motellón & López-Bazo, 2015). It is, however, doubtful whether this assumption holds as the sole source of identification. Therefore, all selection models are based on at least one identifying variable.

Moreover, in light of the possible endogeneity issues and this specific research topic, the Heckman procedure may also be helpful. As the endogenous mechanism in the Human Capital Theory of Becker (1964) states that individuals choose their level of education to maximize their net present value of income over their life span, a short period of economic instability (i.e. an economic crisis) may impact the return to education, however, it is not likely to directly affect the individuals' investment in education. Accordingly, the degree of labour market tightness may vary between higher- and lower-skilled occupations during the different phases of the economic crisis and can thus affect the estimated return to education. However, due to the fact that the probability of having a job (especially for lower educated individuals) drops during an economic crisis, certain individuals may selectively withdraw from the labour force. As a result, the endogenous mechanism may actually affect the estimated wage return to education as unemployed individuals are not part of the sample.

SECTION 4: DATA

Section 4.1: The LISS-dataset

To estimate the wage return to education in the Netherlands, this paper uses data of the LISS (Longitudinal Internet Studies for the Social sciences) panel administered by CentERdata (Tilburg University, The Netherlands). The LISS-dataset covers the years 2008 – 2015 and consists of 5000 households, comprising 8000 individuals. The LISS-dataset is a representative sample of Dutch individuals who participate in monthly Internet surveys. The panel is based on a true probability sample of households drawn from the population register. A longitudinal survey (i.e. the LISS Core Study) is conducted yearly, covering a large variety of domains (e.g. work, education, income and housing). The LISS Core Study used in this paper focused on the respondent's labour market participation, job characteristics and schooling. This particular core study is conducted yearly in April. Non-respondents are contacted again in May (only in 2008 the non-respondents were contacted in July). The core study can be combined with the respondent’s background information, including the respondent’s wage (if reported to the interviewer). Due to the non-response and natural transitions of individuals (some individuals drop out, while others are added), the LISS-dataset is unbalanced. As a result, not every individual in the LISS-dataset is present in each wave. Moreover, as the level of education generally does not change for individuals over time, the dataset is best characterized by a repeated cross-sectional set-up with (a large group of) overlapping individuals.

Given the years covered by the LISS-dataset and the fact that the economic crisis hit the Netherlands in September 2008, this paper is able to examine the effect of the entire business cycle on the wage return to education in the Netherlands during the economic crisis. Moreover, as the LISS-dataset surveys are still conducted on a yearly basis, this research paper can be updated with new information in the future.

Section 4.2: The baseline sample

The baseline sample focuses on men, aged 30 – 55, who work at least 32 hours a week. By focusing on this specific sample, this paper is able to obtain a homogenous group of workers who have a strong commitment to stay in the labour force. Whereas women tend to withdraw from the labour force if the employment possibilities are limited or due to personal circumstances (e.g. bearing or raising children), men tend to be the breadwinner of the household and (try to) remain active in the labour market. This can be especially important as the economic crisis may affect the withdrawal from the labour force. Overall, the baseline sample only focuses on individuals who conduct paid employment. Wage earners who are not conducting paid employment (e.g. self-employed) are excluded from the sample. Moreover, observations with missing education levels, wages and hours of work per week are excluded.

It is informative to know how many observations drop out of the sample due to each selection criteria. The combined sample, for all years, includes a total of 48,769 observations. The number of (unique) individuals in the combined sample is 12,332. In other words, each individuals is, on average, observed four times over the period 2008 – 2015. By only focusing on individuals who are conducting paid employment, a total of 22,663 observations are left. Focusing on males, 11,049 observations remain. By focusing on the prime-age male workers (aged 30 – 55 years) a total of 7,687 observations are left. Given that the sample preferably only includes individuals who are strongly attached to the labour market, the sample only includes individuals who work at least 32 hours per week according to their employment contract. Also, individuals who did not report their weekly working hours are excluded. This leaves the sample with 7,171 observations. By focusing on individuals who have a strong commitment to the labour force, this condition reduces the total number of observations only little. However, of the remaining sample, 26.5 percent does not want to inform the interviewer about their wage. This non-response is explored further in the Heckman approach. Overall, 5,268 male workers between the age of 30 – 55 who are conducting paid employment for at least 32 hours per week, are left. However, of this sample, four individuals did not report their level of education. This reduces the total number of observations by eight. Therefore, the final sample consists of 5,260 observations (a total of 1,592 (unique) individuals), which is around 700 observations per year.

Section 4.3: Variables of interest

In the analysis, the dependent variable is the log of gross hourly wage (*log_hw*). Individuals who report their wage to the interviewer, only report their gross monthly wage. Therefore, gross hourly wage is calculated by taking into account the number of working hours per week according to their employment contract. The main interest will be the gross hourly wage instead of the gross monthly wage as monthly wages also capture the individuals' decision on the number of working hours per week (Strauss & De La Maisonneuve, 2009). If education increases the number of working hours per week and employment prospects, the impact of education on monthly wages will exceed its impact on hourly wages (Vilerts et al., 2015). However, given that the correlation between working hours and educational attainment is very weak (less than 5 percent), it is reasonable to assume that the individuals' decision on the number of working hours per week reflects their individual preferences rather than their educational level. As a robustness check, the log of gross monthly wages will be used (*log_brutoink*). If the number of workings hours per week according to the individuals' employment contract is incorrectly measured or provided, the use of the calculated gross hourly wage introduces measurement errors. Moreover, as hourly workers are less common in the Netherlands, the gross monthly wage may be preferred (Deelen & Verbeek, 2015). Furthermore, both the gross hourly wage as well as the gross monthly wage are corrected for inflation on the basis of the Consumer Price Index (CPI) in which 2015 is set as the base year. Also, to avoid potential heteroscedasticity, robust standard errors are used. Moreover, the robust standard errors are clustered around the individuals' identification number to relax the independence assumption as most individuals in the dataset appear more than once.

The main variable of interest is education. Given the LISS-dataset, this paper is able to distinguish between various levels of education. However, only the level of education is observed (*oplcat*), not the years of education. Therefore, the wage differential model is preferred over the Mincer-equation. However, by transforming the level of education into years of education, the variable years of education can also be examined (*yrseduc*). It should be noted that, for individuals who did not finish their level of education, the transformed years of education will be underestimated. An abstract of the Dutch education system can be obtained in Figure A. 1 and Table A. 1 in the appendix.

Another potentially important variable is work experience. Unfortunately, work experience is not directly observable in the LISS-dataset. Therefore, the potential work experience, proposed by Mincer (1974), will be used. In order to calculate the potential work experience, the (transformed) years of education and the school starting age (assumed to be six) are subtracted from the age of the individual (*exp*). However, as a robustness check, age is used (*age*).

Furthermore, the wage of the worker might also be influenced by tenure. Generally, individuals who work longer with their current employer have obtained various financial benefits over time (e.g. wage increases). It is therefore interesting to examine whether tenure has an effect on the wage of the worker. The variable *tenure* indicates how many months the worker is working for its current employer at the time of the survey. Moreover, workers who started working with their current employer before the start of the economic crisis may had a stronger bargaining position as compared to workers who started working during the economic crisis. As a result, for identical workers, the wage offer may be higher for workers who started working before the economic crisis. Therefore a dummy variable (*tenure_crisis*) is created. This variable uses September 2008 (i.e. the fall of the Lehman Brothers) as the cutoff point between the workers who started working before or during the economic crisis. Although also other cutoff points are possible (e.g. January 2008), September 2008 characterizes a strong hit to the financial system. There is no cutoff point to characterize the end of the economic crisis as the economic crisis of 2008 – 2009 may still impact the economy nowadays. Moreover, a cutoff point to indicate the end of the economic crisis is very much debatable. Therefore, all individuals who started working in September 2008 or later are argued to started working during the economic crisis.

Furthermore, some models will also include various control variables. The first few variables are related to the work of the individual. Whether the worker is employed in a private or public/semi-public organization (*public*). The (log of the) number of workers at the respondent's employment location (*firmsize*). Whether the respondent supervises other workers in their occupation or position (*management*). The workers type of employment (*employment*). In what type of sector the worker is employed at the one-digit level (*sector*). What the current occupation is of the worker (*occupation*). Furthermore, there are also four variables focusing on the respondent's personal situation. These variables are the civil status of the respondent (*burgstat*), the urban character of the place of residence (*sted*), the number of household members (*aantalhh*) and the number of living-at-home children in the household (either from the household head or his/her partner) (*aantalki*). More details and the summary statistics of these variables can be found at the end of this section.

The baseline sample will also be estimated using the instrumental variable approach and the Heckman procedure discussed in Section 3. In the instrumental variable approach, the regression will be identical with the exception that the respondents' years of education will be treated as an endogenous variable which is instrumented by the father's years of education. Although the years of education is also instrumented by both father's and mother's years of education, this is not the main focus as, at that time, women followed less education and were expected to stay at home to take care of the children. As a result, the mother's years of education is much lower than the father's years of education. The main summary statistics can be obtained in Table 1. As the parental education questionnaire is not part of the Core Study, but the Life History Questionnaire (an assembled study), not all individuals in the sample are questioned. Moreover, the questionnaire was conducted in 2012 and non-respondents were contacted again in 2013. However, given the baseline sample, parental education is not likely to change and is therefore applied to all sample years. In the Heckman procedure, the sample selectivity will be accounted for by estimating the selection equation. The inverse Mills ratio's will be included in the wage equation to account for the sample selectivity (of either non-response or non-employment). The selection equations are based on the explanatory variables in the wage equation as well as the civil status of the respondent (*burgstat*), the urban character of place of residence (*sted*) as well as the number of household members (*aantalhh*). If focused on the non-respondents, it can be obtained that there is a significant difference in their civil status (e.g. fewer non- respondents have never been married), few live in extremely urban areas and many live in not urban areas, they also have significantly more household members. If focused on the individuals who are not employed, there is again a significant difference in their civil status (e.g. fewer have been married and more individuals are either divorced or have never been married), many live in extremely urban areas and few live in moderately or slightly urban areas, they also have significantly fewer household members. Moreover, apart from the civil status of the individuals, the urban character of place of residence and the number of household members explains little to none in the wage equation. This confirms the believe that these factors may be more important in the selection equation than in the wage equation.

Section 4.4: The extended sample

Moreover, besides the baseline sample, two different extended samples are used to estimate the wage return to education in the Netherlands during the recent economic crisis. The two extended samples are mainly intended for robustness checks, but also to generalize the results to a larger group of working individuals. The first extended sample includes men and women, who are conducting paid employment, aged 20 – 65, who work at least 32 hours per week. The sample includes a total of 10,549 observations of which there are 3,236 (unique) individuals. Around 65 percent of the individuals in the sample are males. However, the regression is run separately for men and women. The second extended sample is based on the same conditions, with the exception of the weekly working hours constraint. In the second extended sample, the individuals should work at least 12 hours per week. In this case a dummy variable is included for part time workers (i.e. between 12 – 31 hours per week). The sample includes a total of 14,598 observations of which there are 4,316 (unique) individuals. Given the inclusion of part-time workers, the percentage of male workers has decreased to around 51 percent. Also this regression is run separately for men and women. Moreover, where applicable, the extended samples will also be estimated using the instrumental variable approach (to account for the endogenous level of education) and the Heckman procedure (to account for sample selectivity).

Section 4.5: Summary statistics

The maximum number of observations is 5,260 and is based on 1,592 unique individuals. The gross monthly wage is around € 3,700 which is around € 22.50 per hour. As the baseline sample is based on male individuals aged 30 – 55 years, the average age is around 43 years with an average potential work experience of 23.5 years. Around 17 percent of the observations started working during the economic crisis (i.e. September 2008 or later). Furthermore, tenure is high, but becomes lower when younger workers would be included. However, the summary statistics are not implausible[4].

[4] The individual with the maximum tenure was 55 years in 2015, started working in July 1967 and was therefore around 7 years when he started working. Although the working age is very low and unlikely nowadays, only in 1969 a new compulsory schooling system was introduced together with a supervisory body to enforce it. Moreover, prior to 1969 many schooling exceptions were granted. Therefore, the working age is possible. However, more importantly, the exclusion of this individual does not significantly affect the mean and standard definition neither

Table 1: Summary statistics of variables

Variable	# Obs.	Mean	Std. Dev.	Min	Max
Gross monthly wage	5260	3719.95	3474.85	410.43	223751
Gross hourly wage	5260	22.42	20.97	2.63	1358.82
Years of education	5260	13.57	2.29	6	16
Age	5260	43.05	7.27	30	55
Experience	5260	23.48	7.86	8	43
Tenure (in months)	5226	141.68	114.00	0	573
Tenure crisis	5260	0.17	0.38	0	1
Public organization (dummy)	5238	0.29	0.45	0	1
Firm size	4750	436.17	1236.26	0	20000
Management job (dummy)	5186	0.43	0.49	0	1
Number of members in household	5260	3.02	1.39	1	8
Number of children in household	5260	1.20	1.16	0	6
Level of education (categorical)					
Primary school	5260	0.03	0.17	0	1
Vmbo (intermediate secondary education)	5260	0.15	0.36	0	1
Havo/vwo (higher secondary education/preparatory university education)	5260	0.08	0.27	0	1
Mbo (intermediate vocational education)	5260	0.31	0.46	0	1
Hbo (higher vocational education)	5260	0.31	0.46	0	1
Wo (university)	5260	0.13	0.33	0	1
Civil status (categorical)					
Married	5260	0.62	0.48	0	1
Separated	5260	0.00	0.06	0	1
Divorced	5260	0.08	0.27	0	1
Widow or widower	5260	0.00	0.06	0	1
Never been married	5260	0.29	0.45	0	1

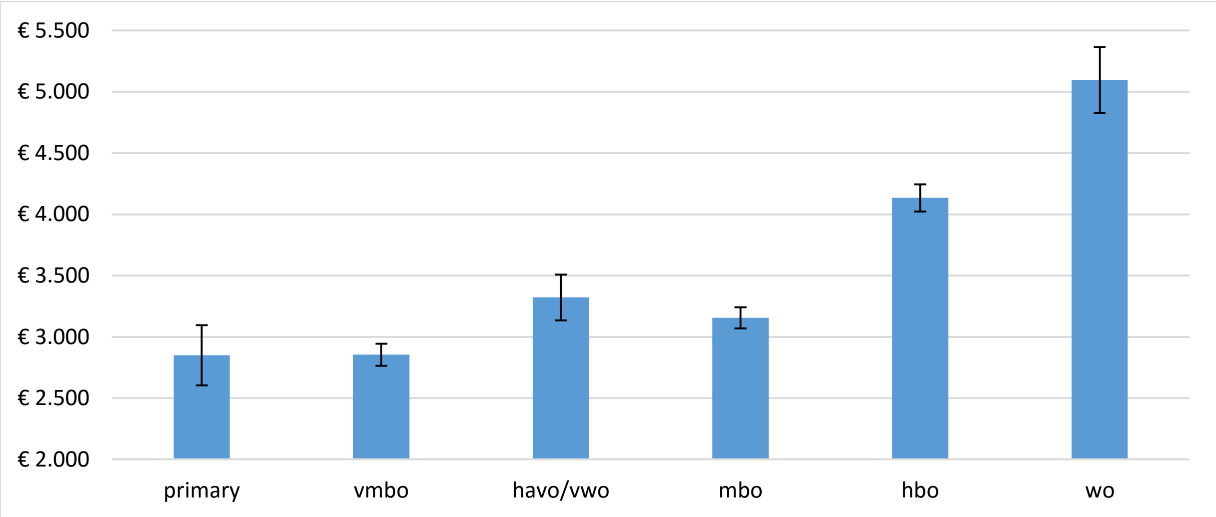
Note: all other control variables (urban character of place of residence, type of employment, sector and occupation) and instrumental variables (e.g. father's and mother's years of education) can be obtained in Table A. 3 and Table A. 4 in the appendix. Moreover, the categorical variables are transformed into dummy variables and are included in the summary statistics.

the coefficients of the regression models (only the third or fourth decimal is affected slightly). Moreover, if this individual is removed, the next highest tenure individual was 55 years in 2011, started working in August 1971 and was therefore around 15 years when he started working. This corresponds to the compulsory schooling system during that time and there is no valid reason to remove this individual from the dataset. Furthermore, dropping the top 15 percent tenure observations (which is very high) still results in a high average tenure (i.e. around 9 years). Therefore, all individuals are kept in the dataset, although the average tenure can be argued to be (relatively) high.

Section 4.6: Data description

This subsection will present and discuss some preliminary results based on the raw data of the baseline sample to answer the research question. It should be noted that the smallest and largest three gross monthly wage observations are removed from the presented figures as they affect some means and confidence intervals disproportionately. However, in the results section, these observations do not significantly affect the results and are therefore not excluded. The same figures, without the exclusion of these observations, can be obtained in the appendix.

Figure 1: Gross monthly wage by educational category



Source: Author's calculations based on the LISS-dataset
Note: the mean and its 90 percent confidence interval of the gross monthly wage are presented for each educational level. The smallest and largest three observations are excluded as they have a disproportionate effect on the mean and 90 percent confidence interval of the gross monthly wage. However, in Figure A. 2 in the appendix, the same figure can be obtained without the exclusion of these six observations.

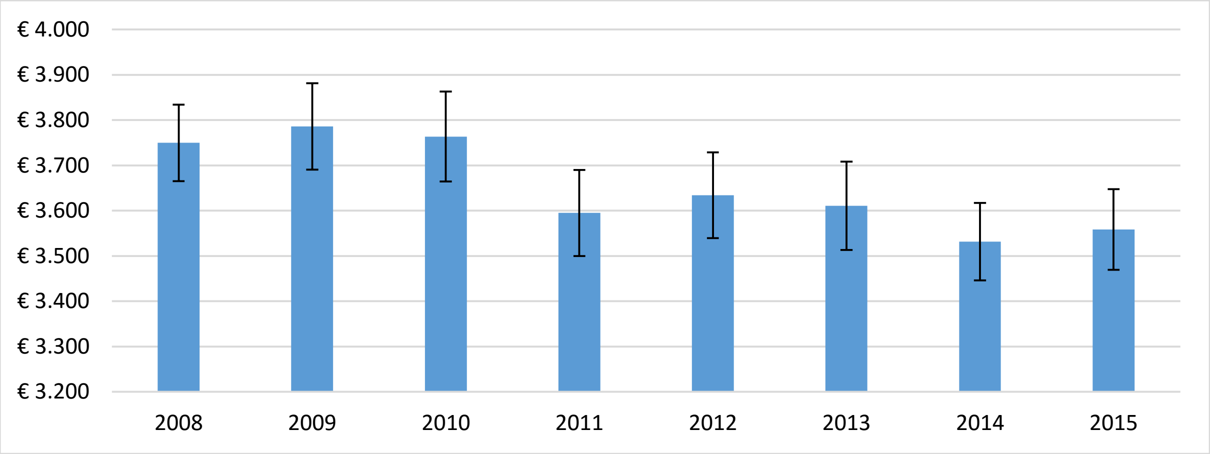
Given the baseline sample, Figure 1 is almost identical when the gross monthly wage is replaced by the gross hourly wage. However, for interpretability, the gross monthly wage is presented. It can be obtained that the gross monthly wage generally rises for every increase in the educational level. However, the differences are larger, the higher the educational level. On average, individuals completing secondary schooling (i.e. vmbo or havo/vwo) have a significantly higher wage than individuals who only completed primary schooling. However, this is not the case if one only completes intermediate secondary education (i.e. vmbo). Also moving from intermediate secondary education (i.e. vmbo) to intermediate vocational education (i.e. mbo) increases wages significantly. Moving from higher secondary education or preparatory university education (i.e. havo/vwo) to higher vocational education (i.e. hbo) or university education (i.e. wo) increases wages the most steeply, with university education averaging the highest gross monthly wage. Given the research question, it can be obtained that, in general, individuals with a higher level of education have a higher gross monthly wage.

In Figure 2a, it can be obtained that the gross monthly wage of individuals in the baseline sample was not directly affected by the economic crisis. This is typical for the labour market as it generally has a delayed response. It can be obtained that the most severe wage decrease was from 2010 to 2011. The wage observed in 2011 is significantly below the wage observed in 2009 which corresponds to a delayed labour market response of around two years. After 2011, the wage seems to remain stable or even slightly increase (although not significantly). However, in 2014, another wage decrease is observed. Although the wage observed in 2014 is not significantly different from its prior years (i.e. 2011 – 2013), it is significantly below the wage observed in the years 2008 – 2010. Despite the slight wage increase in 2015, the wage in 2015 is still significantly below the wage observed in 2008 – 2010. Moreover, as some individuals drop out of the baseline sample (and sometimes resurface again), it may also be the case that the results are affected by the non-response and/or non-employment of certain groups of individuals. The exclusion of these individuals may lead to sample selectivity. This will be examined later using the Heckman procedure.

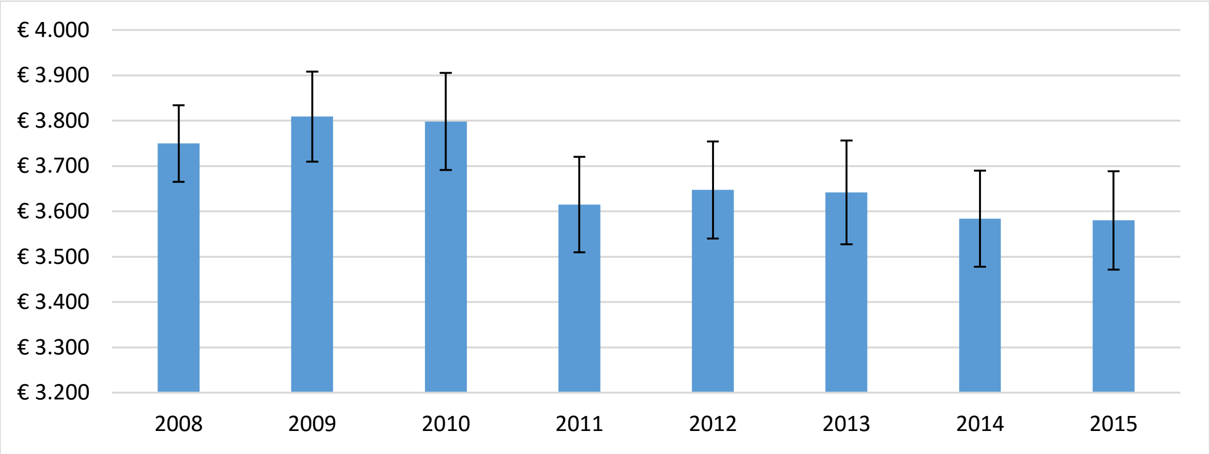
In Figure 2b and Figure 2c, the same figure is presented. However, in this case the individuals are separated by the period in which they entered employment with their current employer. A comparison of Figure 2a and Figure 2b suggest that individuals who started working prior to the economic crisis have a slightly more stable wage pattern than when all individuals are included. Although there remains a large drop in the observed wage from 2010 to 2011, it is no longer significantly. Furthermore, the wage decrease from 2013 to 2014 is weakened. However, the wage observed in 2014 and 2015 remains significantly below the wage observed in the years 2009 and 2010. A comparison of Figure 2a-b to Figure 2c does not provide additional insights as Figure 2c is based on relatively few individuals. As a result, the confidence interval becomes too large to draw conclusions. However, a simple comparison of the average wage indicates that, for all years, the wages of the workers who started working during the economic crisis are always lower than the wages of workers who started working before the economic crisis. Moreover, as expected, there is no shock observed in Figure 2c indicating the start of the economic crisis as all workers are hired after the start of the economic crisis. However, these workers seemed to gain some momentum when companies believed economic conditions were improving, but again experience a sharp decrease in their wage when this did not appear to be the case. Furthermore, between Figure 2b and Figure 2c there may be some confounding factors accounting for their wage differences (e.g. the differences in age, tenure period and potential work experience of these two groups of workers).

Figure 2: Gross monthly wage per year

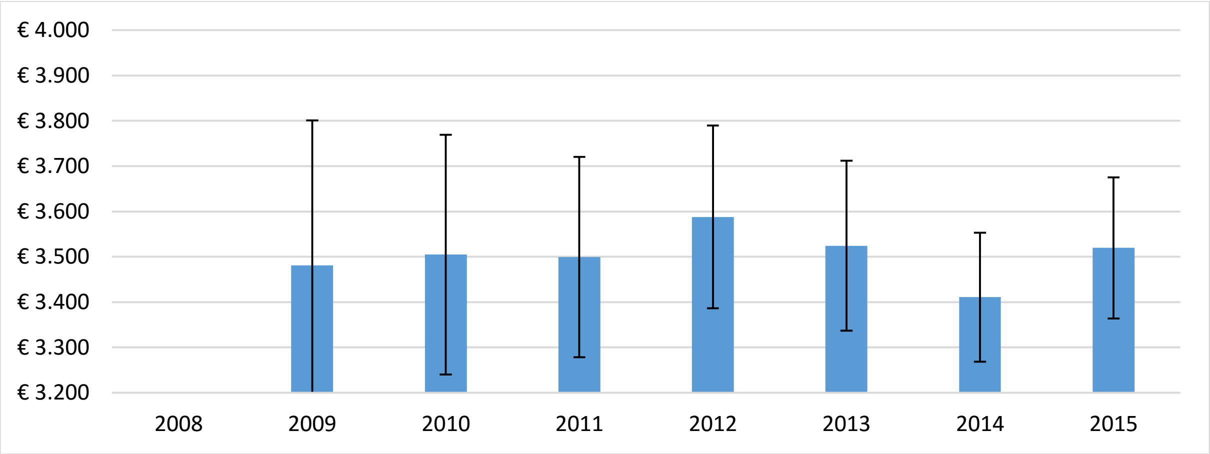
(a) For all individuals



(b) For all individuals who started working before September 2008



(c) For all individuals who started working September 2008 or later



Source: Author's calculations based on the LISS-dataset

Note: the mean and its 90 percent confidence interval of the gross monthly wage are presented for each year. The smallest and largest three observations are excluded as they have a disproportionate effect on the mean and the 90 percent confidence interval of the gross monthly wage. Figure 2a is based on 5,254 observations, Figure 2b is based on 4,337 observations and Figure 2c is based on 917 observations. In Figure A. 3 in the appendix, the same figures can be obtained without the exclusion of these six observations.

SECTION 5: RESULTS

Section 5.1: The baseline results

In this section, the baseline sample will be used to estimate the pooled Mincer-equation and consequently the pooled wage differential model. In both cases, the (log of) gross hourly wage is used as the dependent variable. Moreover, the robustness of both the Mincer and the wage differential model are examined by (i) using the (log of) gross monthly wage as the dependent variable and (ii) by replacing the potential work experience variable.

Section 5.1.1: The pooled Mincer model

The pooled Mincer results are generally applied in literature to examine the wage return to education. The Mincer results for the baseline sample are presented in Table 2. It can be obtained that all constructed models include year dummies. The inclusion of year dummies allows the various models to attribute some of the variation in the data to unobserved events that took place during each year. The first model includes the years of education, potential work experience and the squared potential work experience. This standard Mincer coefficient is most comparable with the related literature given its simplicity. The other models also include various other explanatory variables.

In Table 2 several Mincer models are estimated. The pooled Mincer results suggest that each additional year of education is associated with higher wages of around 7.2 – 8.4 percent during the sample period 2008 – 2015 in the Netherlands. These returns are comparable to the literature examining the wage return to education using a form of cross-sectional data.

Moreover, as for example stated by Vilerts et al. (2015), there is also an indirect impact of education on wages (i.e. career components). More education not only directly affects the wage of the worker, it also promotes the employment in higher paid sectors, occupations and employment type. The inclusion of these (endogenous) variables generally leads to a somewhat lower Mincer coefficient as can be obtained in model five and six of Table 2. The results reveal that about a half of the impact of education on wages in the Netherlands is based on career components. The other half reflects the direct effect of education on wages. An additional year of education increases the gross hourly wage on average by 3.5 percent for employees having the same employment type and working in the same sector and occupation. The inclusion of career components is best compared to Vilerts et al. (2015). Vilerts et al. (2015) also indicated that around half of the impact of education on wages is due to career components while the other half is due to the direct effect of education on wages. Moreover, also the point estimate of the direct effect is very similar (3.8 instead of 3.5 percent observed in this paper). Therefore, the pooled Mincer results are comparable to the related literature.

Focusing shortly on the other explanatory variables. Also these results are largely in line with the related literature. Experience is an important factor in explaining the wages of the workers. Also, both the size of the firm and having a position that supervises other employees has a positive impact on wages. Moreover, corresponding to the literature, married workers (and widowers) earn more than workers who have never been married.

Table 2: The Mincer models

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.084***	0.073***	0.072***	0.072***	0.038***	0.035***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Experience	0.018***	0.016***	0.015***	0.014**	0.021***	0.020***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Experience squared	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		-0.000		-0.000		
		(0.000)		(0.000)		
Public		0.004		0.005		
		(0.018)		(0.018)		
(Log of) firm size		0.036***	0.038***	0.038***		0.024***
		(0.004)	(0.004)	(0.004)		(0.004)
Management		0.155***	0.158***	0.153***		0.060***
		(0.016)	(0.016)	(0.016)		(0.015)
Civil status – married			0.051***	0.050***		0.036**
			(0.019)	(0.019)		(0.016)
Civil status – separated			-0.027	-0.041		-0.048
			(0.113)	(0.116)		(0.107)
Civil status – divorced			-0.010	-0.008		-0.011
			(0.037)	(0.037)		(0.031)
Civil status – widow(er)			0.218**	0.224**		0.245**
			(0.108)	(0.106)		(0.101)
Employment type					Included	Included
Sector					Included	Included
Occupation					Included	Included
Constant	1.550***	1.496***	1.501***	1.508***	2.431***	2.345***
	(0.092)	(0.091)	(0.090)	(0.091)	(0.096)	(0.097)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	5260	4700	4746	4700	5190	4746
R^2	0.253	0.327	0.336	0.333	0.513	0.530
adj. R^2	0.252	0.325	0.333	0.330	0.509	0.526

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The extended version (including employment type, sector and occupation) can be obtained in Table A. 5 in the appendix.

Section 5.1.2: The pooled wage differential model

Also the wage differential model is frequently applied in the literature. However, given that the available educational levels differ for each dataset, the results of the wage differential models are less comparable to the literature than the results of the Mincer models. Moreover, researchers use different reference categories for education. For the simplicity in interpretation, this paper will use primary education as the reference category. In this case, every higher educational level should (in principle) increase the wage premium.

Although the results presented in Table 3 indicate that the wage premium for intermediate secondary education (i.e. vmbo) is not significantly different from primary education, this is more likely to be the result of a relatively low number of observations for individuals who only completed primary education. This may result in an insignificant difference between primary and intermediate secondary education as the power to indicate the significant effect is too low (although this is mostly not the case when focusing on business cycle models). Due to the relatively low number of observations for individuals who only completed primary education, the intermediate secondary education may start to act as the reference category. This is, however, not troublesome as the main interest is in the comparison between lower, middle and higher educated individuals during the recent business cycle in the Netherlands. Furthermore, the results for higher vocational education (i.e. hbo) and university education (i.e. wo) are particularly strong. Regarding the higher vocational education, the wage premium is around 60 – 70 percent. Focusing on university education, the results are even stronger and suggests a wage premium of around 90 – 110 percent. Although not directly comparable, the wage premium obtained in the literature (e.g. Strauss & De La Maisonneuve (2009) and Vilerts et al. (2015)) are fairly similar to the results presented in Table 3.

Although there are some minor exceptions, the results of the wage differential models are fairly similar to the Mincer models. Potential work experience, firm size, supervising other employees and being married (or a widower) has a positive effect on the gross hourly wage of the worker. Moreover, in the wage differential models can also be obtained that workers in the (semi-)public sector have a significantly lower wage than workers working in the private sector.

Furthermore, also in the wage differential models, the career components are important (i.e. the indirect effect of education on wages). The results indicate that for each higher level of education, the fraction of education on wages attributed to career components gets smaller. To illustrate, the direct effect of education on wages is around 40 – 45 percent for individuals who completed havo/vwo, while it is around 52 – 60 percent for individuals who completed university education. This suggests that a higher level of education does not particularly promotes employment in higher paid sectors, occupations and employment type, but rather indicates larger direct benefits of education on wages.

Table 3: The wage differential models

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Educational level - vmbo	0.064	0.054	0.051	0.046	0.026	0.013
	(0.057)	(0.060)	(0.058)	(0.059)	(0.040)	(0.043)
Educational level – havo/vwo	0.265***	0.248***	0.249***	0.246***	0.112***	0.109**
	(0.062)	(0.064)	(0.061)	(0.062)	(0.042)	(0.045)
Educational level – mbo	0.228***	0.185***	0.182***	0.174***	0.100**	0.081*
	(0.058)	(0.060)	(0.057)	(0.059)	(0.039)	(0.042)
Educational level – hbo	0.527***	0.472***	0.465***	0.462***	0.280***	0.256***
	(0.058)	(0.060)	(0.057)	(0.059)	(0.042)	(0.045)
Educational level – wo	0.758***	0.669***	0.652***	0.655***	0.438***	0.393***
	(0.061)	(0.064)	(0.061)	(0.063)	(0.046)	(0.048)
Experience	0.036***	0.033***	0.030***	0.030***	0.031***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Experience squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		-0.000		-0.000		
		(0.000)		(0.000)		
Public		-0.035**		-0.035**		
		(0.017)		(0.017)		
(Log of) firm size		0.026***	0.027***	0.028***		0.020***
		(0.004)	(0.004)	(0.004)		(0.004)
Management		0.145***	0.152***	0.143***		0.059***
		(0.015)	(0.015)	(0.015)		(0.015)
Civil status – married			0.062***	0.059***		0.039**
			(0.018)	(0.018)		(0.015)
Civil status – separated			-0.018	-0.009		-0.026
			(0.115)	(0.120)		(0.117)
Civil status – divorced			0.020	0.021		-0.003
			(0.034)	(0.035)		(0.030)
Civil status – widow(er)			0.214**	0.209**		0.231***
			(0.093)	(0.095)		(0.088)
Employment type					Included	Included
Sector					Included	Included
Occupation					Included	Included
Constant	2.145***	2.049***	2.056***	2.056***	2.603***	2.524***
	(0.074)	(0.079)	(0.076)	(0.078)	(0.080)	(0.083)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	5260	4700	4746	4700	5190	4746
R^2	0.373	0.429	0.434	0.435	0.549	0.562
adj. R^2	0.372	0.426	0.432	0.432	0.545	0.558

Notes: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The extended version (including employment type, sector and occupation) can be obtained in Table A. 6 in the appendix.

Section 5.1.3: Robustness check

Section 5.1.3.1: Alternative dependent variable

As a first robustness check, the gross hourly wage is replaced by the gross monthly wage. Relative to the gross monthly wage, the gross hourly wage may have introduced some measurement errors by correcting it for the number of workings hours per week according to their employment contract. Therefore, the dependent variable in both the Mincer and wage differential models are replaced by the gross monthly wage. All other variables are identical.

In Table 4 the pooled Mincer coefficients and wage premia of the different educational levels are presented where the dependent variable is the gross monthly wage. It can be obtained that both the Mincer coefficients as well as the wage premia for each educational level are very similar to the case where the dependent variable is the gross hourly wage. In the case of the Mincer coefficients, the results are almost identical. Therefore, both the Mincer coefficients as well as the wage premium for each educational level are not sensitive to a change in the dependent variable from gross hourly to gross monthly wage. This also suggest that the transformation of gross hourly to gross monthly wage does not lead to measurement errors.

Table 4: The Mincer and wage differential model based on the gross monthly wage

Mincer model	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.082^{***}	0.073^{***}	0.071^{***}	0.072^{***}	0.038^{***}	0.035^{***}
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	5260	4700	4746	4700	5190	4746
R^2	0.239	0.314	0.322	0.32	0.506	0.522
adj. R^2	0.237	0.312	0.319	0.317	0.503	0.517
Wage differential model	(1)	(2)	(3)	(4)	(5)	(6)
vmbo	0.088	0.083	0.08	0.076	0.047	0.04
	(0.060)	(0.062)	(0.059)	(0.061)	(0.041)	(0.043)
havo/vwo	0.263^{***}	0.258^{***}	0.255^{***}	0.256^{***}	0.111^{**}	0.113^{**}
	(0.066)	(0.066)	(0.063)	(0.065)	(0.043)	(0.046)
mbo	0.241^{***}	0.206^{***}	0.199^{***}	0.195^{***}	0.111^{***}	0.097^{**}
	(0.061)	(0.062)	(0.059)	(0.061)	(0.040)	(0.042)
hbo	0.529^{***}	0.490^{***}	0.474^{***}	0.480^{***}	0.290^{***}	0.270^{***}
	(0.061)	(0.061)	(0.059)	(0.061)	(0.043)	(0.045)
wo	0.761^{***}	0.692^{***}	0.664^{***}	0.678^{***}	0.443^{***}	0.405^{***}
	(0.065)	(0.066)	(0.063)	(0.065)	(0.047)	(0.049)
N	5260	4700	4746	4700	5190	4746
R^2	0.35	0.413	0.415	0.419	0.541	0.553
adj. R^2	0.348	0.411	0.412	0.417	0.537	0.548

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The presented models are identical to the Mincer and wage differential models presented in Table 2 and Table 3, respectively. However, the dependent variable is the gross monthly wage and only the effect of education on the gross monthly wage is presented.

Section 5.1.3.2: Alternative experience variable

Similar to other studies examining the wage return to education (e.g. Vilerts et al. (2015) and López Bóo (2010)), this paper will also replace the experience variable by alternative experience variables. However, as there is no information on actual work experience, there are only few alternatives available. This section will replace potential work experience by age, tenure and leaving the experience variable out of the model. Given the interest in the wage return to years of education and the wage premium for each educational level, only the effect of education on wages is presented in Table 5 and Table 6. However, one important notion should be made. Potential work experience is constructed by subtracting the years of education by age as well as a constant. Therefore, the potential work experience variable is mechanically similar to the case where only age and years of education is included. There is only a rescaling of the point estimate obtained by the different models and should not differ much (Harmon, Oosterbeek, & Walker, 2000). Although this approach is performed often, it cannot be argued to be a strong robustness check. Furthermore, as tenure is highly correlated with potential work experience and age (more than 50 percent), tenure is also used to replace the potential work experience variable. Also, the experience variable is excluded from the analysis as there may be some ambiguity whether experience is a likely wage determinant in some countries (see Vilerts et al. (2015)). It should also be noted that for all experience variables included in the analysis, also the quadratic term is included to capture the concavity of the wage profile. However, only the education coefficients are presented.

Table 5: Different experience variables in the Mincer models

Dep Var: (Log of) gross hourly wage	Model 1	Model 2	Model 3	Model 4
Potential work experience	0.084 (0.004)	0.071 (0.004)	0.038 (0.004)	0.035 (0.004)
Age	0.07*** (0.004)	0.06** (0.004)	0.028** (0.004)	0.026*** (0.004)
Tenure	0.068*** (0.004)	0.058*** (0.004)	0.025*** (0.004)	0.023*** (0.004)
None	0.064*** (0.004)	0.055*** (0.004)	0.022*** (0.004)	0.021*** (0.004)

Note: robust clustered standard errors in parentheses. A *, ** or *** indicate that the variable is, respectively, outside the 90, 95 or 99 percent confidence interval of the baseline result where potential work experience is the experience variable. All coefficients and standard errors are for the variable years of education. Model 1 is based on years of education, experience and experience squared. Model 2, 3 and 4 include an additional set of explanatory variables. Model 2 includes a variable for a public organization, firm size, management and civil status. Model 3 includes career components (i.e. type of employment, sector and occupation). Model 4 includes all variables and therefore combines models 2 and 3. All models include year dummies. Each row is based on a different experience variable.

Based on Table 5, it can be obtained that all alternative Mincer coefficients are significantly different from the Mincer coefficients where potential work experience is used. When age is used as the experience variable, this may be related to the rescaling of the point estimates. More weight is given to age and less weight is given to education. This may suggest that the rescaling attributes to little power to education. The significant difference in using tenure and no experience variable is as expected. Tenure is seldom used as the sole source of experience and therefore likely to influence the education variable. Moreover, experience is relevant in the Dutch labour market and should therefore not be removed from the model.

Table 6: Different experience variables in the wage differential models

Dep Var: (Log of) gross hourly wage	Level of education	Model 1	Model 2	Model 3	Model 4
Potential work experience	vmbo	*0.064*	*0.048*	*0.026*	*0.013*
	havo/vwo	0.265	0.247	0.112	0.109
	mbo	0.228	0.180	0.100	0.081
	hbo	0.527	0.466	0.280	0.256
	wo	0.758	0.655	0.438	0.393
Age	vmbo	*0.034*	*0.023*	*0.006*	*-0.004*
	havo/vwo	0.216	0.206	0.077	0.080
	mbo	0.149	0.114	*0.042*	*0.030*
	hbo	0.433	0.386	0.209*	0.194
	wo	0.645*	0.560	0.351*	0.317
Tenure	vmbo	*0.033*	*0.021*	*0.004*	*-0.005*
	havo/vwo	0.206	0.200	*0.065*	*0.072*
	mbo	0.136	0.102	*0.029**	*0.018*
	hbo	0.425*	0.377	0.188**	0.175*
	wo	0.630**	0.543*	0.321**	0.291**
None	vmbo	*0.025*	*0.018*	*-0.004*	*-0.013*
	havo/vwo	0.178	0.184	*0.041**	*0.054*
	mbo	0.117*	*0.090*	*0.012*	*0.004**
	hbo	0.394**	0.356*	0.158***	0.153**
	wo	0.585***	0.506**	0.281***	0.257***

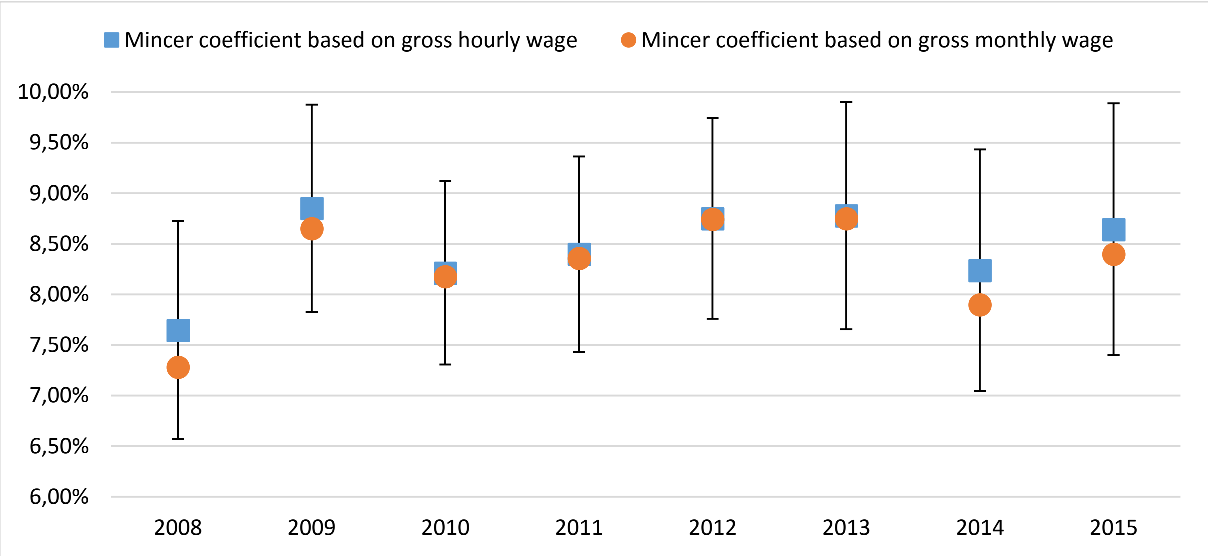
Note: all models are based on the robust clustered standard errors (not displayed). A *, ** or *** indicate that the variable is, respectively, outside the 90, 95 or 99 percent confidence interval of the baseline result where potential work experience is used. All coefficients are for the variable level of education. Moreover, an italic coefficient indicates an insignificant effect on the gross hourly wage. Model 1 is based on the level of education, experience and experience squared. Model 2, 3 and 4 include an additional variables. Model 2 includes a variable for a public organization, firm size, management and civil status. Model 3 includes career components (i.e. type of employment, sector and occupation). Model 4 combines models 2 and 3. All models include year dummies. Each row is based on a different experience variable.

Focusing on Table 6, the use of age as the experience variable generally does not lead to a significantly different wage premium compared to the use of potential work experience. This suggests that in the wage differential models, the rescaling of the point estimates has little impact. However, also in the wage differential models, tenure and no experience are mostly significantly different from the use of potential work experience. Similar reasons as in the Mincer model apply. Overall, it can be obtained that opting for potential work experience, which is most common in the literature if no actual work experience is available, seems to result in the largest education coefficients. All other experience variables therefore seem to understate the wage return to education.

Section 5.2: The wage return to education during the recent economic crisis

The pooled Mincer and wage differential model have shown to correspond with the related literature. However, the pooled models are not able to indicate whether the wage return to education has changed during the recent business cycle in the Netherlands. Moreover, if the wage return to education has indeed change, it is also not able to indicate the direction of this change. Therefore, the yearly Mincer and wage differential model are graphically presented below. The estimates where the dependent variable is replaced by the gross monthly wage are also presented. Given that the estimates do not differ significantly, also the yearly Mincer and wage differential models are robust to the use of both gross hourly and gross monthly wage.

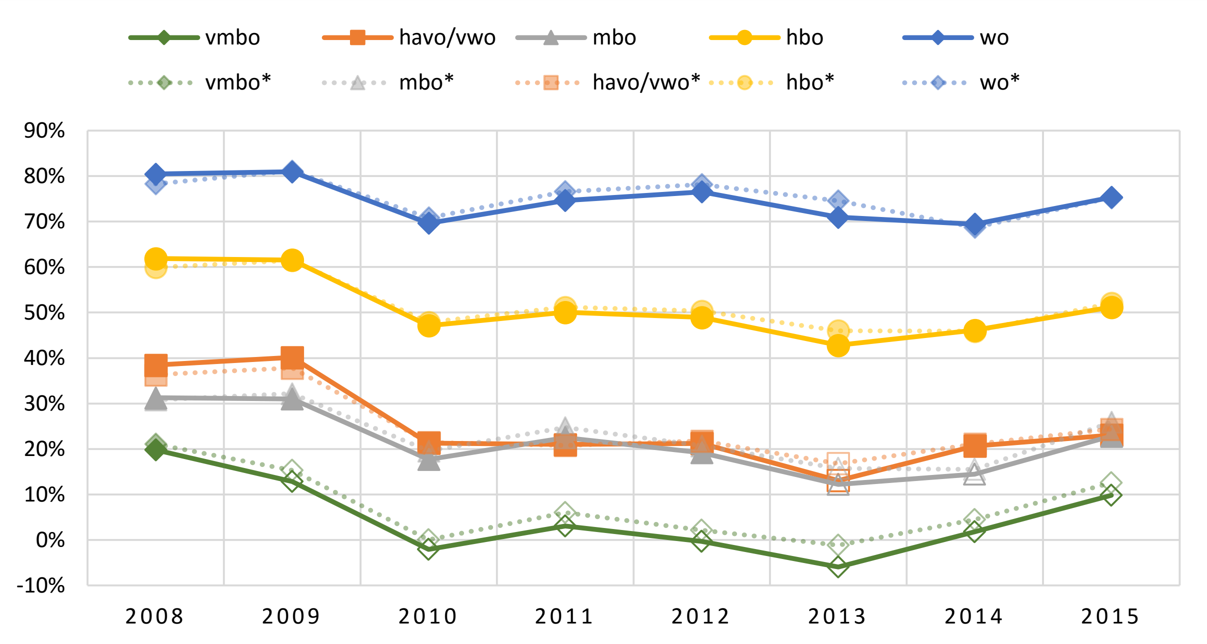
Figure 3: The Mincer coefficient over time



Source: Author's calculations based on the LISS-dataset
Note: Each dot represents a separate estimation where the dependent variable is the (log of) gross hourly wage, years of education is the variable of interest (displayed) and the control variables are potential work experience and the squared potential work experience. Moreover, the 90 percent confidence interval are based on the robust clustered standard errors. A filled marker indicates a significant coefficient at the 10 percent level. The Mincer coefficients when the gross monthly wage are included for comparison. The yearly number of observations over 2008 to 2015 are respectively, 885; 701; 678; 548; 635; 583; 647; 583.

Figure 3 presents the yearly Mincer coefficients and the 90 percent confidence interval over the business cycle in the Netherlands. None of the Mincer coefficients are significantly different from one another. As can be obtained from Figure 3, a large jump in the Mincer coefficient can be observed from 2008 to 2009 while a drop is observed from 2009 to 2010. This may be related to the fact that in 2009, the Netherlands was hit hardest by the economic crisis and GDP declined by roughly 3.8 percent (CBS, 2016). Furthermore, from 2011 to 2013 onwards the wage return to education has increased again, although not significantly. As in 2011, concerns about the necessary debt restructuring came to light, the economic crisis intensified (Milne & Oakley, 2011). In 2014, the Netherlands showed some signs of recovery as the unemployment rate started to decline and the GDP growth rate increased (FD, 2015b). However, a clear interpretation cannot be given as the yearly Mincer coefficients are not significantly different.

Figure 4: The wage premium of education over time

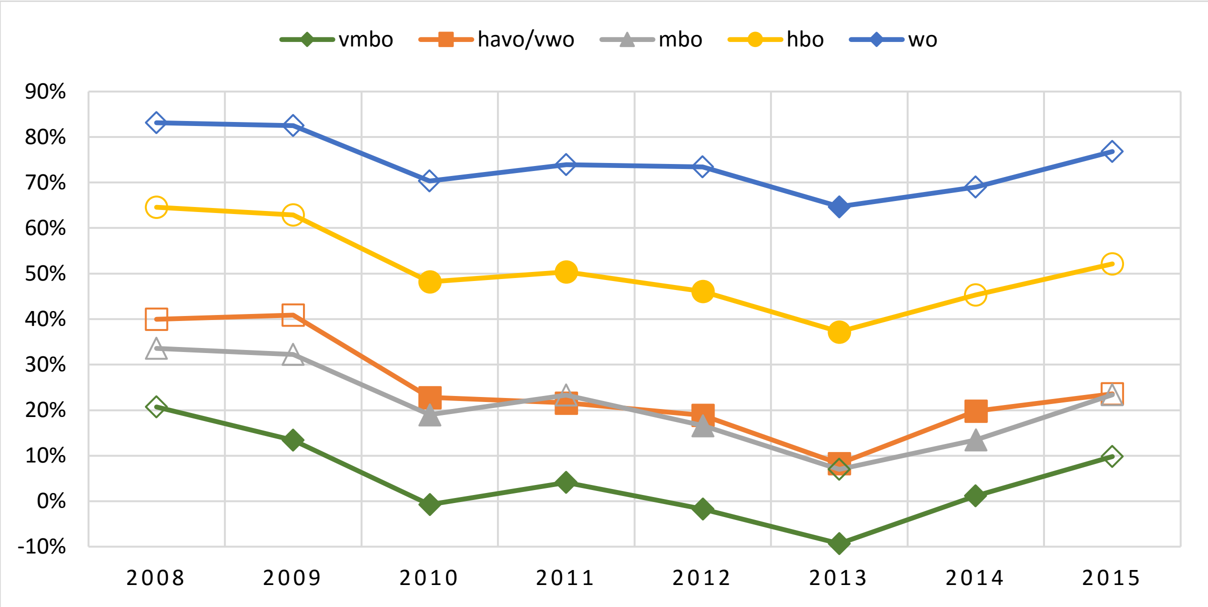


Source: Author's calculations based on the LISS-dataset
Note: Each dot represents a separate estimation where the dependent variable is the (log of) gross hourly wage, the level of education is the variable of interest (displayed) and the control variables are potential work experience and the squared potential work experience. The estimations are all based on the robust clustered standard errors. A filled marker indicates a significant coefficient at the 10 percent level. The reference category is primary education. The wage premium of each educational level based on the gross monthly wage is included and denoted by an asterisk (*) in the legend. The yearly number of observations over 2008 to 2015 are respectively, 885; 701; 678; 548; 635; 583; 647; 583.

Figure 4 illustrates the wage premium of each educational level, relative to primary education. Based on this figure, it can be obtained that the wage premium fluctuates more when the level of education is lower. Therefore, during the sample period, the wage premium of university education has been the most stable whereas the wage premium of workers who only completed secondary schooling (i.e. vmbo or havo/vwo) has been the most volatile. Compared to Figure 3, a similar, although more flat, pattern is observed. A clear drop is obtained in the year 2010 and 2013, while the period between these two drops is characterized by a stable or slightly increasing wage premium for each educational level.

In order to examine how the wage return to education has changed precisely over the recent economic crisis, the wage premium of the various educational levels are interacted with year dummies. The focus is on the level of education, not the years of education, as it is able to provide more detailed information on the wage return to education during the economic crisis. Figure 5 is constructed based on the model where the level of education, year dummies, the interaction between these two, potential work experience and the squared potential work experience are included. As can be obtained from Figure 5, the results suggest there is a significant drop in the wage premium of all educational levels in both 2010 as well as 2013 (except wo in 2010). The period between 2010 and 2013 is characterized by a stable or slightly increasing wage premium. However, the wage premium in the period between 2010 and 2013 is still significantly below the reference year 2008.

Figure 5: Wage premium interacted with year dummies



Source: Author's calculations based on the LISS-dataset
Note: The dots are based on the interaction model where the dependent variable is the (log of) gross hourly wage and the independent variables are the level of education, year dummies, the interaction between these two, potential work experience and the squared potential work experience. The estimation is based on the robust clustered standard errors. A filled marker indicates that both the wage premium as well as its interaction term with the year of interest is significant. The reference category is primary education and the reference year is 2008.

Focusing on the interaction results presented in Table A. 7 in the appendix, the same models as in the Section 5.1 are estimated, but all educational levels are interacted with year dummies. Based on the interaction models, it can be obtained that the main conclusions are similar to the results presented in Figure 5. However, one difference can be observed. It is namely the case that in the other models in Table A. 7 (models two – six) in the appendix, the significant negative interaction term is generally limited to the years 2010 and 2013 (in some instances also 2014). This suggest that the wage premium of the educational levels in 2011 and 2012 are not significantly below the wage premium observed in the reference year 2008. Given that the labour market generally responds one to two years later, the significant drop in the wage premium in 2010 seems to result directly from the start of the economic crisis, whereas the significant drop in the wage premium in 2013 seems to be the result of increasing tensions due to concerns about the necessary debt restructuring or deteriorating economic circumstances.

It can be obtained that all individuals suffered a decrease in their wage premium, however, in general the drop in the wage premium is lower the higher the level of education. In other words, especially the lower educated individuals suffer significantly during the economic crisis, whereas the higher educated individuals suffered only marginally.

The educational levels are also interacted with the unemployment rate in the Netherlands. Three approaches are used. In the first approach, no correction is made for the potentially delayed responsiveness of the labour market. In the second and third approach, a one and two year correction is made (i.e. the unemployment rate is leading one and two years, respectively). In other words, the unemployment rate observed in the Netherlands in, for example 2012, is placed in the year 2011 or 2010, respectively. The results are presented in Table A. 8 to Table A. 10 in the appendix. Also these results indicate that higher educated individuals suffer less than lower or middle educated individuals. Moreover, when the unemployment rate is leading one or two years, the wage premium of the individuals with university education does not respond significantly to an increase in the unemployment rate.

It is also possible to interact the educational levels with the GDP growth rate in the Netherlands. However, in this case, an opposite correction is made for the potentially delayed responsiveness of the labour market. A steep increase or decrease in the GDP growth will not directly affect the labour market, it is likely that it takes one year to affect the labour market. In other words, the GDP growth rate is lagged one year so that the observed GDP growth in the Netherlands in, for example 2012, is placed in the year 2013. The results are presented in Table A. 11 in the appendix. The results show that when the GDP growth is lagging one year, all interaction terms are significant. In all cases, a decrease in the GDP growth rate has a negative effect on the gross hourly wage of workers. More specifically, the lower educated an individual, the more they suffer from an decrease in the GDP growth rate. The opposite also applies, lower educated benefit more from an increase in the GDP growth rate than higher educated individuals.

It is difficult to make strong comparisons with other research papers focusing on the wage return to education during business cycles as countries generally have a (completely) different labour market which makes drawing comparisons especially difficult. A comparison can be made with respect to López Bóo (2010), who examined various supply shocks and crises in Argentina, but also examined the effect of GDP and the unemployment rate. Their results suggest that during both shocks in 1995 and 2001, the impact on the wage level was lower for higher educated individuals. After the 2001 crisis, the wage premium fell faster for the less educated workers than for college graduates. Moreover, their results suggested that GDP had a particularly positive effect on college completers as compared to primary completers and the unemployment rate had, especially for less educated individuals, a negative effect on wages. Compared to this papers, a similar effect is found for the year dummies and the unemployment rate, but an opposite effect is found for the GDP growth rate. On the other hand, Vilerts et al. (2015) showed that during the economic crisis the wage return to education increased significantly, especially for higher educated individuals, and decreased slightly during the subsequent period of economic recovery. The counter-cyclical result does not seem to be present in the Netherlands.

Section 5.3: The effect of tenure during the recent economic crisis

Aside from the interest in the wage return to education over the recent economic crisis, this paper is also interested in examining the effect of tenure during this period. As stated earlier, workers who started working with their current employer before the economic crisis may had a stronger bargaining position as compared to workers who started working during the economic crisis. As the recent economic crisis may have impacted the workers relative bargaining position, it is interesting to examine this in detail. Therefore, the tenure dummy indicating whether the worker started working before or during the economic crisis is interacted with the years of education.

Table 7: Interaction of the tenure dummy and years of education

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.081***	0.070***	0.070***	0.069***	0.036***	0.033***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Tenure dummy	-0.257	-0.314**	-0.286**	-0.293**	-0.192	-0.235**
	(0.174)	(0.132)	(0.131)	(0.131)	(0.118)	(0.105)
Tenure dummy # years of education	0.018	0.022**	0.020**	0.020**	0.014	0.017**
	(0.013)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)
N	5260	4725	4746	4725	5190	4746
R^2	0.255	0.329	0.337	0.335	0.514	0.531
adj. R^2	0.253	0.327	0.335	0.332	0.510	0.527

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
With some exceptions, all six models are identical to Table 2. The exceptions are that the models in Table 7 additionally include the tenure dummy and the interaction term of the tenure dummy and years of education. Also, it does not include the continuous tenure variable.

The Mincer models in Table 7 indicate that workers who started working during the economic crisis (i.e. September 2008 or later) have a significantly lower wage, of around 30 percent, compared to workers who started working before the economic crisis. This is, however, based on the assumption that the years of education is zero, which is never the case as all respondents completed primary education (i.e. 6 years of education). Therefore, given the minimum and maximum years of education, workers who started working during the economic crisis have a 18 percent lower wage when they only completed primary education and potentially a 4 percent higher wage when they completed university education. More specifically, the turning point of the overall effect is at somewhat more than 14 years depending on the chosen Mincer model.

Therefore, the results seem to suggest that individuals who completed higher vocational education (i.e. hbo) and university education (i.e. wo) were not affected, or maybe even positively affected, by the change in the relative bargaining position. On the other hand, workers who completed less than higher vocational education (i.e. hbo) were affected negatively and this effect is stronger for individuals with fewer years of education. Moreover, the results in Table 7 also indicate that workers who started working during the economic crisis have a slightly higher wage return to education of around 2 percent. This may be related to the fact that the shock of the economic crisis created a sort of selection process in which the most unproductive and inefficient workers were removed from the labour force (or in other words: only the most productive and efficient workers remained in the labour force). As a result, for the remaining workers in the labour force, the wage return to education is slightly higher.

Both results are, however, not significant when the same approach is applied to the wage differential model. This is most likely the result of too few individuals who started working during the economic crisis. If these individuals are separated by their educational level (instead of combined in the years of education variable), the effect is reduced too much to be significant.

One can also examine whether these results changed during the business cycle by interacting the tenure dummy, years of education and year dummies. However, as can be obtained in Table 8 none of the results remain significant. This may suggest that the analysis asks too much of the available data. Moreover, when examining the (insignificant) results in Table 8, the coefficients are generally not very different over the business cycle. This suggests that the impact of the economic crisis on the relative bargaining position was a one-time abrupt decrease in the relative bargaining position of workers who started working during the economic crisis. The results do not suggest that workers who started working during the (early) recovery of the economic crisis (i.e. the year 2014) suffered significantly less from the decrease in the relative bargaining position relative to workers who started working shortly after the start of the economic crisis. This may change when future years (if economically more prosperous) are included in the sample. Moreover, also in this case, when the same approach is applied to the wage differential model, the results are not significant and therefore not presented.

Table 8: Interaction of the tenure dummy, years of education and year dummies

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.079***	0.066***	0.067***	0.065***	0.034***	0.030***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Year 2009 # years of education	0.008	0.009*	0.007	0.008	0.008*	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year 2010 # years of education	-0.001	0.000	-0.001	-0.000	-0.002	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Year 2011 # years of education	0.002	0.005	0.005	0.005	0.004	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Year 2012 # years of education	0.003	0.003	0.003	0.003	0.002	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Year 2013 # years of education	-0.001	0.003	0.002	0.003	0.000	0.001
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Year 2014 # years of education	0.001	0.007	0.006	0.007	0.003	0.005
	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Year 2015 # years of education	0.006	0.007	0.006	0.007	-0.000	0.000
	(0.009)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Tenure dummy	-0.143	-0.272	-0.246	-0.248	-0.169	-0.222
	(0.229)	(0.228)	(0.223)	(0.222)	(0.176)	(0.189)
Tenure dummy # years of education	0.011	0.020	0.019	0.019	0.013	0.017
	(0.016)	(0.016)	(0.016)	(0.016)	(0.013)	(0.013)
Year 2009 # tenure dummy	-0.147	-0.035	-0.080	-0.075	-0.117	-0.010
	(0.386)	(0.359)	(0.353)	(0.353)	(0.294)	(0.309)
Year 2010 # tenure dummy	-0.252	0.043	0.038	0.030	-0.244	-0.176
	(0.247)	(0.313)	(0.311)	(0.310)	(0.216)	(0.259)
Year 2011 # tenure dummy	-0.021	0.141	0.149	0.134	0.061	0.138
	(0.255)	(0.308)	(0.307)	(0.305)	(0.201)	(0.235)
Year 2012 # tenure dummy	-0.117	-0.133	-0.115	-0.126	-0.035	-0.081
	(0.260)	(0.277)	(0.274)	(0.273)	(0.183)	(0.221)
Year 2013 # tenure dummy	-0.212	-0.179	-0.158	-0.158	-0.016	0.029
	(0.244)	(0.276)	(0.271)	(0.270)	(0.188)	(0.229)
Year 2014 # tenure dummy	-0.071	-0.057	-0.063	-0.063	0.063	-0.019
	(0.254)	(0.280)	(0.274)	(0.272)	(0.197)	(0.220)
Year 2009 # tenure dummy # years	0.006	-0.002	0.001	0.001	0.006	-0.001
of education	(0.027)	(0.025)	(0.025)	(0.025)	(0.021)	(0.022)
Year 2010 # tenure dummy # years	0.017	-0.003	-0.003	-0.002	0.016	0.013
of education	(0.018)	(0.022)	(0.022)	(0.022)	(0.016)	(0.018)
Year 2011 # tenure dummy # years	0.002	-0.009	-0.010	-0.009	-0.004	-0.008
of education	(0.018)	(0.022)	(0.022)	(0.021)	(0.014)	(0.017)
Year 2012 # tenure dummy # years	0.007	0.006	0.004	0.005	0.000	0.003
of education	(0.018)	(0.019)	(0.019)	(0.019)	(0.013)	(0.016)
Year 2013 # tenure dummy # years	0.014	0.010	0.008	0.008	0.001	-0.003
of education	(0.017)	(0.019)	(0.019)	(0.019)	(0.014)	(0.016)
Year 2014 # tenure dummy # years	0.004	0.002	0.002	0.002	-0.007	0.000
of education	(0.018)	(0.020)	(0.020)	(0.020)	(0.015)	(0.016)
N	5260	4725	4746	4725	5190	4746
R^2	0.256	0.331	0.338	0.336	0.514	0.532
adj. R^2	0.251	0.326	0.333	0.331	0.509	0.526

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
With some exceptions, all six models are identical to Table 2. The exceptions are that the models in Table 8 additionally include the tenure dummy and the interaction term of the tenure dummy, years of education and year dummies. Also, it does not include the continuous tenure variable.

Section 5.4: The instrumental variable results

As education is often argued to be endogenous, it is worthwhile to examine the results when education is treated as an endogenous variable. In order to achieve this, the parental level of education is used to instrument the respondent's level of education. However, given the different categories for parental education, the level of education is transformed into years of education. The summary statistics of the parental level of education and the corresponding years can be obtained in Table A. 4 in the appendix. Moreover, not all workers in the dataset have received or answered the questions regarding parental education. Around 65 percent of the individuals in the baseline sample reported the highest level of education their father had completed and around 66 percent reported the highest level of education their mother had completed. Given the remaining number of observations, the instrumental variable (IV) results should still provide the reader with a clear direction of the factors important in explaining the gross hourly wage. The results should also indicate whether there is an upward or a downward bias in the effect of education on wages.

The IV results are presented in Table 9 and uses father's years of education to instrument the respondents' years of education. Given the baseline sample, their parents will be near retirement or are retired for quite some years. During the times their parents conducted education, the notion was that males should attend education and work thereafter, while women should support the household. As a result, females completed fewer years of education. Even more illustrative, around 32 percent of the fathers completed a higher level of education than secondary education, whereas for mothers this is only 12 percent.

Furthermore, whereas the standard Mincer models incorporate potential work experience, the IV results presented in Table 9 use age to indicate the working experience of the individual. The reason for this is that potential work experience is, besides age and school starting age, based on years of education. When years of education is treated as an endogenous variable, also potential work experience is affected. To circumvent this, age is used instead of potential work experience. An alternative would be to adopt age as the experience variable in all models presented in this paper, however, given that potential work experience is generally preferred in the literature (as this resembles the actual work experience variable closely), this direction is also taken in this paper. To be complete, Table A. 12 in the appendix presents the baseline models where age is used instead of potential work experience.

Table 9: The Mincer IV models

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.129***	0.119***	0.116***	0.123***	0.067*	0.058
	(0.023)	(0.026)	(0.025)	(0.026)	(0.037)	(0.038)
Age	0.063***	0.056***	0.047***	0.052***	0.043***	0.036***
	(0.017)	(0.018)	(0.017)	(0.019)	(0.013)	(0.013)
Age squared	-0.001***	-0.001**	-0.000**	-0.000**	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		0.000		0.000		
		(0.000)		(0.000)		
Public		-0.038		-0.038		
		(0.030)		(0.030)		
(Log of) firm size		0.027***	0.028***	0.027***		0.025***
		(0.008)	(0.008)	(0.008)		(0.006)
Management		0.134***	0.142***	0.129***		0.067***
		(0.026)	(0.025)	(0.026)		(0.020)
Civil status – married			0.051*	0.047*		0.038*
			(0.026)	(0.027)		(0.020)
Civil status – separated			0.053	0.075		0.115*
			(0.060)	(0.071)		(0.070)
Civil status – divorced			0.064	0.061		0.026
			(0.053)	(0.054)		(0.046)
Civil status – widow(er)			0.183	0.174		0.238
			(0.197)	(0.220)		(0.151)
Employment type					Included	Included
Sector					Included	Included
Occupation					Included	Included
Constant	-0.354	-0.198	0.004	-0.184	1.156*	1.330*
	(0.537)	(0.575)	(0.531)	(0.577)	(0.668)	(0.693)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	3429	3123	3149	3123	3406	3149

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Years of education is instrumented by father's years of education.

The results in Table 9 suggest that when education is instrumented by father's years of education, the estimate of the wage return to education is significantly higher than the Mincer coefficients in the standard Mincer model when education is not instrumented. Based on the theoretical foundation of the ability bias discussed in the literature review, this is not as expected. However, empirically the results are similar to the literature as researchers generally find education to have a larger impact when instrumented. Therefore, given the contradiction between theory and empirics and the ongoing discussion on the validity of parental education as instrument for the respondent's level of education, one needs to examine this in more detail. If the education coefficients are larger due to endogeneity bias corrections, the results are valid and correctly interpretable. However, doubts can arise if the increase in the coefficients is due to other reasons. Three potential reasons are discussed below.

First, individuals reporting their parental level of education may be significantly different from individuals not reporting their parental level of education. Therefore, it is necessary to compare the two groups. The first group either did not report their father's level of education or was not asked to report it. In the second group, all individuals reported their father's level of education. A comparison of these two groups suggests that in most cases the groups are not significantly different. However, to some extent they are significantly different. As can be obtained in Table A. 13 and Table A. 14 in the appendix, the results suggest a significant difference in years of education, age and potential work experience. The individuals in the IV sample have generally (slightly) more years of education, are older and therefore have more potential work experience. However, it is questionable whether these relatively small differences account for the large increase in the Mincer coefficients.

Second, the father's level of education (and even stronger for mother's level of education) is more condensed than the respondent's level of education in the baseline sample. The average years of education of the respondents is 13.6, whereas this is only 10.9 years for their fathers (and 9.7 years for their mothers). As a result, for the same gross hourly wages, the average effect of an additional year of education is larger when education is instrumented. This reason can attribute to larger Mincer coefficients in the IV approach. This condensed effect becomes even stronger when both father's and mother's years of education is used to instrument the respondents' years of education (see Table A. 15 in the appendix).

Third, the quality of the instrument may be insufficient. Therefore, various tests are conducted to assess the validity and relevance of the instrument(s) used in the IV approach. The first stage results can be obtained in Table A. 16 in the appendix. Focusing on the father's years of education as instrument, the results clearly indicate that father's years of education is highly correlated with the respondents' years of education. The instrument therefore proves not to be weak. However, the validity of the instrument is still debatable. As only one instrument is used, the instrument is exactly identified and the Hansen J statistic can therefore not be used to shed some light on the validity of the instrument. An alternative is to incorporate both father's and mother's years of education to assess the validity of the instrument, despite the doubts about the use of mother's years of education as instrument. The first stage results of both father's and mother's years of education can be obtained in Table A. 17 in the appendix. The first stage shows that the results become less strong, but the instruments remain highly correlated with the respondents' years of education. Focusing on the validity of the instruments, the Hansen J statistic is not rejected. The instruments are therefore uncorrelated with the error term and are correctly excluded from the estimated model. Even though an actual validity test of the instruments is not available, these results suggest that the instruments do not have a direct influence on the wages of the individuals. Although discussions regarding the validity of the instrument remains present, the first stage results at least suggest the instrument is both valid and relevant.

Overall, based on the exploration of these reasons, the education coefficient in the IV approach may be somewhat larger due to various reasons. However, the true causal effect of years of education on wages is presumably somewhere between the Mincer coefficients obtained in the baseline results and the IV approach. The Mincer coefficients in the baseline results can therefore potentially be argued to be a lower bound effect of education on wages.

Section 5.5: Heckman selection correction approach

In estimating the wage return to education, only individuals who work and reveal their wage to the interviewer are present in the sample. However, a bias may arise if individuals who do not work or individuals who do not reveal their wage are significantly different from workers who do work and reveal their wage. Therefore, researchers have resorted to the Heckman selection correction approach. As discussed in Section 3, this approach can be used to correct for the bias due to the non-response and/or non-employment of the baseline sample.

Focusing on the baseline sample of male workers aged 30 – 55 working at least 32 hours per week, it is not likely that either non-response or non-employment leads to a significant bias in the wage return to education. The Heckman procedure is generally applied in samples that include women or other age groups (i.e. young and/or old workers). Despite this, this section will try to correct for non-response and non-employment in the sample based on the individuals' civil status, urban character of place of residence and the number of household members (these variables are discussed in detail in Section 4.3). It is, however, important to keep in mind that the Heckman model is far from perfect and contains caveats. Moreover, based on the baseline sample, it is more likely to suffer from sample selection bias due to non-response than due to non-employment. On the other hand, the economic crisis may have affected certain groups of individuals disproportionately. Therefore, both non-response and non-employment sample selectivity is examined. It is, however, not possible to do this simultaneously.

The non-response and non-employment are examined for both years of education as well as the level of education. The results can be obtained in Table A. 18 and Table A. 19 in the appendix. Two different definitions of non-employment are used. The first one focused only on individuals who lost their job, whereas the second one focused on all individuals who are not employed (e.g. individuals taking care of the housekeeping). Given the very low censored sample of non-employment, the econometrics of the Heckman procedure may be unstable. Therefore, the results of the non-response are argued to be more reliable.

In general, the Heckman procedure indicates there is significant sample selectivity due to non-response at the 1 percent level. Not correction for the non-response leads to negative sample selectivity. In this case, the estimated coefficients of the years of education and the level of education may underestimate the marginal effect on the wages of workers if one does not correct for this selectivity. This may suggest that individuals not revealing their wage to the interviewer have a higher than average wage (and maybe therefore do not report their wage).

The Heckman procedure also indicates there is some sample selectivity due to non-employment. These results are, however, less strong. Not correcting for the non-employment leads to positive sample selectivity. In this case, the estimated coefficient of the years of education and the level of education may overestimate the marginal effect on the wages of workers if one does not correct for this selectivity. This may suggest that individuals who do not have a job, are especially individuals with a lower than average wage return to education. This corresponds to the general notion that especially lower educated individuals find it difficult to keep their job during an economic crisis.

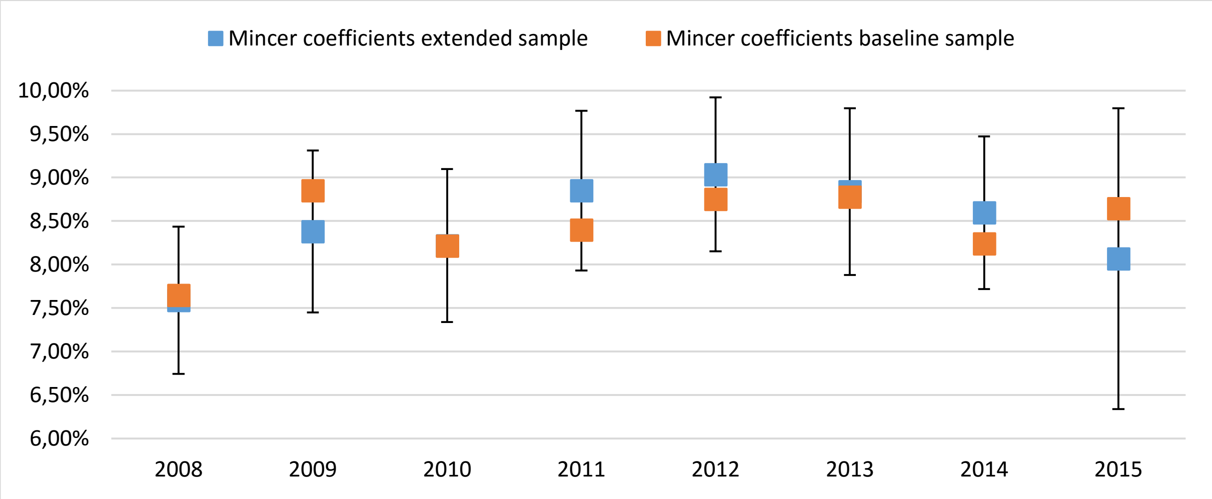
In absolute terms, the sample selectivity due to non-response is generally larger or equally large as the sample selectivity due to non-employment. This suggests that the overall sample selectivity is only marginally negative. However, caution should be taken when considering the results of the Heckman model. Overall, the results are in line with the general notion that the baseline results can be argued to be a lower bound effect of education on wages.

Section 5.6: Extending the sample

Section 5.6.1: Results of the extended samples

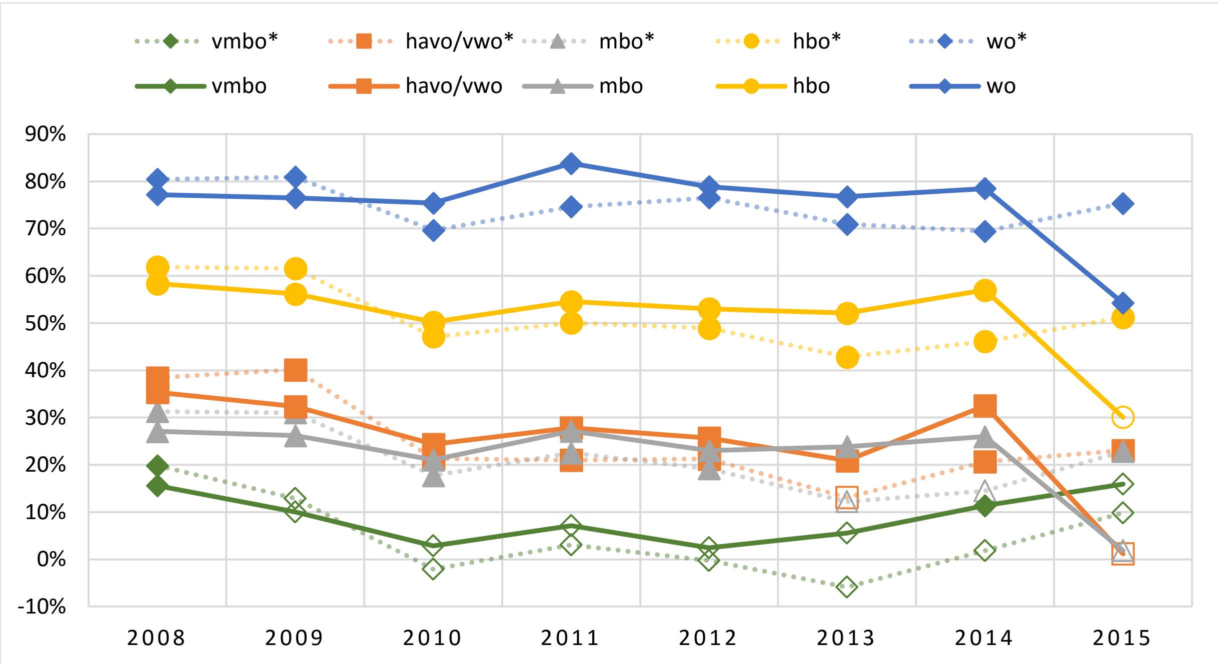
The extended samples are used as a robustness check and to generalize the results to other age groups (e.g. young and old workers) as well as female workers. The yearly Mincer coefficients and the wage premium of education over time are presented in Figure 6 and Figure 7, respectively. Both figures generally present a very similar pattern for male workers. Although there are differences, these differences generally remain well within the 90 percent confidence interval of the baseline results. The same six models as in Section 5.1 (i.e. the baseline results) are also estimated for each extended sample and for men and women separately. These results can be obtained in Table A. 20 and Table A. 21 in the appendix.

Figure 6: The Mincer coefficients over time



Source: Author's calculations based on the LISS-dataset
Note: each dot represents a separate estimation where the dependent variable is the (log of) gross hourly wage, years of education is the variable of interest (displayed) and the control variables are potential work experience and the squared potential work experience. The data is based on the extended sample 2 and consists of male individuals aged 20 – 65 working full time (i.e. at least 32 hours per week) or part time (i.e. 12 – 31 hours per week). Moreover, the 90 percent confidence interval are based on the robust clustered standard errors. A filled marker indicates a significant coefficient at the 10 percent level. The Mincer coefficients of the baseline sample are included for comparison. The yearly number of observations over 2008 to 2015 are respectively, 1246; 999; 1014; 812; 928; 861; 956; 885.

Figure 7: The wage premium of education over time



Source: Author's calculations based on the LISS-dataset
Note: Each dot represents a separate estimation where the dependent variable is the (log of) gross hourly wage, the level of education is the variable of interest (displayed) and the control variables are potential work experience and the squared potential work experience. The data is based on the extended sample 2 and consists of male individuals aged 20 – 65 working full time (i.e. at least 32 hours per week) or part time (i.e. 12 – 31 hours per week). The estimations are all based on the robust clustered standard errors. A filled marker indicates a significant coefficient at the 10 percent level. The reference category is primary education. The wage premium of each educational level in the baseline sample is included and denoted by an asterisk (*) in the legend. The yearly number of observations over 2008 to 2015 are respectively, 1246; 999; 1014; 812; 928; 861; 956; 885.

Focusing on male workers, it can be obtained that the results are very much comparable to the baseline results presented in Section 5.1. The differences are marginal and therefore suggest that young and old age groups are similar to prime-aged workers. Based on the Mincer coefficients, there is no significant difference in the wage return to education between full time and part time workers. However, there are some significant differences when examining the wage differential models. Based on the results, part time male workers (mainly higher educated individuals) have a significantly higher wage return to education. This result can, however, also be based on the relative small amount of part time male workers per educational category.

Focusing on female workers, the wage return to education is generally lower than the wage return of their male counterparts. This is especially the case in the wage differential models. As a reference, the baseline results are also estimated for females. Similar to males, the female baseline results are comparable to the results obtained in the extended models. This suggests that also for females, young and old age groups are similar to prime-aged female workers. Moreover, it can also be obtained that the wage return to education is not significantly different between part time and full time female workers. This is both the case in the Mincer-equations as well as the wage differential models.

These extended samples are also used to examine the impact of the recent economic crisis on the wage return to education and for comparison to the baseline results. Similar to Section 5.2, the focus is on the wage differential models as these can present the most detailed information. The results are only presented for full time male and female workers as these are the most illustrative. The results can be obtained in Table A. 22 and Table A. 23 in the appendix.

Focusing on full time male workers, the same observations are made as in Section 5.2. The results suggest there is a significant drop in the wage premium of all educational levels (except wo) in both 2010 and 2013. Moreover, also the interaction of education with the unemployment rate and GDP growth rate are examined. When focused on full time male workers, these results are similar to the baseline results, although less strong. The inclusion of part time male workers leads to a somewhat less significant effect. This may be the result of part time male workers being less strongly attached to the labour force than full time male workers. The inclusion of part time male workers generally reduces its significance (in the case of the GDP growth rate) or even becomes insignificant (in the case of the unemployment rate).

Focusing on female workers, the results are less clear. When the sample includes full time female workers, the results are the most strong and indicate a significant drop in the wage premium for all educational levels in the years 2011 and 2015 (in some cases also the year 2014). It is, however, less clear how the significant drop in the wage premium in 2015 is related to the economic crisis. On the one hand, it may be a delayed response, but on the other hand, it may also be related to the fact that women tend to be less strongly attached to the labour force. More women may have entered the labour force again in 2014 and 2015 and have reduced the wage premium. The inclusion of part time female workers leaves only a significant drop in the wage premium for the years 2014 and 2015. This may be related to the fact that more women started to enter the labour market again in 2014 and 2015, while at the start of the economic crisis many left the labour market. Moreover, also the interaction of education with the unemployment rate and the GDP growth rate are examined. The interaction terms do illustrate a similar effect as their male counterparts, the results are, however, mostly insignificant. Nonetheless, the results, primarily focusing on full time female workers, suggest there is a similar tendency for women to be impacted by the economic crisis as their male counterparts. This tendency is however not strong enough to be significant.

Similar to Section 5.3, the effect of the economic crisis on the relative bargaining position is also examined for the extended sample. Both interaction models to examine the relative bargaining position during the recent business cycle are estimated for male and female workers. Once again, the Mincer model is applied as this model presents the most clear results. Moreover, the focus is primarily on full time workers. When part time workers are included in the analysis, the results may present a biased view as their motivation to maintain their work is likely to be significantly different from full time workers. However, a short remark regarding part time workers is made. The results for full time male workers can be obtained in Table A. 24 in the appendix and the results for full time female workers in Table A. 25 in the appendix.

When focused on full time male workers, the results show a similar effect. Given the minimum and maximum years of education, male workers who started working during the economic crisis have a 24 percent lower wage when they only completed primary education and potentially a 3 percent higher wage when they completed university education. The turning point of the overall effect is, however, somewhat higher, namely around 15 years depending on the chosen Mincer model. Therefore, these results are slightly stronger to state that only male individuals who completed university education (i.e. wo) were not affected. Male workers who completed less than university education were affected negatively and this effect is stronger for individuals with fewer years of education. Moreover, similar to the baseline results, also these results indicate that workers who started working during the economic crisis have a slightly higher wage return to education of around 2 percent. Similar reasons may apply.

Furthermore, the same analysis is conducted but also interacted with year dummies to examine whether these results changed during the business cycle. Using the baseline sample, these results were not significant. However, based on the coefficients, the results did not seem to differ much during the business cycle. Although not all interaction terms are significant in the extended sample, the general conclusion of the baseline sample remains similar. The results suggest that in some years workers are slightly more affected by a decrease in their relative working position. However, this is primarily the case for individuals with only a few years of education. In all years, individuals with a university education were not significantly negative affected by a decrease in their relative bargaining position. Moreover, when the extended sample of male workers also includes part time workers, the results become less significant. The main results, however, remain present. This is partly related to the fact that only few male workers work part time (around 5 percent).

When focused on full time female workers, the results are quite different. This may be related to the large fraction of part time female workers which are also active on the Dutch labour market. Only half of all women work full time and may still not be strongly attached to the labour force, despite the fact that they work full time. When examining whether the relative bargaining position has a significant impact on the wage of full time female workers, the results are not significant. Besides the fact that the coefficient are generally much smaller than their male counterparts, the sign of the coefficients are also reversed. When the same analysis is conducted but also interacted with year dummies to examine whether these results changed during the business cycle, most results become significant, but the sign remains the same. Moreover, the results fluctuate heavily. In most years, the results suggest that the relative bargaining position of lower and middle educated individuals improved, whereas the relative bargaining position of higher educated individuals decreased. However, in some years (e.g. 2011) opposite results are found which are in line with the findings for full time male workers. Therefore, a clear interpretation for full time female workers cannot be given. This may be related to their attachment to the labour force, but may also be related to other factors (e.g. a relatively low number of observations for full time female workers). Furthermore, when the extended sample of female workers also includes part time workers, the results become insignificant for almost all coefficients. As a result, a clear and robust interpretation cannot be given for female workers.

Section 5.6.2: The instrumental variable results for the extended sample

Similar to the baseline results, also in the extended samples the respondents' years of education are instrumented by the father's years of education to deal with the potential endogeneity. The results are presented in Table A. 26 in the appendix. The focus is only on male individuals as Stata is not able to estimate the robust covariance matrix for females due to the fact that too few clusters (i.e. unique individuals) are available. Although Stata does present the results, the results may be subject to various problems and this could lead to less or even unreliable estimates. Moreover, the male results are more important given that the largest fraction employed is male. The result indicate a similar wage return to education. In some instances, the wage return to education is slightly larger, however, this is only marginal. When correcting for part time workers, the wage return to education decreases slightly. The largest difference in the wage return to education can be obtained when career components are included (i.e. model five and six). The increase in the wage return to education may be related to individuals included (i.e. young and old male workers), but may also be due to the stark increase in the number of observations. In general, the baseline IV results comprising prime-aged male workers (aged 30 – 55 years) remain similar when younger and older male workers are included.

Section 5.6.3: Heckman selection correction approach for the extended sample

Also the Heckman selection correction approach is applied to the extended sample. However, the focus in the Heckman procedure is only on male individuals working full time. There may be various other effects present if the focus is also on part time male workers. This may even be more the case when focusing on female workers. The results for full time male workers are presented in Table A. 27 and Table A. 28 in the appendix. The results of the extended sample without correcting for sample selectivity is also presented. Compared to the baseline sample of male individuals aged 30 – 55 working full time, not correcting for sample selectivity leads to a very similar wage return to education.

Focusing on all full time male workers aged 20 – 65 years, the results suggest significant sample selectivity due to non-response and little sample selectivity due to non-employment. The results of sample selectivity due to non-response are stronger than in the baseline sample. Not correcting for the non-response leads to negative sample selectivity in which the wage return to education may underestimate the marginal effect of education on the wages of the workers. On the other hand, not correcting for non-employment leads to positive sample selectivity in which the wage return to education may overestimate the marginal effect of education on the wages of the workers. However, the non-employment sample selectivity is less strong compared to the baseline sample. Therefore, the results remain similar to the Heckman procedure using the baseline sample. Especially sample selectivity due to non-response seems to be present. This suggest that the results can be argued to be a lower bound effect of education on wages. This corresponds to the findings of Fersterer & Winter-Ebmer (2003) for male individuals. However, once again, caution should be taken when considering the results of the Heckman model.

SECTION 6: DISCUSSION

The general results obtained from this paper are in line with expectations and the literature review. Research papers examining the wage return to education, all suggest that education has a strong positive association with wages. Moreover, research papers, focusing on the wage return to education during an economic crisis, all suggest the wage return is significantly affected by the economic crisis. However, it is not straightforward how precisely an economic crisis affects the wage return to education. This can depend on the type of economic crisis (e.g. severity and the responsible factors), the characteristics of the labour market (e.g. labour flexibility, dismissal laws), governmental and non-governmental actions (e.g. monetary and/or financial policy actions) and many others. The results of this paper are therefore specific to the Netherlands and the recent economic crisis. To illustrate, the result that higher educated individuals suffer less than lower educated individuals may partly be due to the availability of education-level appropriate jobs in the Netherlands during the recent economic crisis. This job competition may lead to a crowding out of workers along the educational segments as university educates (i.e. wo) displace workers with higher vocational education (i.e. hbo), and workers with higher vocational education (i.e. hbo) displace workers with intermediate vocational education (i.e. mbo) and this continues until the lowest educated individuals, it can be obtained that the lower educated the individual, the more they suffer from this displacement process. The fact that Vilerts et al. (2015) finds a counter-cyclical effect of education on wages, especially for higher educated individuals, is most likely specific to Latvia as other papers focusing on economic crises are more in line with this research, although also here differences exist. Therefore, each economic crisis affected the wage return to education significantly, the results are however not generalizable to other countries and/or economic crises.

Moreover, the finding that higher educated individuals suffered less from the recent economic crisis than lower or middle educated individuals does not suggest that in order to reduce the impact of an economic crisis everyone should increase their level of education. The educational choice of the individual is likely to be endogenous and therefore depending on their unobserved ability. In other words, although one individual may choose to continue from intermediate vocational education (i.e. mbo) to higher vocation education (i.e. hbo) to reduce the negative impact the economic crisis may have on this individual, this research does not suggest that if, by any means, all individuals would have a higher level of education, the impact of the economic crisis would be any lower. This interpretation of the results is incorrect. If the results would be the other extreme, that lower educated individuals suffered less from the economic crisis than middle or higher educated individuals, the policy advice is still not the opposite. Even here, it is not the case that individuals should decrease their level of education to reduce the negative impact the economic crisis may have on them. The results should be interpreted as how they are presented, namely this recent economic crisis in the Netherlands affected the wage return to education less the higher educated the individual is.

Although this paper is able to present robust evidence that education is positively associated with higher wages in the Netherlands and that the wage return to education decreased significantly in 2010 and 2013 due to the economic crisis, there are some topics and limitations worth discussing. These are generally related to the LISS-dataset, the research method and/or the results. This section will end with a short discussion on a more ideal dataset to measure the wage return to education (during an economic crisis).

When critically examining the dataset, there are some drawbacks in exploiting the LISS-dataset for this particular research question. First of all, the core study is first conducted in April 2008. Although this is prior to the outbreak of the economic crisis, it may already have affected the Dutch labour market which could bias the wage return to education in 2008. Related to this is that prior to the start of the economic crisis in 2008, economic growth was relatively high. Therefore, the wage return to education in 2008 may actually been affected by the prosperous economic conditions. Information on the wage return to education some years prior to the start of the economic crisis would have been valuable if available. Moreover, as many others, the LISS-dataset does not provide information on the change in the Dutch labour supply or demand during various periods (or the degree of labour market tightness between higher- and lower-skilled occupation during the different phases of the economic crisis). For example, an influx of immigrants from other European countries may have impacted the individuals with a lower level of education. In general, a stark increase in the labour supply (labour demand) may actually decrease (increase) the wage return to education in a given year for a certain group of individuals. This could partly explain the stark increase in the wage return to education for full time female workers in the year 2015 (see Table A. 23 in the appendix). Only McGuinness et al. (2009) seems to be able to take this (partly) into account. However, by focusing on the baseline sample, this issue should be reduced strongly.

The research method is based on the Human Capital Earnings Function of Mincer. However, the question is whether this is the best approach to examine the wage return to education during an economic crisis. The concern of the Mincer framework is generally related to its functional form and its homogeneous return to education (Card, 1999). Recent papers, not focused on business cycles, started to explore non-parametric research methods (e.g. Heckman et al. (2008) and Henderson et al. (2011)). It is too soon to state which research method is best suitable, especially during business cycles. However, alternatives should be taken into account in future research. Moreover, despite the research method, many researchers still use the years or level of education and thereby implicitly assume that education is the sole systemic source of skill differences. Therefore, Hanushek et al. (2015) focused more on a general human capital model in which the cognitive skills are examined. It is interesting to see how this alternative skill variable will develop in the future. Also, the use of potential work experience when no actual work experience variable is available, is used often. It is, however, worthwhile to examine how different experience variables affect the wage return to education and whether this leads to a bias. According to Hanushek et al. (2015), the estimates tend to be slightly smaller when potential work experience is used instead of actual work experience, but remain very similar. However, it is no guarantee that this would also be the case in this research paper.

Also the results of this research paper are critically examined. The results suggest that the wage return to education is significantly affected during the recent economic crisis based on the interaction terms of the year dummies, unemployment rate and the GDP growth rate. These results suggest that especially the years 2010 and 2013 showed a significant drop in the wage premium for males in all educational levels. However, the results also showed that the higher the educational level of the individual, the less the individual suffered from a drop in the wage premium during the economic crisis. These results are confirmed by the unemployment rate and the GDP growth rate. Therefore, the results not only suggest that lower educated individuals suffer more during the economic crisis, an increase in the GDP growth also benefit lower educated individuals more than higher educated individuals. This may be related to the job loss and job finding probability of lower educated individuals. As lower educated individuals are generally the first to be laid-off, they may also be the first to get their job back. However, this conclusion is based on the fact that the labour supply and demand of workers remained (relatively) stable during the sample period. Moreover, this conclusion is also based on two other implicit assumptions. First, during the sample period, the only large (exogenous) shock to the Dutch labour market resulted from the economic crisis or factors related to the economic crisis (e.g. housing crises, debt crisis, bankruptcies). Second, the delayed responsiveness of the Dutch labour market is generally one to two years.

Focusing on the first implicit assumption, there are very little (if any) large shocks to the Dutch labour market, other than the economic crisis, that may have affected the wage return to education to change significantly during the sample period. However, if there is a large shock to the Dutch labour market for which this paper did not account, the economic crisis based argument for the decrease in the wage return to education could be rendered insignificant.

Focusing on the second implicit assumption, there is uncertainty about the delayed responsiveness of the Dutch labour market, especially during an economic crisis. Focusing on male individuals, the significant drop in the wage premium in the year 2010 and 2013 is as expected and likely to be characterized by the delayed responsiveness of the Dutch labour market by roughly one to two years. However, the significant drop in the wage premium for female workers in 2015 is (at least) not directly attributable to the delayed responsiveness of the Dutch labour market as a result of the economic crisis. This decrease may actually be related to the increase (decrease) in the labour supply (labour demand) of certain groups of female workers. Therefore, together with the unobservability of labour supply, labour demand and other large shocks, the uncertainty about the actual delayed responsiveness of the Dutch labour market may lead to some uncertainty in the results.

Furthermore, the baseline sample was chosen to obtain a homogenous group of workers that are all strongly attached to the labour force. These prime-aged workers will therefore respond (relatively) similar to an economic crisis as they will try to keep their job in various ways (e.g. working harder or accepting a wage reduction) and after a job loss will try to return to the labour market as soon as possible. However, by extending the sample to include young (i.e. 20 – 29 years), old (56 – 65 years) and part time workers (i.e. 12 – 31 hours per week), the group of individuals may become more heterogeneous and respond differently to an economic crisis. Young workers may focus again on education, old workers may be drawn to retirement and part-time workers may focus more on supporting the household. If the young, old and part-time workers who drop out of the labour market are significantly different from their counterparts who (try to) remain in the labour force, a bias in the effect of education on wages may be created when the sample is extended to also include these groups of workers. Although the results do not suggest that there are significant differences in the wage return to education during the recent economic crisis for these groups, unobserved differences across and within groups may be present and bias the results. For example, males and females are not examined together as their wage return to education is generally significantly different. Moreover, this research paper is, also given the number of observations, not able to control for all heterogeneous effects. On the other hand, the inclusion of young, old and part time workers also increases the number of observations. Therefore, instead of biasing the results, it may also provide generalizability and robustness.

The last discussion is related to a combination of the LISS-dataset, the research method and the estimation results. In this type of research paper, there are generally three forms of biases. These are the endogeneity (i.e. ability) bias, the measurement error and the sample selection bias.

To start with the endogeneity bias, there are various ways to control for this bias, for example by focusing on educational reforms (e.g. Meghir & Palme (2005) and Webbink (2007)) or IQ scores (e.g. Levin & Plug (1999) and Card (2001)), however, the only alternative available in the LISS-dataset is parental education. As discussed in Section 3, there is an ongoing debate on the validity of parental education as instrument. As parental education may directly affect the wage of the worker, the validity condition is violated. However, as stated by Hoogerheide et al. (2012), a violation of the validity condition does not have far reaching implications as the results generally remain similar. However, as parental education is not part of the original dataset, but an assembled study conducted in 2012 and 2013, the only information available (for a group of individuals) is the father's and/or mother's level of education. If this was part of the original questionnaire, it is likely that more background information would be available (e.g. parental occupation) and also for more (or even all) respondents. Although Section 5 examines the validity of the IV approach, other unobserved factors may be relevant. Therefore, in this case, correcting for the endogeneity bias may actually create another bias if there is an unexplored factor causing the increase in the IV coefficients. However, also the empirical results in the literature review suggest that the ability bias corrected education coefficient is generally larger than when no correction is applied. Although caution is necessary, this suggests that the baseline results can be argued to be a lower bound of the true effect of education on wages. Therefore, it is not likely that due to this bias, the results become invalid.

The measurement error is very difficult to solve. The measurement error can arise when individuals are asked to report their years or level of education. However, it is more likely that individuals misreport the number of years they followed education rather than the highest level of education they completed. Given that the level of education is provided in the LISS-dataset, the measurement error is likely to be limited. If the interest is in the Mincer type of model, one can transform the level of education to years of education. However, in this case the years of education may be underestimated (if an individual took longer to complete their level of education) or overestimated (if an individual completed their level of education faster). A potential solution to reduce this measurement bias is to complement the question with two additional questions, namely whether they had to redo a year (i.e. grade retention) or skipped a year of education due to high grades. Moreover, another follow-up question could be focused for which type of education this was the case. Based on this information and the level of education, the years of education could be calculated. However, the only information available in this dataset is the level of education. Therefore, it is not possible to reduce the potential measurement error of education. On the other hand, there is no evidence of remarkable or conflicting results in the reported education levels.

Continuing to the sample selection bias, the LISS-dataset has information on non-response and non-employment. This is an advantage over other datasets which only obtain employed individuals reporting their wage. This may bias the results. In order to examine the sample selection bias, the Heckman procedure is conducted. However, the LISS-dataset contains very little information that can be used as identifying variables. Based on research papers discussed in the literature review, several factors are examined of which the civil status, the urban character of place of residence and the number of household members were potentially the best identifying factors for the non-response and non-employment. However, these variables may be too weak, especially in some years, to identify the non-response and non-employment satisfactory. As a result, the Heckman model may be based on the functional form and is therefore not able to account sufficiently for the sample selection bias. The Heckman procedure is therefore far from perfect without strong identifying variables. For future research, it would be useful to examine which factors contribute to the non-response and non-employment of Dutch citizens (also during an economic crisis), and to incorporate these factors as part of the questionnaire. In this way, the sample selection bias can be tackled better.

Focusing on future research, various researchers have opted to focus on twin (or sibling) studies to control for the various individual specific characteristics (e.g. ability) by using a fixed-effects estimator on a sample of identical twins or to focus on educational reforms by implementing an IV approach. However, based on the literature review, there is another interesting way to examine the wage return to education which can also be used during an economic crisis. Ideally, one would have a large dataset, in terms of design similar to the LISS-dataset, in which a significant fraction of the individuals in the dataset reinvested in their level of education after they started working. In this way, it is possible to provide an ability free estimate based on the individuals that reinvested in their level of education. This is similar to the dataset of Park (2011), however, in the dataset of Park (2011) all individuals reinvested in their level of education after a period of working. This approach would be characterized by a panel Fixed Effect approach. Furthermore, this ideal dataset should also incorporate family background information (e.g. parental education and occupation). In this way, it is possible to compare the ability free estimate (based on the reinvestment in education) to the ability corrected approach (based on instrumenting education by parental education). Moreover, if this questionnaire was not only conducted during the economic crisis, but also some years prior to and after the economic crisis, it may help in examining whether the ability bias fluctuated during an economic crisis. At the moment, this question cannot be answered. Although this ideal dataset is able to at least partially correct for the ability bias, the measurement and sample selection bias are still present. As stated earlier, the measurement error could be partly tackled by a more comprehensive questionnaire on education. The sample selection bias is, however, more difficult to solve and may be especially important during an economic crisis. As discussed earlier, specific research on sample selection could reveal which identifying variables can account (sufficiently) for the non-response and non-employment. These identifying variables should then be incorporated in the questionnaire. An alternative to circumvent the non-response bias is by obtaining income information directly from the tax authorities. This is, however, very unlikely to happen. An alternative for the non-employment is to force individuals to be monitored during the time they are unemployed. Especially individuals who have lost their job and have little prospect on a new job may become discouraged and drop out of the survey. This should be prevented as these individuals may contain valuable information on the sample selection bias due to non-employment. However, it is not likely that this ideal dataset is available soon. Therefore, the current research approach is the best available.

SECTION 7: CONCLUSION

Based on the results, it can be obtained that there is a strong positive association between education and wages. The pooled Mincer results suggested that each additional year of education was associated with higher wages of around 7.2 – 8.4 percent. About half was due to the indirect impact of education on wages (i.e. career components). More education not only directly affected the wage of the worker, it also promoted the employment in higher paid sectors, occupation and employment type. For individuals in the same sector, occupation and employment type, an additional year of education was associated with a higher wage of around 3.5 percent. Also the pooled wage differential models suggest an increasing wage premium for each higher education level. Especially higher vocational education (i.e. hbo) and university education (i.e. wo) have a high wage premium relative to primary education, respectively 60 – 70 percent and 90 – 110 percent. Also in the wage differential models the career components are important. However, the results indicate that for each higher educational level, the fraction attributed to these career components gets smaller. The career component accounts for around 55 – 60 percent for individuals who completed higher secondary education or preparatory university education (i.e. havo/vwo), while it is around 40 – 48 percent for individuals who completed university education (i.e. wo). This suggests that a higher level of education not particularly promotes employment in higher paid sectors, occupation and employment type, but rather indicates larger direct benefits of education on wages.

Whereas the pooled results are related to the entire period (2008 – 2015), this paper is interested in examining whether the wage return to education changed in the Netherlands over the recent economic crisis. In order to examine this, the (wage premium of each) educational level was interacted with year dummies, the unemployment rate and the GDP growth rate in the Netherlands. These results indicated that the wage return to education changed significantly in the Netherlands over the recent economic crisis. During the period 2010 – 2013, all individuals suffered from a decrease in the wage premium. The year 2010 and 2013 showed the most strong decline in the wage premium. The decrease in the wage premium was observed by all individuals, however, the higher the educational level of the individual, the less the individual suffered from a decreasing wage premium during the economic crisis. This result is confirmed by the unemployment rate and GDP growth rate. The results suggested that higher educated individuals suffer less than lower or middle educated individuals from an increase in the unemployment rate or a decrease in the GDP growth rate. This corresponds to the notion that the wage premium of higher educated individuals are the most stable during an economic crisis, while the wage premium of lower educated individuals are the most volatile during an economic crisis.

Furthermore, this paper also examined whether the economic crisis had an effect on the relative bargaining position of workers who started working during the economic crisis. The results confirmed that the relative bargaining position of these workers were affected. While individuals who completed higher vocational education (i.e. hbo) and university education (i.e. wo) were not affected, or maybe even positively affected, by the change in the relative bargaining position, workers who completed less than higher vocational education (i.e. hbo) were affected negatively and this effect was stronger for individuals with fewer years of education. Moreover, the results also suggested the impact of the economic crisis on the relative bargaining position of these workers was characterized by a one-time abrupt decrease. Therefore, the impact of the economic crisis on the relative bargaining position of workers did not significantly change during later years of the economic crisis.

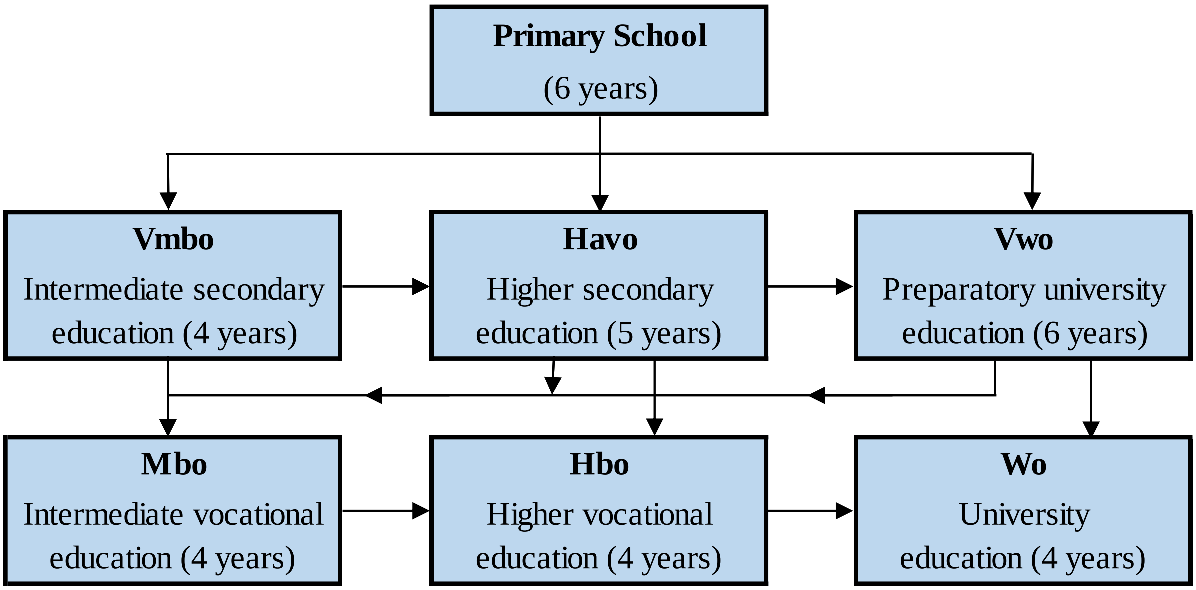
This paper also tried to account for the potential biases by examining the results based on the instrumental variable approach and the Heckman selection correction approach. The instrumental variable approach suggested there is a downward ability bias, this is in line with empirical findings for other countries. The Heckman procedure suggested there is evidence of negative sample selection due to non-response and some minor degree of positive sample selection due to non-employment. However, both the instrumental variable approach and the Heckman procedure suggested that the wage return to education obtained in the baseline results can be argued to be a lower bound effect of education on wages.

Furthermore, as a robustness check and to generalize the results to a large group of working individuals, the baseline sample is extended to also include young (20 – 29 years), old (56 – 65), part time (12 – 31 hours per week) and female workers. With the exception of the female worker analysis, the extended sample confirmed the baseline results, the impact of the economic crisis on the wage return to education and the change in the relative bargaining position of workers who started working during the economic crisis. Moreover, the extended sample also found a downward ability bias in the instrumental variable approach, negative sample selection due to non-response and some minor degree of positive sample selection due to non-employment in the Heckman procedure. Overall, to answer the research question, the results confirmed that the recent economic crisis affected the wage return to education significantly in the Netherlands.

SECTION 8: APPENDIX

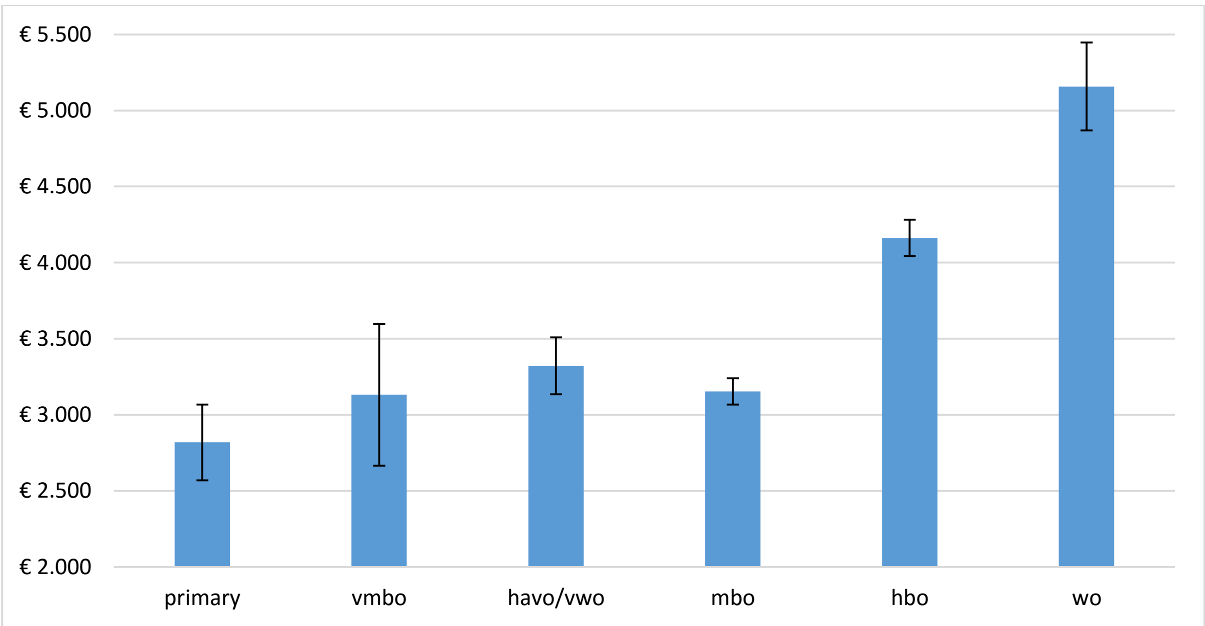
Section 8.1: Figures

Figure A. 1: An abstract of the Dutch schooling system



Source: Author's calculations based on the LISS-dataset
Note: In the Netherlands, every individual starts at the primary school. After finishing primary school, the individual will go to secondary school. Based on its skill level, this will either be vmbo, havo or vwo. After finishing this level of education, the individuals will generally continue along the vertical column. More specifically, the individual will continue to mbo after vmbo, hbo after havo and wo after vwo. However, the various arrows also indicate that, for example, finishing mbo gives access to hbo. Moreover, although it is rare, a student finishing vwo has the possibility to go to mbo.

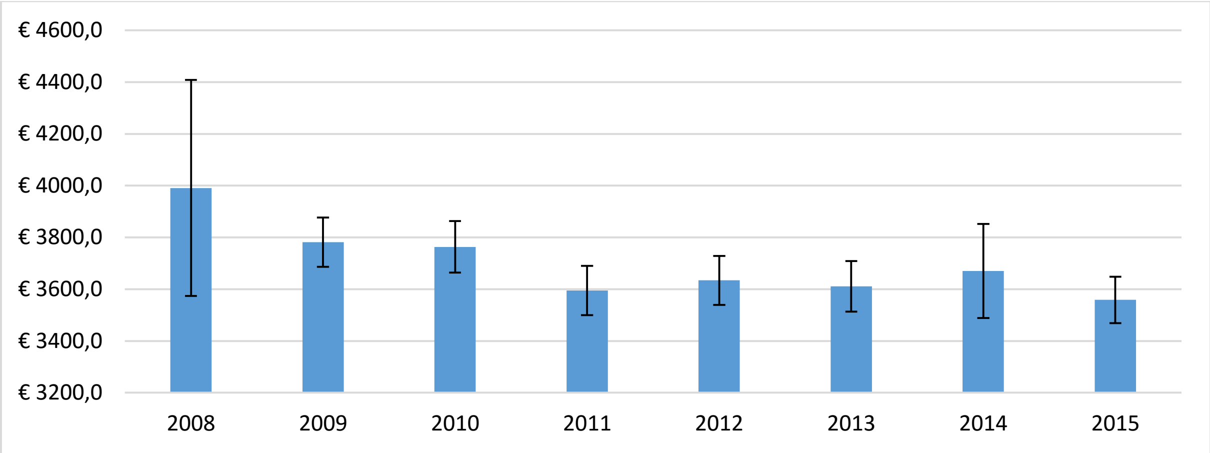
Figure A. 2: Gross monthly wage by educational category



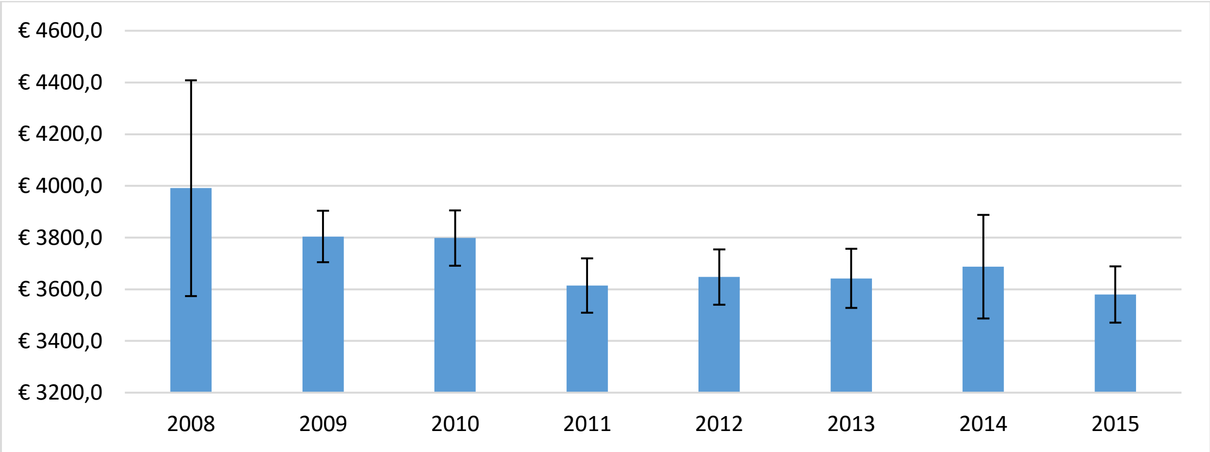
Source: Author's calculations based on the LISS-dataset
Note: the mean and its 90 percent confidence interval of the gross monthly wage are presented for each educational level. The figure is based on all observations.

Figure A. 3: Gross monthly wage per year

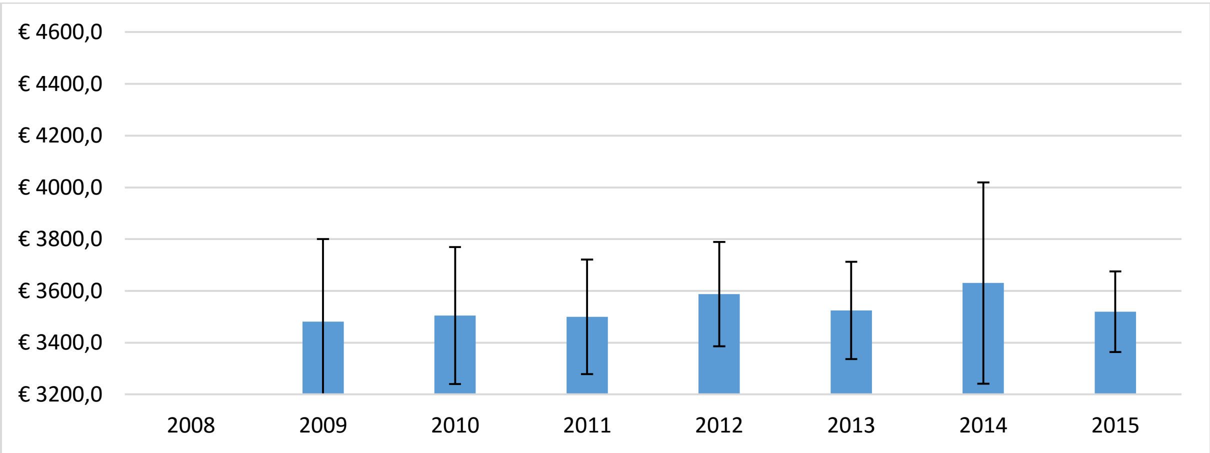
(a) For all individuals



(b) For all individuals who started working before September 2008



(c) For all individuals who started working September 2008 or later



Source: Author's calculations based on the LISS-dataset
Note: the mean and its 90 percent confidence interval of the gross monthly wage are presented for each year. The figure is based on all observations. Figure A. 3a is based on 5,260 observations, Figure A. 3b is based on 4,342 observations and Figure A. 3c is based on 918 observations.

Section 8.2: Tables

Table A. 1: Level of education according to CBS categories in the Netherlands

Dutch system	International definition	Education	Years of education
Primary school	Primary school	Low	6
Vmbo	Intermediate secondary education	Low	10
Havo/Vwo	Higher secondary education/preparatory university education	Middle	12
Mbo	Intermediate vocational education	Middle	14
Hbo	Higher vocational education	High	15
Wo	University	High	16

See: CBS (2015) and the LISS-dataset (also see: Scherpenzeel & Das (2010))
Note: For comparability both the Dutch educational levels as well as the international definitions are included. Moreover, the educational groups (i.e. lower, middle and higher educated) are also included and correspond to the CBS (2015) categories. The level of education is also transformed into years of education.

Table A. 2: List of variables

Variable	Code	Definition
(Log of) Gross monthly wage	log_brutoink	The log of gross monthly wage
(Log of) Gross hourly wage	log_hw	The log of gross hourly wage
Years of education	yrseduc	The transformed years of education
Age	age	Age
Age squared	age_sq	Age squared
Experience	exp	Potential work experience
Experience squared	exp_sq	Potential work experience squared
Tenure (in months)	tenure	Job tenure in months
Tenure squared (in months)	tenure_sq	Job tenure in months squared
Tenure crisis dummy	tenure_crisis	Started working after September 2008 (=1)
Public organization	public	Individual works at private(= 0) or (semi-)public organization (= 1)
(Log of) Firm size	log_firmsize	The log of the firm size at the individuals' location
Management job	management	If the individual supervises other workers (= 1)
Number of household members	aantalhh	The number of household members
Number of children in household	aantalki	The number of living-at-home children
Level of education	oplcat	Level of education according to categories Statistics Netherlands
Type of employment	employment	The type of employment of the individual
Sector	sector	The sector the worker is employed
Type of occupation	occupation	The occupation of the worker
Civil status	burgstat	The civil status of the respondent
Urbanization	sted	Urban character of place of residence (density per km2)

Table A. 3: Summary statistics of the other variables

Variable	# Obs.	Mean	Std. Dev.	Min	Max
Urban character of place of residence (density per km2) (categorical)					
Extremely urban (2500 or more)	5231	0.14	0.35	0	1
Very urban (1500 to 2500)	5231	0.27	0.45	0	1
Moderately urban (1000 to 1500)	5231	0.25	0.43	0	1
Slightly urban (500 to 1000)	5231	0.21	0.41	0	1
Not urban (less than 500)	5231	0.13	0.33	0	1
Type of employment (categorical)					
Employee in permanent employment	5260	0.95	0.23	0	1
Employee in temporary employment	5260	0.04	0.21	0	1
Temp-staffer	5260	0.01	0.08	0	1
Director of a limited liability or private limited company	5260	0.00	0.04	0	1
Majority shareholder director	5260	0.00	0.05	0	1
Sector (categorical)					
Agriculture, forestry, fishery, hunting	5191	0.02	0.15	0	1
Mining	5191	0.00	0.04	0	1
Industrial production	5191	0.19	0.39	0	1
Utilities production, distribution and/or trade (electricity, natural gas, steam, water)	5191	0.02	0.14	0	1
Construction	5191	0.07	0.26	0	1
Retail trade (including repairs of consumer goods)	5191	0.07	0.26	0	1
Catering	5191	0.02	0.13	0	1
Transport, storage and communication	5191	0.07	0.25	0	1
Financial	5191	0.07	0.25	0	1
Business services (including real estate, rental)	5191	0.08	0.27	0	1
Government services, public administration and mandatory social insurances	5191	0.13	0.34	0	1
Education	5191	0.05	0.22	0	1
Healthcare and welfare	5191	0.05	0.23	0	1
Environmental services, culture, recreation and other services	5191	0.01	0.11	0	1
Other	5191	0.14	0.34	0	1
Type of occupation (categorical)					
Higher academic or independent profession (e.g. architect, physician, scholar, academic instructor, engineer)	5190	0.10	0.30	0	1
Higher supervisory profession (e.g. manager, director, owner of large company, supervisory civil servant)	5190	0.14	0.35	0	1
Intermediate academic or independent profession (e.g. teacher, artist, nurse, social worker, policy assistant)	5190	0.17	0.37	0	1
Intermediate supervisory or commercial profession (e.g. head representative, department manager, shopkeeper)	5190	0.19	0.39	0	1
Other mental work (e.g. administrative assistant, accountant, sales assistant, family carer)	5190	0.17	0.38	0	1
Skilled and supervisory manual work (e.g. car mechanic, foreman, electrician)	5190	0.13	0.33	0	1
Semi-skilled manual work (e.g. driver, factory worker)	5190	0.09	0.28	0	1
Unskilled and trained manual work (e.g. cleaner, packer)	5190	0.01	0.11	0	1
Agrarian profession (e.g. farm worker, independent agriculturalist)	5190	0.01	0.10	0	1

Table A. 4: Summary statistics of the instrumental variables

Variable	# Years	# Obs.	Mean	Std. Dev.	Min	Max
Father's years of education	n/a	3429	10.89	3.25	3	18
Mother's years of education	n/a	3486	9.66	2.63	3	18
Highest level of education completed by father						
Elementary school not completed	3	3912	0.01	0.12	0	1
Only elementary school	6	3912	0.14	0.34	0	1
Junior vocational education	10	3912	0.16	0.36	0	1
Junior general secondary education	10	3912	0.22	0.42	0	1
Senior general secondary education	11	3912	0.03	0.17	0	1
Pre-university education	12	3912	0.07	0.26	0	1
Senior vocational education	14	3912	0.08	0.27	0	1
University of applied sciences	15	3912	0.10	0.29	0	1
University	16	3912	0.05	0.21	0	1
Post-academic (e.g. notary, medical, Ph.D.)	18	3912	0.02	0.15	0	1
I don't know	n/a	3912	0.12	0.33	0	1
Highest level of education completed by mother						
Elementary school not completed	3	3912	0.04	0.19	0	1
Only elementary school	6	3912	0.14	0.35	0	1
Junior vocational education	10	3912	0.31	0.46	0	1
Junior general secondary education	10	3912	0.26	0.44	0	1
Senior general secondary education	11	3912	0.02	0.15	0	1
Pre-university education	12	3912	0.03	0.16	0	1
Senior vocational education	14	3912	0.04	0.20	0	1
University of applied sciences	15	3912	0.04	0.19	0	1
University	16	3912	0.01	0.10	0	1
Post-academic (e.g. notary, medical, Ph.D.)	18	3912	0.00	0.04	0	1
I don't know	n/a	3912	0.11	0.31	0	1

Note: the parental level of education are transformed into parental years of education. In the table can be obtained what the corresponding years of education is relative to the level of education.

Table A. 5: The Mincer models
Extended version of Table 2

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.084^{***}	0.073^{***}	0.072^{***}	0.072^{***}	0.038^{***}	0.035^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Experience	0.018^{***}	0.016^{***}	0.015^{***}	0.014^{**}	0.021^{***}	0.020^{***}
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Experience squared	-0.000	-0.000	-0.000	-0.000	-0.000^{**}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		-0.000		-0.000		
		(0.000)		(0.000)		
Public		0.004		0.005		
		(0.018)		(0.018)		
(Log of) firm size		0.036^{***}	0.038^{***}	0.038^{***}		0.024^{***}
		(0.004)	(0.004)	(0.004)		(0.004)
Management		0.155^{***}	0.158^{***}	0.153^{***}		0.060^{***}
		(0.016)	(0.016)	(0.016)		(0.015)
Civil status – married			0.051^{***}	0.050^{***}		0.036^{**}
			(0.019)	(0.019)		(0.016)
Civil status – separated			-0.027	-0.041		-0.048
			(0.113)	(0.116)		(0.107)
Civil status – divorced			-0.010	-0.008		-0.011
			(0.037)	(0.037)		(0.031)
Civil status – widow(er)			0.218^{**}	0.224^{**}		0.245^{**}
			(0.108)	(0.106)		(0.101)
Employment – temporary					-0.150^{***}	-0.143^{***}
					(0.031)	(0.033)
Employment – temp-staffer					-0.342^{***}	-0.326^{***}
					(0.080)	(0.085)
Employment – director of a limited …					0.149	0.163
					(0.112)	(0.108)
Employment – majority shareholder …					0.108	0.132
					(0.150)	(0.135)
Sector – mining					0.094	0.062
					(0.205)	(0.221)
Sector – Industrial production					-0.057	-0.075
					(0.047)	(0.047)
Sector – Utilities production, …					-0.061	-0.097^{*}
					(0.059)	(0.059)
Sector – Construction					-0.068	-0.066
					(0.051)	(0.049)
Sector – Retail trade					-0.162^{***}	-0.146^{***}
					(0.053)	(0.051)
Sector – Catering					-0.185^{**}	-0.197^{***}
					(0.074)	(0.074)
Sector – Transport, storage and …					-0.115^{**}	-0.129^{**}
					(0.056)	(0.055)
Sector – Financial					0.052	0.037
					(0.053)	(0.052)
Sector – Business services					-0.031	-0.029
					(0.051)	(0.050)
Sector – Government services, …					-0.053	-0.071
					(0.048)	(0.047)
Sector – Education					-0.189^{***}	-0.193^{***}
					(0.051)	(0.051)
Sector – Healthcare and welfare					-0.146^{***}	-0.167^{***}
					(0.051)	(0.051)
Sector – Environmental services, …					-0.121^{**}	-0.137^{**}
					(0.056)	(0.055)
Sector – Other					-0.131^{***}	-0.130^{***}
					(0.048)	(0.048)

Occupation – Higher supervisory profession					0.184***	0.155***
					(0.030)	(0.030)
Occupation – Intermediate academic or …					-0.158***	-0.130***
					(0.026)	(0.026)
Occupation – Intermediate supervisory …					-0.136***	-0.143***
					(0.028)	(0.027)
Occupation – Other mental work					-0.296***	-0.278***
					(0.029)	(0.029)
Occupation – Skilled and supervisory …					-0.373***	-0.357***
					(0.032)	(0.031)
Occupation – Semi-skilled manual work					-0.402***	-0.362***
					(0.039)	(0.039)
Occupation – Unskilled and trained …					-0.571***	-0.547***
					(0.067)	(0.075)
Occupation – Agrarian profession					-0.470***	-0.459***
					(0.052)	(0.054)
Constant	1.550***	1.496***	1.501***	1.508***	2.431***	2.345***
	(0.092)	(0.091)	(0.090)	(0.091)	(0.096)	(0.097)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	5260	4700	4746	4700	5190	4746
R^2	0.253	0.327	0.336	0.333	0.513	0.530
adj. R^2	0.252	0.325	0.333	0.330	0.509	0.526

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Reference category of civil status is “never been married”, of employment “employee in permanent employment”, of sector “agriculture, forestry, fishery, hunting” and the reference of occupation is “higher academic or independent professional”.

Table A. 6: The wage differential models
Extended version of Table 3

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Educational level - vmbo	0.064	0.054	0.051	0.046	0.026	0.013
	(0.057)	(0.060)	(0.058)	(0.059)	(0.040)	(0.043)
Educational level – havo/vwo	0.265***	0.248***	0.249***	0.246***	0.112***	0.109**
	(0.062)	(0.064)	(0.061)	(0.062)	(0.042)	(0.045)
Educational level – mbo	0.228***	0.185***	0.182***	0.174***	0.100**	0.081*
	(0.058)	(0.060)	(0.057)	(0.059)	(0.039)	(0.042)
Educational level – hbo	0.527***	0.472***	0.465***	0.462***	0.280***	0.256***
	(0.058)	(0.060)	(0.057)	(0.059)	(0.042)	(0.045)
Educational level – wo	0.758***	0.669***	0.652***	0.655***	0.438***	0.393***
	(0.061)	(0.064)	(0.061)	(0.063)	(0.046)	(0.048)
Experience	0.036***	0.033***	0.030***	0.030***	0.031***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Experience squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		-0.000		-0.000		
		(0.000)		(0.000)		
Public		-0.035**		-0.035**		
		(0.017)		(0.017)		
(Log of) firm size		0.026***	0.027***	0.028***		0.020***
		(0.004)	(0.004)	(0.004)		(0.004)
Management		0.145***	0.152***	0.143***		0.059***
		(0.015)	(0.015)	(0.015)		(0.015)
Civil status – married			0.062***	0.059***		0.039**
			(0.018)	(0.018)		(0.015)
Civil status – separated			-0.018	-0.009		-0.026
			(0.115)	(0.120)		(0.117)
Civil status – divorced			0.020	0.021		-0.003
			(0.034)	(0.035)		(0.030)
Civil status – widow(er)			0.214**	0.209**		0.231***
			(0.093)	(0.095)		(0.088)
Employment – temporary					-0.144***	-0.136***
					(0.032)	(0.034)
Employment – temp-staffer					-0.305***	-0.299***
					(0.081)	(0.086)
Employment – director of a limited …					0.154*	0.165**
					(0.079)	(0.080)
Employment – majority shareholder …					0.123	0.142
					(0.157)	(0.139)
Sector – Mining					0.091	0.081
					(0.185)	(0.202)
Sector – Industrial production					-0.080	-0.089*
					(0.050)	(0.049)
Sector – Utilities production, …					-0.101*	-0.125**
					(0.058)	(0.059)
Sector – Construction					-0.082	-0.078
					(0.055)	(0.052)
Sector – Retail trade					-0.170***	-0.152***
					(0.055)	(0.053)
Sector – Catering					-0.199***	-0.209***
					(0.075)	(0.077)
Sector – Transport, storage and …					-0.120**	-0.130**
					(0.056)	(0.056)
Sector – Financial					0.009	0.000
					(0.055)	(0.053)
Sector – Business services					-0.081	-0.072
					(0.054)	(0.053)
Sector – Government services, …					-0.091*	-0.100**
					(0.051)	(0.049)

Sector – Education					-0.251***	-0.247***
					(0.053)	(0.052)
Sector – Healthcare and welfare					-0.181***	-0.194***
					(0.053)	(0.053)
Sector – Environmental services, …					-0.152***	-0.169***
					(0.059)	(0.057)
Sector – Other					-0.148***	-0.142***
					(0.051)	(0.050)
Occupation – Higher supervisory …					0.208***	0.175***
					(0.029)	(0.029)
Occupation – Intermediate academic …					-0.079***	-0.063**
					(0.025)	(0.025)
Occupation – Intermediate supervisory					-0.031	-0.049*
…					(0.028)	(0.027)
Occupation – Other mental work					-0.185***	-0.181***
					(0.029)	(0.030)
Occupation – Skilled and supervisory …					-0.244***	-0.241***
					(0.034)	(0.033)
Occupation – Semi-skilled manual work					-0.294***	-0.264***
					(0.039)	(0.040)
Occupation – Unskilled and trained …					-0.500***	-0.482***
					(0.074)	(0.081)
Occupation – Agrarian profession					-0.444***	-0.436***
					(0.071)	(0.075)
Constant	2.145***	2.049***	2.056***	2.056***	2.603***	2.524***
	(0.074)	(0.079)	(0.076)	(0.078)	(0.080)	(0.083)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	5260	4700	4746	4700	5190	4746
R^2	0.373	0.429	0.434	0.435	0.549	0.562
adj. R^2	0.372	0.426	0.432	0.432	0.545	0.558

Notes: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Reference category of educational level is “primary education”, of civil status is “never been married”, of employment “employee in permanent employment”, of sector “agriculture, forestry, fishery, hunting” and the reference of occupation is “higher academic or independent professional”.

Table A. 7: Wage premium interacted with year dummies

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Experience	0.037***	0.034***	0.031***	0.031***	0.031***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Experience squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Educational level - vmbo	0.207***	0.196**	0.192**	0.184**	0.143**	0.118*
	(0.076)	(0.078)	(0.078)	(0.079)	(0.063)	(0.065)
Educational level – havo/vwo	0.400***	0.357***	0.356***	0.351***	0.194***	0.174***
	(0.076)	(0.078)	(0.077)	(0.078)	(0.061)	(0.063)
Educational level – mbo	0.336***	0.287***	0.285***	0.277***	0.170***	0.143**
	(0.069)	(0.071)	(0.070)	(0.071)	(0.054)	(0.056)
Educational level – hbo	0.646***	0.573***	0.573***	0.563***	0.359***	0.323***
	(0.069)	(0.071)	(0.070)	(0.071)	(0.056)	(0.058)
Educational level – wo	0.831***	0.744***	0.726***	0.730***	0.502***	0.449***
	(0.074)	(0.075)	(0.074)	(0.076)	(0.060)	(0.062)
Year 2009	0.011	0.015	0.021	0.020	0.008	0.005
	(0.065)	(0.059)	(0.059)	(0.060)	(0.052)	(0.051)
Year 2010	0.146**	0.171**	0.182**	0.174**	0.121*	0.131**
	(0.074)	(0.078)	(0.075)	(0.077)	(0.062)	(0.063)
Year 2011	0.077	0.089	0.072	0.093	0.038	0.036
	(0.083)	(0.092)	(0.088)	(0.090)	(0.062)	(0.066)
Year 2012	0.119	0.078	0.077	0.074	0.069	0.033
	(0.081)	(0.104)	(0.102)	(0.102)	(0.071)	(0.093)
Year 2013	0.191**	0.216**	0.210**	0.213**	0.135*	0.149**
	(0.095)	(0.088)	(0.088)	(0.089)	(0.072)	(0.071)
Year 2014	0.105	0.253**	0.231*	0.241*	0.057	0.073
	(0.107)	(0.122)	(0.127)	(0.126)	(0.090)	(0.125)
Year 2015	0.014	-0.025	0.031	-0.025	0.017	0.027
	(0.128)	(0.208)	(0.180)	(0.201)	(0.094)	(0.135)
vmbo # year 2009	-0.073	-0.077	-0.085	-0.078	-0.077	-0.071
	(0.076)	(0.071)	(0.070)	(0.071)	(0.066)	(0.065)
vmbo # year 2010	-0.214**	-0.234***	-0.243***	-0.229***	-0.182**	-0.186**
	(0.084)	(0.087)	(0.085)	(0.086)	(0.075)	(0.076)
vmbo # year 2011	-0.166*	-0.184*	-0.162*	-0.181*	-0.119	-0.114
	(0.092)	(0.101)	(0.097)	(0.099)	(0.074)	(0.077)
vmbo # year 2012	-0.224**	-0.155	-0.152	-0.144	-0.152*	-0.094
	(0.091)	(0.113)	(0.111)	(0.111)	(0.081)	(0.102)
vmbo # year 2013	-0.300***	-0.324***	-0.307***	-0.311***	-0.240***	-0.243***
	(0.104)	(0.099)	(0.099)	(0.100)	(0.083)	(0.083)
vmbo # year 2014	-0.195*	-0.351***	-0.320**	-0.329**	-0.152	-0.155
	(0.116)	(0.131)	(0.136)	(0.135)	(0.100)	(0.133)
vmbo # year 2015	-0.109	-0.066	-0.113	-0.056	-0.120	-0.121
	(0.137)	(0.214)	(0.187)	(0.207)	(0.103)	(0.142)
havo/vwo # year 2009	0.009	0.001	0.010	0.002	0.014	0.015
	(0.073)	(0.067)	(0.067)	(0.067)	(0.059)	(0.059)
havo/vwo # year 2010	-0.172**	-0.161*	-0.171**	-0.161*	-0.121*	-0.118*
	(0.084)	(0.086)	(0.084)	(0.085)	(0.070)	(0.071)
havo/vwo # year 2011	-0.184*	-0.144	-0.124	-0.142	-0.074	-0.056
	(0.094)	(0.102)	(0.098)	(0.100)	(0.071)	(0.075)
havo/vwo # year 2012	-0.211**	-0.134	-0.126	-0.124	-0.123	-0.059
	(0.092)	(0.114)	(0.111)	(0.111)	(0.078)	(0.100)
havo/vwo # year 2013	-0.317***	-0.302***	-0.295***	-0.294***	-0.223***	-0.229***
	(0.105)	(0.099)	(0.099)	(0.100)	(0.079)	(0.080)
havo/vwo # year 2014	-0.202*	-0.309**	-0.279**	-0.290**	-0.116	-0.119
	(0.117)	(0.132)	(0.136)	(0.135)	(0.098)	(0.132)
havo/vwo # year 2015	-0.164	-0.081	-0.126	-0.068	-0.115	-0.097
	(0.137)	(0.215)	(0.187)	(0.208)	(0.101)	(0.141)
mbo # year 2009	-0.014	-0.024	-0.031	-0.031	-0.012	-0.013
	(0.068)	(0.062)	(0.062)	(0.063)	(0.054)	(0.054)
mbo # year 2010	-0.146*	-0.171**	-0.180**	-0.173**	-0.120*	-0.130**
	(0.077)	(0.081)	(0.079)	(0.080)	(0.064)	(0.065)
mbo # year 2011	-0.103	-0.105	-0.090	-0.112	-0.051	-0.051

	(0.086)	(0.095)	(0.091)	(0.093)	(0.065)	(0.068)
mbo # year 2012	-0.170**	-0.115	-0.111	-0.112	-0.095	-0.053
	(0.084)	(0.107)	(0.105)	(0.105)	(0.073)	(0.095)
mbo # year 2013	-0.266***	-0.266***	-0.261***	-0.264***	-0.175**	-0.182**
	(0.098)	(0.092)	(0.092)	(0.093)	(0.074)	(0.074)
mbo # year 2014	-0.201*	-0.327***	-0.297**	-0.311**	-0.121	-0.125
	(0.109)	(0.124)	(0.128)	(0.128)	(0.092)	(0.126)
mbo # year 2015	-0.102	-0.039	-0.081	-0.031	-0.068	-0.070
	(0.130)	(0.209)	(0.181)	(0.202)	(0.096)	(0.136)
hbo # year 2009	-0.017	-0.010	-0.020	-0.015	-0.004	0.001
	(0.067)	(0.061)	(0.060)	(0.062)	(0.053)	(0.053)
hbo # year 2010	-0.164**	-0.174**	-0.188**	-0.176**	-0.124*	-0.128*
	(0.077)	(0.080)	(0.077)	(0.079)	(0.064)	(0.065)
hbo # year 2011	-0.142*	-0.129	-0.116	-0.132	-0.065	-0.059
	(0.085)	(0.094)	(0.090)	(0.092)	(0.064)	(0.068)
hbo # year 2012	-0.185**	-0.125	-0.129	-0.119	-0.113	-0.073
	(0.084)	(0.107)	(0.105)	(0.105)	(0.073)	(0.095)
hbo # year 2013	-0.274***	-0.269***	-0.264***	-0.262***	-0.194***	-0.198***
	(0.098)	(0.091)	(0.091)	(0.092)	(0.074)	(0.073)
hbo # year 2014	-0.193*	-0.287**	-0.273**	-0.272**	-0.113	-0.112
	(0.110)	(0.125)	(0.129)	(0.129)	(0.093)	(0.127)
hbo # year 2015	-0.125	-0.052	-0.108	-0.048	-0.105	-0.107
	(0.131)	(0.210)	(0.182)	(0.203)	(0.096)	(0.137)
wo # year 2009	-0.006	0.004	-0.014	-0.000	0.005	0.006
	(0.069)	(0.064)	(0.063)	(0.064)	(0.056)	(0.055)
wo # year 2010	-0.128	-0.152*	-0.160**	-0.151*	-0.113*	-0.120*
	(0.079)	(0.082)	(0.079)	(0.081)	(0.067)	(0.068)
wo # year 2011	-0.092	-0.109	-0.081	-0.113	-0.064	-0.058
	(0.090)	(0.097)	(0.093)	(0.095)	(0.069)	(0.071)
wo # year 2012	-0.097	-0.085	-0.073	-0.082	-0.066	-0.042
	(0.089)	(0.111)	(0.109)	(0.108)	(0.078)	(0.100)
wo # year 2013	-0.184*	-0.205**	-0.195**	-0.205**	-0.157**	-0.174**
	(0.102)	(0.096)	(0.096)	(0.097)	(0.079)	(0.079)
wo # year 2014	-0.141	-0.266**	-0.237*	-0.251*	-0.109	-0.102
	(0.117)	(0.131)	(0.135)	(0.135)	(0.099)	(0.132)
wo # year 2015	-0.063	-0.003	-0.050	0.002	-0.089	-0.079
	(0.135)	(0.211)	(0.184)	(0.205)	(0.100)	(0.139)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		-0.000		-0.000		
		(0.000)		(0.000)		
Public		-0.036**		-0.036**		
		(0.017)		(0.017)		
(Log of) firm size		0.027***	0.027***	0.028***		0.020***
		(0.004)	(0.004)	(0.004)		(0.004)
Management		0.145***	0.151***	0.143***		0.060***
		(0.015)	(0.015)	(0.015)		(0.015)
Civil status – married			0.060***	0.058***		0.038**
			(0.018)	(0.018)		(0.015)
Civil status – separated			-0.015	-0.007		-0.021
			(0.113)	(0.119)		(0.116)
Civil status – divorced			0.020	0.020		-0.004
			(0.034)	(0.035)		(0.030)
Civil status – widow(er)			0.209**	0.206**		0.229**
			(0.095)	(0.097)		(0.090)
Employment type					Included	Included
Sector					Included	Included
Occupation					Included	Included
Constant	2.025***	1.938***	1.944***	1.947***	2.518***	2.449***
	(0.086)	(0.088)	(0.087)	(0.088)	(0.090)	(0.092)
N	5260	4700	4746	4700	5190	4746
R^2	0.377	0.432	0.438	0.438	0.551	0.564
adj. R^2	0.371	0.426	0.431	0.431	0.544	0.557

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reference category of educational level is “primary education”, of civil status is “never been married”, of employment “employee in permanent employment”, of sector “agriculture, forestry, fishery, hunting” and occupation is “higher academic or independent professional”. The reference year is 2008.

Table A. 8: Wage premium interacted with unemployment rate (0 year leading)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
vmbo	0.356^{**}	0.428^{**}	0.401^{**}	0.398^{**}	0.256^{*}	0.251^{*}
	(0.171)	(0.176)	(0.178)	(0.180)	(0.140)	(0.149)
havo/vwo	0.636^{***}	0.641^{***}	0.633^{***}	0.622^{***}	0.364^{***}	0.362^{**}
	(0.173)	(0.179)	(0.180)	(0.181)	(0.140)	(0.150)
mbo	0.546^{***}	0.540^{***}	0.519^{***}	0.514^{***}	0.295^{**}	0.281^{**}
	(0.164)	(0.167)	(0.168)	(0.170)	(0.132)	(0.139)
hbo	0.845^{***}	0.811^{***}	0.802^{***}	0.788^{***}	0.500^{***}	0.482^{***}
	(0.165)	(0.168)	(0.169)	(0.171)	(0.133)	(0.140)
wo	0.972^{***}	0.946^{***}	0.906^{***}	0.921^{***}	0.632^{***}	0.588^{***}
	(0.173)	(0.176)	(0.176)	(0.179)	(0.142)	(0.149)
Unemployment rate (0 yr. leading)	0.027	0.045	0.045	0.044	0.015	0.022
	(0.030)	(0.030)	(0.029)	(0.030)	(0.023)	(0.025)
vmbo # Unemployment rate (0 yr. leading)	-0.055^{*}	-0.073^{**}	-0.069^{**}	-0.069^{**}	-0.043^{*}	-0.046^{*}
	(0.032)	(0.031)	(0.031)	(0.031)	(0.025)	(0.026)
havo/vwo # Unemployment rate (0 yr. leading)	-0.069^{**}	-0.077^{**}	-0.075^{**}	-0.073^{**}	-0.047^{*}	-0.049^{*}
	(0.032)	(0.032)	(0.032)	(0.032)	(0.025)	(0.027)
mbo # Unemployment rate (0 yr. leading)	-0.060^{*}	-0.070^{**}	-0.066^{**}	-0.067^{**}	-0.037	-0.040
	(0.031)	(0.030)	(0.030)	(0.030)	(0.024)	(0.025)
hbo # Unemployment rate (0 yr. leading)	-0.060^{*}	-0.067^{**}	-0.066^{**}	-0.064^{**}	-0.041^{*}	-0.044^{*}
	(0.031)	(0.030)	(0.030)	(0.030)	(0.024)	(0.025)
wo # Unemployment rate (0 yr. leading)	-0.042	-0.056^{*}	-0.051^{*}	-0.053^{*}	-0.037	-0.039
	(0.032)	(0.031)	(0.031)	(0.031)	(0.025)	(0.026)
Year 2009	0.011	0.007	0.003	0.007	0.009	0.006
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Year 2010	0.027^{***}	0.025^{***}	0.022^{**}	0.025^{***}	0.025^{***}	0.024^{***}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)
Year 2011	-0.012	-0.010	-0.012	-0.011	0.000	-0.002
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Year 2012	0.007	0.003	-0.000	0.000	0.013	0.010
	(0.010)	(0.011)	(0.011)	(0.011)	(0.008)	(0.010)
Year 2013	0.036^{***}	0.028^{**}	0.021	0.023^{*}	0.033^{***}	0.026^{**}
	(0.012)	(0.013)	(0.013)	(0.013)	(0.010)	(0.012)
Year 2014	0.027^{**}	0.029^{**}	0.022^{*}	0.026^{**}	0.026^{**}	0.027^{**}
	(0.011)	(0.013)	(0.013)	(0.013)	(0.010)	(0.012)
N	5260	4700	4746	4700	5190	4746

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other explanatory variables are not displayed. However, the models are identical (with the exception of the interaction terms displayed above) to the models in Table 3. The reference year is 2008. The unemployment is neither leading nor lagging and the year 2015 is omitted.

Table A. 9: Wage premium interacted with unemployment rate (1 year leading)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
vmbo	0.456**	0.474**	0.430**	0.443**	0.302*	0.257
	(0.198)	(0.202)	(0.203)	(0.205)	(0.162)	(0.174)
havo/vwo	0.734***	0.688***	0.664***	0.667***	0.415**	0.372**
	(0.203)	(0.208)	(0.208)	(0.209)	(0.163)	(0.176)
mbo	0.621***	0.568***	0.535***	0.544***	0.322**	0.276*
	(0.189)	(0.192)	(0.193)	(0.195)	(0.154)	(0.164)
hbo	0.924***	0.849***	0.828***	0.825***	0.536***	0.490***
	(0.191)	(0.192)	(0.193)	(0.195)	(0.154)	(0.164)
wo	0.995***	0.962***	0.901***	0.941***	0.633***	0.582***
	(0.201)	(0.202)	(0.203)	(0.205)	(0.165)	(0.176)
Unemployment rate (1 yr. leading)	0.033	0.047	0.042	0.046	0.017	0.019
	(0.032)	(0.031)	(0.031)	(0.031)	(0.025)	(0.028)
vmbo # Unemployment rate (1 yr. leading)	-0.069**	-0.076**	-0.069**	-0.072**	-0.049*	-0.044
	(0.033)	(0.033)	(0.033)	(0.033)	(0.027)	(0.029)
havo/vwo # Unemployment rate (1 yr. leading)	-0.081**	-0.078**	-0.073**	-0.075**	-0.052*	-0.046
	(0.034)	(0.034)	(0.034)	(0.034)	(0.027)	(0.029)
mbo # Unemployment rate (1 yr. leading)	-0.069**	-0.069**	-0.064**	-0.067**	-0.039	-0.035
	(0.032)	(0.032)	(0.032)	(0.032)	(0.026)	(0.028)
hbo # Unemployment rate (1 yr. leading)	-0.069**	-0.068**	-0.065**	-0.065**	-0.044*	-0.041
	(0.032)	(0.032)	(0.032)	(0.032)	(0.026)	(0.028)
wo # Unemployment rate (1 yr. leading)	-0.043	-0.054	-0.046	-0.052	-0.034	-0.033
	(0.034)	(0.033)	(0.033)	(0.033)	(0.027)	(0.030)
Year 2009	0.010	0.005	0.002	0.004	0.008	0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Year 2010	0.009	0.010	0.010	0.011	0.009	0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Year 2011	-0.004	-0.009	-0.009	-0.010	0.005	-0.001
	(0.010)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)
Year 2012	0.040***	0.017	0.016	0.013	0.035***	0.023*
	(0.013)	(0.015)	(0.015)	(0.015)	(0.012)	(0.013)
Year 2013	0.028**	0.012	0.010	0.009	0.022*	0.011
	(0.013)	(0.014)	(0.014)	(0.014)	(0.012)	(0.013)
N	4677	4210	4252	4210	4612	4252

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other explanatory variables are not displayed. However, the models are identical (with the exception of the interaction terms displayed above) to the models in Table 3. The reference year is 2008. The unemployment rate is leading 1 year and the year 2014 is omitted. The year 2015 is dropped as there is no information available on the unemployment rate of 2016.

Table A. 10: Wage premium interacted with unemployment rate (2 year leading)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
vmbo	0.550**	0.518*	0.459*	0.491*	0.352*	0.283
	(0.263)	(0.267)	(0.267)	(0.269)	(0.206)	(0.218)
havo/vwo	0.874***	0.741***	0.712***	0.726***	0.480**	0.387*
	(0.270)	(0.273)	(0.273)	(0.274)	(0.207)	(0.220)
mbo	0.662***	0.563**	0.520**	0.547**	0.342*	0.277
	(0.255)	(0.258)	(0.257)	(0.260)	(0.198)	(0.209)
hbo	1.012***	0.902***	0.866***	0.883***	0.586***	0.522**
	(0.256)	(0.258)	(0.257)	(0.260)	(0.198)	(0.209)
wo	1.042***	1.003***	0.915***	0.988***	0.674***	0.611***
	(0.267)	(0.267)	(0.267)	(0.269)	(0.209)	(0.220)
Unemployment rate (2 yr. leading)	0.036	0.040	0.034	0.040	0.018	0.015
	(0.039)	(0.040)	(0.039)	(0.040)	(0.030)	(0.032)
vmbo # Unemployment rate (2 yr. leading)	-0.081**	-0.077*	-0.067	-0.073*	-0.054*	-0.045
	(0.041)	(0.041)	(0.041)	(0.041)	(0.032)	(0.034)
havo/vwo # Unemployment rate (2 yr. leading)	-0.099**	-0.080*	-0.075*	-0.078*	-0.060*	-0.046
	(0.042)	(0.043)	(0.042)	(0.042)	(0.032)	(0.034)
mbo # Unemployment rate (2 yr. leading)	-0.071*	-0.062	-0.055	-0.060	-0.040	-0.033
	(0.040)	(0.040)	(0.040)	(0.040)	(0.031)	(0.033)
hbo # Unemployment rate (2 yr. leading)	-0.079**	-0.071*	-0.065	-0.069*	-0.050	-0.043
	(0.040)	(0.040)	(0.040)	(0.040)	(0.031)	(0.033)
wo # Unemployment rate (2 yr. leading)	-0.047	-0.055	-0.043	-0.054	-0.037	-0.034
	(0.041)	(0.042)	(0.041)	(0.042)	(0.032)	(0.035)
Year 2009	-0.010	-0.007	-0.009	-0.006	-0.007	-0.008
	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Year 2010	0.018**	0.018**	0.018**	0.020**	0.016**	0.018**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Year 2011	0.035***	0.022*	0.021*	0.020	0.033***	0.027**
	(0.011)	(0.012)	(0.012)	(0.012)	(0.010)	(0.011)
Year 2012	0.033***	0.019*	0.020**	0.018*	0.029***	0.026***
	(0.008)	(0.010)	(0.010)	(0.010)	(0.008)	(0.009)
N	4030	3672	3711	3672	3974	3711

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other explanatory variables are not displayed. However, the models are identical (with the exception of the interaction terms displayed above) to the models in Table 3. The reference year is 2008. The unemployment rate is leading 2 years and the year 2013 is omitted. The years 2014 and 2015 are dropped as there is no information available on the unemployment rate of 2016 and 2017.

Table A. 11: Wage premium interacted with GDP growth rate (1 year lagging)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
vmbo	0.042	0.023	0.022	0.017	0.007	-0.008
	(0.056)	(0.057)	(0.054)	(0.056)	(0.038)	(0.041)
havo/vwo	0.245^{***}	0.223^{***}	0.225^{***}	0.221^{***}	0.097^{**}	0.092^{**}
	(0.062)	(0.061)	(0.058)	(0.060)	(0.041)	(0.043)
mbo	0.209^{***}	0.158^{***}	0.158^{***}	0.148^{***}	0.085^{**}	0.064
	(0.057)	(0.057)	(0.054)	(0.056)	(0.038)	(0.040)
hbo	0.508^{***}	0.446^{***}	0.441^{***}	0.437^{***}	0.266^{***}	0.240^{***}
	(0.056)	(0.057)	(0.054)	(0.056)	(0.041)	(0.043)
wo	0.742^{***}	0.646^{***}	0.630^{***}	0.632^{***}	0.424^{***}	0.378^{***}
	(0.060)	(0.062)	(0.058)	(0.060)	(0.045)	(0.047)
GDP growth rate (1 yr. lagging)	0.010	-0.004	-0.007	-0.006	0.008	0.003
	(0.012)	(0.013)	(0.012)	(0.012)	(0.010)	(0.010)
vmbo # GDP growth rate (1 yr. lagging)	0.030^{**}	0.036^{***}	0.036^{***}	0.035^{***}	0.025^{**}	0.027^{***}
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
havo/vwo # GDP growth rate (1 yr. lagging)	0.027^{**}	0.029^{**}	0.030^{**}	0.029^{**}	0.020^{**}	0.022^{**}
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
mbo # GDP growth rate (1 yr. lagging)	0.025^{**}	0.030^{**}	0.030^{***}	0.030^{**}	0.019^{**}	0.021^{**}
	(0.011)	(0.012)	(0.011)	(0.012)	(0.009)	(0.009)
hbo # GDP growth rate (1 yr. lagging)	0.025^{**}	0.029^{**}	0.030^{***}	0.029^{**}	0.020^{**}	0.021^{**}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)
wo # GDP growth rate (1 yr. lagging)	0.020^{*}	0.026^{**}	0.026^{**}	0.025^{**}	0.018^{*}	0.020^{**}
	(0.011)	(0.012)	(0.011)	(0.012)	(0.009)	(0.009)
Year 2009	0.060^{***}	0.044^{***}	0.036^{***}	0.039^{***}	0.049^{***}	0.039^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Year 2010	0.247^{***}	0.188^{***}	0.166^{***}	0.172^{***}	0.204^{***}	0.175^{***}
	(0.036)	(0.039)	(0.038)	(0.038)	(0.032)	(0.035)
Year 2011	0.030^{***}	0.022^{*}	0.016	0.017	0.034^{***}	0.027^{**}
	(0.011)	(0.012)	(0.012)	(0.012)	(0.010)	(0.011)
Year 2012	0.016	0.009	0.005	0.006	0.020^{**}	0.016
	(0.010)	(0.011)	(0.011)	(0.011)	(0.009)	(0.010)
Year 2013	0.097^{***}	0.075^{***}	0.062^{***}	0.065^{***}	0.083^{***}	0.068^{***}
	(0.019)	(0.021)	(0.020)	(0.021)	(0.017)	(0.019)
Year 2014	0.065^{***}	0.057^{***}	0.047^{***}	0.051^{***}	0.056^{***}	0.052^{***}
	(0.015)	(0.017)	(0.017)	(0.017)	(0.013)	(0.015)
N	5260	4700	4746	4700	5190	4746

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other explanatory variables are not displayed. However, the models are identical (with the exception of the interaction terms displayed above) to the models in Table A. 11 in the appendix. The reference year is 2008. The GDP growth rate is lagging 1 year and the year 2015 is omitted.

Table A. 12: Age instead of potential work experience

Dep Var:		(1)	(2)	(3)	(4)	(5)	(6)
(Log of) gross hourly wage - based on Table 2	Years of education	0.070***	0.061***	0.060***	0.060***	0.028***	0.026***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	N	5260	4700	4746	4700	5190	4746
	R^2	0.255	0.329	0.337	0.334	0.513	0.531
	adj. R^2	0.254	0.327	0.335	0.332	0.51	0.526
(Log of) gross monthly wage - based on Table 4	Years of education	0.069***	0.061***	0.060***	0.060***	0.028***	0.026***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	N	5260	4700	4746	4700	5190	4746
	R^2	0.241	0.315	0.323	0.321	0.507	0.522
	adj. R^2	0.239	0.313	0.32	0.318	0.503	0.518
(Log of) gross hourly wage - based on Table 3	vmbo	0.034	0.034	0.027	0.028	0.006	-0.004
		(0.055)	(0.059)	(0.056)	(0.057)	(0.039)	(0.042)
	havo/vwo	0.216***	0.213***	0.210***	0.213***	0.077*	0.080*
		(0.059)	(0.061)	(0.058)	(0.060)	(0.041)	(0.043)
	mbo	0.149***	0.125**	0.119**	0.118**	0.042	0.03
		(0.055)	(0.057)	(0.054)	(0.056)	(0.038)	(0.040)
	hbo	0.433***	0.399***	0.389***	0.394***	0.209***	0.194***
		(0.055)	(0.057)	(0.055)	(0.056)	(0.040)	(0.043)
	wo	0.645***	0.581***	0.561***	0.573***	0.351***	0.317***
		(0.058)	(0.061)	(0.058)	(0.060)	(0.043)	(0.046)
	N	5260	4700	4746	4700	5190	4746
	R^2	0.373	0.429	0.434	0.434	0.548	0.561
	adj. R^2	0.371	0.426	0.432	0.432	0.544	0.557
(Log of) gross monthly wage - based on Table 4	vmbo	0.06	0.06	0.057	0.053	0.026	0.021
		(0.058)	(0.060)	(0.058)	(0.059)	(0.040)	(0.042)
	havo/vwo	0.217***	0.219***	0.217***	0.219***	0.075*	0.082*
		(0.062)	(0.063)	(0.061)	(0.062)	(0.042)	(0.044)
	mbo	0.167***	0.141**	0.139**	0.135**	0.052	0.044
		(0.057)	(0.059)	(0.056)	(0.058)	(0.038)	(0.041)
	hbo	0.441***	0.413***	0.402***	0.408***	0.219***	0.206***
		(0.057)	(0.059)	(0.056)	(0.058)	(0.041)	(0.043)
	wo	0.655***	0.600***	0.578***	0.593***	0.357***	0.329***
		(0.061)	(0.063)	(0.061)	(0.062)	(0.045)	(0.047)
	N	5260	4700	4746	4700	5190	4746
	R^2	0.35	0.413	0.415	0.42	0.54	0.552
	adj. R^2	0.348	0.411	0.412	0.417	0.536	0.547

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The models are identical to the models in the tables referred to. However, in all of these models the variable age is replaced by potential work experience. All other control variables remained identical. Generally, the education coefficient is 10 – 15 percent smaller when age instead of potential work experience is used.

Table A. 13: Differences between individuals who reported vs. who did not reported their father's level of education

	Mean		Significance level	# Obs.
Variables	Group_f=0	Group_f=1		
Gross monthly wage	3546.917	3812.341		5260
Gross hourly wage	21.376	22.980		5260
Years of education	13.302	13.716	**	5260
Age	41.597	43.830	***	5260
Potential work experience	22.295	24.114	***	5260
Tenure	134.653	145.413		5226
Tenure crisis dummy	0.165	0.179		5260
Firm size	404.916	452.025		4750
Public	0.285	0.287		5238
Management	0.428	0.425		5186
Number of household members	2.899	3.077		5260
Number of children	1.099	1.251		5260

Note: group_f=0 indicates individuals who did not report or where not asked to report their father's level of education and group_f=1 indicates individuals who did report their father's level of education. A *, ** or *** indicates a significance level of, respectively, 10, 5 or 1 percent. The constructed significance levels are based on robust clustered standard errors. The differences between the two groups are examined per variable (not all at once), therefore the number of observations are included.

Table A. 14: Differences between individuals who reported vs. who did not report either their father's or mother's level of education

	Mean		Significance level	# Obs.
Variables	Group_fm=0	Group_fm=1		
Gross monthly wage	3586.137	3777.294		5260
Gross hourly wage	21.590	22.778		5260
Years of education	13.336	13.673	*	5260
Age	41.074	43.901	***	5260
Potential work experience	21.738	24.228	***	5260
Tenure	128.771	147.180	**	5226
Tenure crisis	0.167	0.178		5260
Firm size	384.882	457.253		4750
Public	0.265	0.295		5238
Management	0.451	0.416		5186
Number of household members	2.852	3.085	**	5260
Number of children	1.067	1.255	**	5260

Note: group_fm=0 indicates individuals who did not report or where not asked to report their father's or mother's level of education and group_fm=1 indicates individuals who did report their father's or mother's level of education. A *, ** or *** indicates a significance level of, respectively, 10, 5 or 1 percent. The constructed significance levels are based on robust clustered standard errors. The differences between the two groups are examined per variable (not all at once), therefore the number of observations are included.

Table A. 15: The Mincer IV models
Both father's and mother's years of education are used as instrument

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.149***	0.135***	0.132***	0.139***	0.092**	0.087*
	(0.028)	(0.030)	(0.029)	(0.030)	(0.046)	(0.047)
Age	0.064***	0.059***	0.051***	0.056***	0.042***	0.037**
	(0.018)	(0.019)	(0.018)	(0.020)	(0.014)	(0.014)
Age squared	-0.001**	-0.001**	-0.000**	-0.001**	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure		0.000		0.000		
		(0.000)		(0.000)		
Tenure squared		0.000		0.000		
		(0.000)		(0.000)		
Public		-0.040		-0.041		
		(0.032)		(0.032)		
(Log of) firm size		0.024***	0.024***	0.024***		0.022***
		(0.008)	(0.008)	(0.008)		(0.006)
Management		0.129***	0.139***	0.126***		0.067***
		(0.028)	(0.026)	(0.027)		(0.022)
Civil status – married			0.043	0.039		0.033
			(0.028)	(0.028)		(0.022)
Civil status – separated			0.050	0.081		0.138**
			(0.067)	(0.074)		(0.068)
Civil status – divorced			0.053	0.050		0.035
			(0.057)	(0.059)		(0.047)
Civil status – widow(er)			-0.099	-0.139		0.012
			(0.112)	(0.135)		(0.132)
Employment type					Included	Included
Sector					Included	Included
Occupation					Included	Included
Constant	-0.679	-0.488	-0.313	-0.482	0.759	0.841
	(0.618)	(0.644)	(0.596)	(0.647)	(0.819)	(0.841)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	3233	2957	2982	2957	3213	2982

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Reference category of civil status is "never been married", of employment "employee in permanent employment", of sector "agriculture, forestry, fishery, hunting" and the reference of occupation is "higher academic or independent professional". Years of education is instrumented by father's and mother's years of education.

Table A. 16: Summary results for first-stage regression tests of the IV results
Only father's education as instrument

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Single endogenous regressors:						
Standard F-statistic:	46.56	36.61	39.05	37.25	16.3	14.59
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW X2 - tests of underidentification:	46.76	36.84	39.30	37.53	16.5	14.81
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW F-statistic for weak identification:	46.56	36.61	39.05	37.25	16.3	14.59
Underidentification test:						
Kleibergen-Paap rk LM statistic:	38.37	32.55	34.52	33.33	15.52	14.07
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Overidentification test of all instruments:						
Hansen J statistic:	N/A	N/A	N/A	N/A	N/A	N/A
Weak-instrument-robust inference:						
Anderson-Rubin Wald test (F-stat):	32.68	21.29	22.04	23.25	3.53	2.38
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.12)
Anderson-Rubin Wald test (X2):	32.82	21.42	22.18	23.42	3.57	2.41
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.12)
Stock-Wright LM S statistic:	31.65	21.56	22.36	23.62	4.29	2.97
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.08)
Endogeneity:						
Endogeneity test:	9.56	6.53	6.46	7.66	1.41	0.82
	(0.00)	(0.01)	(0.01)	(0.01)	(0.24)	(0.37)

Note: p-values in parentheses. SW is the Sanderson-Windmeijer test for underidentifcation and weak identification. The SW test is modified and improved over the Angrist-Pischke test. The SW F-statistic for weak identification does not report p-values. The test-statistics can be compared to the Stock-Yogo critical values. The Stock-Yogo Weak ID F-test critical values for single endogenous regressors are: 16.38 (10% maximal IV size), 8.96 (15% maximal IV size), 6.66 (20% maximal IV size) and 5.53 (25% maximal IV size). For more details, see Baum et al. (2010). The models are identical to the models constructed in Table 9. The endogeneity test is based on the robust clustered standard errors.

Table A. 17: Summary results for first-stage regression tests of the IV results
Both father's and mother's education as instrument

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Single endogenous regressors:						
Standard F-statistic:	18.33	14.89	16.22	15.23	5.9	5.32
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
SW X2 - tests of underidentification:	36.83	29.99	32.68	30.71	11.96	10.82
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SW F-statistic for weak identification:	18.33	14.89	16.22	15.23	5.9	5.32
Underidentification test:						
Kleibergen-Paap rk LM statistic:	30.79	26.38	28.49	27.1	11.32	10.31
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)
Overidentification test of all instruments:						
Hansen J statistic:	1.87	2.42	2.17	2.43	2.63	3.02
	(0.17)	(0.12)	(0.14)	(0.12)	(0.10)	(0.08)
Weak-instrument-robust inference:						
Anderson-Rubin Wald test (F-stat):	20.37	14.2	15.21	15.34	4.66	4.55
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Anderson-Rubin Wald test (X2):	40.94	28.6	30.65	30.94	9.44	9.24
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Stock-Wright LM S statistic:	34.87	25.05	26.55	26.75	9.48	9.43
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Endogeneity:						
Endogeneity test:	11.91	8.00	8.28	9.01	2.81	2.49
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.11)

Notes: p-values in parentheses. SW is the Sanderson-Windmeijer test for underidentifcation and weak identification. The SW test is modified and improved over the Angrist-Pischke test. The SW F-statistic for weak identification does not report p-values. The test-statistics can be compared to the Stock-Yogo critical values. The Stock-Yogo Weak ID F-test critical values for single endogenous regressors are: 19.93 (10% maximal IV size), 11.59 (15% maximal IV size), 8.75 (20% maximal IV size) and 7.25 (25% maximal IV size). For more details, see Baum et al. (2010). These models are identical to the model constructed in Table A. 15 in the appendix. The endogeneity test is based on the robust clustered standard errors.

Table A. 18: Heckman selection model (years of education)

Dep Var: (Log of) gross hourly wage		2008	2009	2010	2011	2012	2013	2014	2015	pooled
Baseline results	Years of education	0.076***	0.089***	0.082***	0.084***	0.088***	0.088***	0.082***	0.086***	0.084***
		(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.004)
	N	885	701	678	548	635	583	647	583	5260
	R^2	0.21	0.291	0.299	0.331	0.278	0.27	0.182	0.219	0.253
Non-response	Years of education	0.089***	0.099***	0.094***	0.090***	0.092***	0.093***	0.092***	0.094***	0.093***
		(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.01)	(0.009)	(0.009)	(0.005)
	N	1218	945	926	757	854	753	864	809	7126
	N (censored)	334	244	250	211	222	174	225	235	1895
	lambda	0.317	0.189	0.304	0.167	0.151	0.14	0.331	0.197	0.252
	chi^2 (comparison test)	13.622	4.291	66.102	3.656	1.496	0.549	19.255	3.682	23.493
	p-value	0.000	0.038	0.000	0.056	0.221	0.459	0.000	0.055	0.000
Non-employment (1)	Years of education	0.076***	0.087***	0.080***	0.080***	0.084***	0.085***	0.081***	0.081***	0.082***
		(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.004)
	N	912	726	721	581	666	622	700	623	5551
	N (censored)	28	25	45	35	34	43	61	49	320
	lambda	-0.013	-0.109	-0.073	-0.196	-0.188	-0.206	-0.07	-0.18	-0.066
	chi^2 (comparison test)	0.304	0.746	1.001	4.99	4.963	6.483	4.83	5.74	4.728
	p-value	0.581	0.388	0.317	0.025	0.026	0.011	0.028	0.017	0.03
Non-employment (2)	Years of education	0.076***	0.084***	0.077***	0.088***	0.082***	0.082***	0.080***	0.087***	0.080***
		(0.007)	(0.007)	(0.006)	(0.011)	(0.006)	(0.007)	(0.007)	(0.014)	(0.004)
	N	991	792	800	648	731	680	776	699	6115
	N (censored)	107	91	124	100	99	101	137	125	884
	lambda	-0.026	-0.116	-0.093	0.085	-0.157	-0.168	-0.061	0.02	-0.062
	chi^2 (comparison test)	1.238	3.285	2.688	0.21	4.391	4.278	2.139	0.008	3.246
	p-value	0.266	0.07	0.101	0.646	0.036	0.039	0.144	0.93	0.072

Note: robust (clustered) standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The standard errors are clustered when the regression is pooled. In total eight separate year regressions and one pooled regressions is estimated for each type of model. The dependent variable is the (log of) gross hourly wage and the independent variables are years of education, experience and experience squared. In the pooled regression, also year dummies are included. With the exception of the baseline results, all selection equations are based on the explanatory variables, the civil status (*burgstat*), urban character of the place of residence (*sted*) and the number of household members (*aantalhh*). All heckman selection models are based on the maximum likelihood estimation procedure. N is the total number of observations in the wage equation. N (censored) is the number of observations in the selection equation. Lambda is the inverse Mills ratio and represents the selection term. The chi^2 and its corresponding p-value are used to indicate the presence of sample selectivity. Non-employment (1) only includes individuals who lost their job, non-employment (2) also includes all other individuals who are not employed. The non-employment (2) regression for the year 2011 does not contain the variable *sted* in the selection equation due to an otherwise infinite number of iterations.

Table A. 19: Heckman selection model (level of education)

Dep Var: (Log of) gross hourly wage		2008	2009	2010	2011	2012	2013	2014	2015	pooled
Baseline results	vmbo	0.198***	0.129	-0.021	0.03	-0.003	-0.059	0.018	0.098	0.064
		(0.075)	(0.118)	(0.063)	(0.071)	(0.071)	(0.088)	(0.101)	(0.127)	(0.057)
	havo/vwo	0.384***	0.401***	0.213***	0.210***	0.212***	0.13	0.207*	0.231*	0.265***
		(0.077)	(0.121)	(0.071)	(0.078)	(0.078)	(0.094)	(0.107)	(0.133)	(0.062)
	mbo	0.313***	0.310***	0.177***	0.225***	0.192***	0.122	0.145	0.228*	0.228***
		(0.072)	(0.118)	(0.063)	(0.071)	(0.072)	(0.09)	(0.1)	(0.129)	(0.058)
	hbo	0.619***	0.615***	0.471***	0.501***	0.489***	0.428***	0.461***	0.512***	0.527***
		(0.073)	(0.118)	(0.064)	(0.071)	(0.073)	(0.091)	(0.1)	(0.128)	(0.058)
	wo	0.804***	0.809***	0.696***	0.746***	0.765***	0.709***	0.694***	0.753***	0.758***
		(0.076)	(0.121)	(0.069)	(0.077)	(0.077)	(0.094)	(0.107)	(0.132)	(0.061)
	N	885	701	678	548	635	583	647	583	5260
	R^2	0.304	0.4	0.435	0.452	0.42	0.428	0.308	0.337	0.373
Non-response	vmbo	0.198**	0.124	-0.07	0.033	-0.007	-0.066	0.056	0.114	0.056
		(0.084)	(0.12)	(0.07)	(0.075)	(0.071)	(0.089)	(0.109)	(0.13)	(0.062)
	havo/vwo	0.452***	0.437***	0.226***	0.255***	0.236***	0.159	0.308***	0.276*	0.311***
		(0.086)	(0.113)	(0.078)	(0.083)	(0.081)	(0.097)	(0.118)	(0.141)	(0.067)
	mbo	0.365***	0.340***	0.171**	0.241***	0.195***	0.128	0.208*	0.252*	0.246***
		(0.079)	(0.111)	(0.07)	(0.075)	(0.073)	(0.091)	(0.109)	(0.132)	(0.062)
	hbo	0.722***	0.672***	0.508***	0.554***	0.508***	0.451***	0.551***	0.555***	0.581***
		(0.08)	(0.106)	(0.07)	(0.076)	(0.076)	(0.094)	(0.113)	(0.139)	(0.062)
	wo	0.889***	0.865***	0.740***	0.788***	0.789***	0.736***	0.796***	0.816***	0.811***
		(0.084)	(0.112)	(0.076)	(0.081)	(0.079)	(0.096)	(0.12)	(0.142)	(0.066)
	N (uncensored)	1218	945	926	757	854	753	864	809	7126
	N (censored)	334	244	250	211	222	174	225	235	1895
	lambda	0.299	0.153	0.255	0.173	0.093	0.098	0.275	0.137	0.215
	chi^2 (comparison test)	13.829	3.263	66.396	11.156	1.635	1.942	12.004	1.366	16.991
	p-value	0.000	0.071	0.000	0.001	0.201	0.163	0.001	0.243	0.000
Nonemployment (1)	vmbo	0.198***	0.098	-0.024	0.023	0.011	-0.076	0.019	0.075	0.055
		(0.075)	(0.115)	(0.064)	(0.071)	(0.071)	(0.091)	(0.101)	(0.128)	(0.057)
	havo/vwo	0.384***	0.380***	0.205***	0.195**	0.211***	0.098	0.208*	0.192	0.250***
		(0.077)	(0.119)	(0.072)	(0.079)	(0.079)	(0.098)	(0.107)	(0.135)	(0.062)
	mbo	0.311***	0.274**	0.161**	0.212***	0.190***	0.107	0.141	0.194	0.211***
		(0.072)	(0.115)	(0.065)	(0.072)	(0.073)	(0.093)	(0.1)	(0.131)	(0.057)
	hbo	0.618***	0.576***	0.446***	0.478***	0.483***	0.393***	0.447***	0.463***	0.506***
		(0.072)	(0.114)	(0.065)	(0.071)	(0.074)	(0.096)	(0.1)	(0.131)	(0.057)
	wo	0.804***	0.768***	0.672***	0.733***	0.764***	0.688***	0.692***	0.721***	0.741***
		(0.076)	(0.118)	(0.07)	(0.078)	(0.077)	(0.097)	(0.108)	(0.134)	(0.06)
	N (uncensored)	912	726	721	581	666	622	700	623	5551
	N (censored)	28	25	45	35	34	43	61	49	320
	lambda	-0.012	-0.183	-0.155	-0.125	-0.167	-0.172	-0.079	-0.135	-0.071
	chi^2 (comparison test)	0.494	7.165	15.346	3.648	7.77	3.384	7.405	4.963	6.009
	p-value	0.482	0.007	0.000	0.056	0.005	0.066	0.007	0.026	0.014
Non-employment (2)	vmbo	0.192**	0.081	-0.05	-0.016	-0.026	-0.107	-0.003	0.03	0.037
		(0.075)	(0.112)	(0.065)	(0.073)	(0.073)	(0.094)	(0.102)	(0.134)	(0.058)
	havo/vwo	0.376***	0.349***	0.162**	0.147*	0.188**	0.076	0.184*	0.156	0.230***
		(0.078)	(0.115)	(0.073)	(0.082)	(0.081)	(0.1)	(0.107)	(0.14)	(0.062)
	mbo	0.302***	0.249**	0.118*	0.158**	0.140*	0.067	0.112	0.144	0.186***
		(0.072)	(0.112)	(0.066)	(0.076)	(0.076)	(0.096)	(0.101)	(0.138)	(0.058)
	hbo	0.608***	0.541***	0.397***	0.420***	0.435***	0.355***	0.417***	0.407***	0.477***
		(0.073)	(0.111)	(0.066)	(0.076)	(0.078)	(0.1)	(0.102)	(0.142)	(0.058)
	wo	0.795***	0.740***	0.632***	0.680***	0.718***	0.649***	0.662***	0.667***	0.714***
		(0.077)	(0.115)	(0.072)	(0.082)	(0.08)	(0.101)	(0.11)	(0.143)	(0.062)
	N (uncensored)	991	792	800	646	731	680	776	699	6115
	N (censored)	107	91	124	100	99	101	137	125	884
	lambda	-0.035	-0.166	-0.155	-0.137	-0.171	-0.178	-0.087	-0.133	-0.088
	chi^2 (comparison test)	5.825	16.38	26.658	6.985	11.454	6.719	8.799	3.355	6.662
	p-value	0.016	0.000	0.000	0.008	0.001	0.01	0.003	0.067	0.01

Note: robust (clustered) standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The standard errors are clustered when the regression is pooled. In total eight separate year regressions and one pooled regressions is estimated for each type of model. The dependent variable is the (log of) gross hourly wage and the independent variables are the level of education, experience and experience squared. In the pooled regression, also year dummies are included. The reference category is primary education. With the exception of the baseline results, all selection equations are based on the explanatory variables, the civil status (*burgstat*), urban character of the place of residence (*sted*) and the number of household members (*aantalhh*). All heckman selection models are based on the maximum likelihood estimation procedure. N is the total number of observations in the wage equation. N (censored) is the number of observations in the selection equation. Lambda is the inverse Mills ratio and represents the selection term. The chi^2 and its corresponding p-value are used to indicate the presence of sample selectivity. Non-employment (1) only includes individuals who lost their job, non-employment (2) also includes all other individuals who are not employed. The non-employment (2) regression for the year 2011 does not contain the variable *burgstat* in the selection equation due to an otherwise infinite number of iterations.

Table A. 20: Overview results - years of education

Dep Var: (Log of) gross hourly wage		(1)	(2)	(3)	(4)	(5)	(6)
Baseline results - males	Years of education	0.084***	0.073***	0.072***	0.072***	0.038***	0.035***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	N	5260	4700	4746	4700	5190	4746
	R^2	0.253	0.327	0.336	0.333	0.513	0.53
	adj. R^2	0.252	0.325	0.333	0.33	0.509	0.526
Extended sample (1) - males	Years of education	0.082***	0.072***	0.072***	0.071***	0.039***	0.036***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	N	7291	6483	6565	6483	7203	6565
	R^2	0.3	0.365	0.373	0.371	0.495	0.527
	adj. R^2	0.299	0.364	0.371	0.369	0.493	0.524
Extended sample (2) - males	Years of education	0.084***	0.074***	0.074***	0.073***	0.042***	0.040***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	N	7701	6861	6950	6861	7610	6950
	R^2	0.303	0.358	0.364	0.362	0.477	0.5
	adj. R^2	0.302	0.356	0.362	0.36	0.475	0.497
Extended sample (2*) - males	Years of education	0.083***	0.073***	0.073***	0.072***	0.040***	0.038***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	N	7701	6861	6950	6861	7610	6950
	R^2	0.306	0.365	0.372	0.37	0.488	0.514
	adj. R^2	0.305	0.364	0.37	0.368	0.485	0.511
Baseline results - females	Years of education	0.069***	0.059***	0.063***	0.060***	0.034***	0.034***
		(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
	N	2162	1852	1867	1852	2117	1867
	R^2	0.162	0.284	0.315	0.32	0.401	0.485
	adj. R^2	0.158	0.278	0.309	0.313	0.391	0.473
Extended sample (1) - females	Years of education	0.071***	0.063***	0.066***	0.064***	0.037***	0.037***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
	N	3258	2769	2789	2769	3196	2789
	R^2	0.237	0.327	0.344	0.351	0.431	0.491
	adj. R^2	0.235	0.323	0.341	0.346	0.425	0.484
Extended sample (2) - females	Years of education	0.073***	0.061***	0.067***	0.061***	0.040***	0.038***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
	N	6897	5820	5857	5820	6773	5857
	R^2	0.169	0.249	0.235	0.256	0.309	0.357
	adj. R^2	0.168	0.247	0.233	0.253	0.305	0.352
Extended sample (2*) - females	Years of education	0.072***	0.061***	0.065***	0.061***	0.037***	0.034***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
	N	6897	5820	5857	5820	6773	5857
	R^2	0.174	0.252	0.236	0.257	0.309	0.358
	adj. R^2	0.172	0.249	0.234	0.255	0.305	0.353

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The same models are estimated as in Table A. 5 in the appendix. The baseline results only includes full time workers (i.e. a minimum of 32 hours per week) aged 30 -55 years, either males or females. The extended sample (1) includes full time workers aged 20 – 65, either males or females. The extended sample (2) includes full time and part time workers (i.e. 12 - 31 hours per week), either males or females. The extended sample (2*) is identical to extended sample (2), however, all six models correct for part time workers by including the interaction term of part time * years of education. If the interaction terms are significant, these are included. Generally, gross hourly wage as the dependent variable is sufficient to control for part time workers.

Table A. 21: Overview results - level of education

Dep Var: (Log of) gross hourly wage		(1)	(2)	(3)	(4)	(5)	(6)
	vmbo	0.064	0.054	0.051	0.046	0.026	0.013
		(0.057)	(0.060)	(0.058)	(0.059)	(0.040)	(0.043)
	havo/vwo	0.265***	0.248***	0.249***	0.246***	0.112***	0.109**
		(0.062)	(0.064)	(0.061)	(0.062)	(0.042)	(0.045)
Baseline results	mbo	0.228***	0.185***	0.182***	0.174***	0.100**	0.081*
		(0.058)	(0.060)	(0.057)	(0.059)	(0.039)	(0.042)
	hbo	0.527***	0.472***	0.465***	0.462***	0.280***	0.256***
		(0.058)	(0.060)	(0.057)	(0.059)	(0.042)	(0.045)
	wo	0.758***	0.669***	0.652***	0.655***	0.438***	0.393***
		(0.061)	(0.064)	(0.061)	(0.063)	(0.046)	(0.048)
	N	5260	4700	4746	4700	5190	4746
	R^2	0.373	0.429	0.434	0.435	0.549	0.562
	adj. R^2	0.372	0.426	0.432	0.432	0.545	0.558
	vmbo	0.034	0.041	0.035	0.033	0.002	0.007
		(0.056)	(0.054)	(0.052)	(0.052)	(0.041)	(0.041)
	havo/vwo	0.241***	0.224***	0.224***	0.221***	0.098**	0.101***
		(0.058)	(0.055)	(0.052)	(0.053)	(0.040)	(0.039)
Extended sample (1)	mbo	0.207***	0.174***	0.169***	0.162***	0.090**	0.079**
		(0.053)	(0.051)	(0.048)	(0.050)	(0.037)	(0.036)
	hbo	0.493***	0.449***	0.442***	0.438***	0.267***	0.251***
		(0.054)	(0.052)	(0.049)	(0.050)	(0.039)	(0.039)
	wo	0.732***	0.662***	0.644***	0.647***	0.450***	0.415***
		(0.058)	(0.057)	(0.054)	(0.056)	(0.044)	(0.045)
	N	7291	6483	6565	6483	7203	6565
	R^2	0.396	0.449	0.455	0.455	0.529	0.558
	adj. R^2	0.395	0.447	0.453	0.453	0.526	0.555
	vmbo	0.063	0.077	0.076	0.073	0.037	0.048
		(0.054)	(0.051)	(0.049)	(0.050)	(0.041)	(0.041)
	havo/vwo	0.266***	0.255***	0.257***	0.253***	0.133***	0.141***
		(0.055)	(0.051)	(0.049)	(0.050)	(0.041)	(0.041)
Extended sample (2)	mbo	0.232***	0.207***	0.203***	0.197***	0.123***	0.118***
		(0.051)	(0.048)	(0.046)	(0.047)	(0.038)	(0.038)
	hbo	0.527***	0.492***	0.488***	0.484***	0.313***	0.304***
		(0.051)	(0.049)	(0.047)	(0.048)	(0.042)	(0.043)
	wo	0.761***	0.703***	0.689***	0.691***	0.496***	0.471***
		(0.055)	(0.054)	(0.051)	(0.053)	(0.046)	(0.047)
	N	7701	6861	6950	6861	7610	6950
	R^2	0.395	0.438	0.443	0.443	0.51	0.53
	adj. R^2	0.394	0.436	0.442	0.441	0.508	0.527
	vmbo	0.041	0.051	0.043	0.044	0.013	0.019
		(0.056)	(0.053)	(0.051)	(0.052)	(0.041)	(0.041)
	havo/vwo	0.252***	0.237***	0.235***	0.234***	0.114***	0.118***
		(0.058)	(0.054)	(0.052)	(0.053)	(0.041)	(0.040)
	mbo	0.220***	0.190***	0.182***	0.178***	0.106***	0.096***
		(0.053)	(0.051)	(0.048)	(0.049)	(0.037)	(0.037)
	hbo	0.506***	0.464***	0.455***	0.454***	0.284***	0.269***
		(0.054)	(0.051)	(0.049)	(0.050)	(0.041)	(0.040)
	wo	0.744***	0.676***	0.656***	0.662***	0.463***	0.430***
Extended sample (2*)		(0.058)	(0.057)	(0.054)	(0.055)	(0.045)	(0.046)
	vmbo#parttime	0.299**	0.315**	0.397***	0.346**	0.298*	0.352**
		(0.124)	(0.131)	(0.122)	(0.135)	(0.159)	(0.161)
	havo/vwo#parttime	0.180*	0.156	0.207**	0.171	0.232*	0.231
		(0.099)	(0.108)	(0.098)	(0.115)	(0.138)	(0.144)
	mbo#parttime	0.11	0.128	0.174	0.149	0.148	0.162
		(0.110)	(0.122)	(0.115)	(0.129)	(0.146)	(0.155)
	hbo#parttime	0.272***	0.282***	0.336***	0.301***	0.331**	0.351**
		(0.099)	(0.107)	(0.096)	(0.111)	(0.138)	(0.142)
	wo#parttime	0.210*	0.231**	0.281***	0.249**	0.318**	0.330**
		(0.108)	(0.116)	(0.105)	(0.119)	(0.147)	(0.151)

	N	7701	6861	6950	6861	7610	6950
	R^2	0.398	0.446	0.451	0.451	0.521	0.545
	adj. R^2	0.397	0.444	0.449	0.449	0.518	0.542
Baseline results - females	vmbo	-0.177**	-0.187**	-0.152**	-0.158**	-0.158**	-0.137**
		(0.077)	(0.080)	(0.074)	(0.078)	(0.062)	(0.058)
	havo/vwo	0.077	0.01	0.053	0.039	-0.005	0.007
		(0.086)	(0.087)	(0.082)	(0.087)	(0.067)	(0.063)
	mbo	-0.028	-0.051	0	-0.017	-0.107*	-0.065
		(0.080)	(0.081)	(0.075)	(0.082)	(0.063)	(0.058)
	hbo	0.258***	0.211***	0.257***	0.235***	0.111*	0.127**
		(0.078)	(0.079)	(0.073)	(0.079)	(0.059)	(0.053)
	wo	0.510***	0.431***	0.470***	0.456***	0.288***	0.292***
		(0.084)	(0.083)	(0.077)	(0.083)	(0.064)	(0.058)
	N	2162	1852	1867	1852	2117	1867
	R^2	0.333	0.412	0.433	0.436	0.478	0.542
	adj. R^2	0.329	0.406	0.427	0.429	0.468	0.53
Extended sample (1) - females	vmbo	-0.169***	-0.175***	-0.147**	-0.151**	-0.163***	-0.135***
		(0.062)	(0.065)	(0.061)	(0.065)	(0.047)	(0.047)
	havo/vwo	0.063	0.025	0.057	0.049	-0.012	0.014
		(0.069)	(0.071)	(0.067)	(0.071)	(0.056)	(0.056)
	mbo	0.002	-0.014	0.029	0.014	-0.075	-0.028
		(0.064)	(0.066)	(0.062)	(0.067)	(0.054)	(0.054)
	hbo	0.268***	0.226***	0.264***	0.247***	0.132***	0.151***
		(0.061)	(0.064)	(0.059)	(0.064)	(0.049)	(0.048)
	wo	0.511***	0.455***	0.488***	0.477***	0.302***	0.314***
		(0.066)	(0.068)	(0.063)	(0.068)	(0.054)	(0.052)
	N	3258	2769	2789	2769	3196	2789
	R^2	0.381	0.438	0.449	0.454	0.498	0.539
	adj. R^2	0.379	0.434	0.445	0.449	0.492	0.531
Extended sample (2) - females	vmbo	-0.112**	-0.165***	-0.160***	-0.163***	-0.124***	-0.151***
		(0.052)	(0.050)	(0.051)	(0.050)	(0.047)	(0.049)
	havo/vwo	0.079	0.03	0.045	0.03	0.011	0.002
		(0.054)	(0.054)	(0.055)	(0.054)	(0.048)	(0.051)
	mbo	0.069	0.004	0.035	0.008	-0.017	-0.026
		(0.049)	(0.049)	(0.050)	(0.049)	(0.044)	(0.047)
	hbo	0.330***	0.235***	0.276***	0.234***	0.177***	0.149***
		(0.048)	(0.048)	(0.049)	(0.048)	(0.044)	(0.047)
	wo	0.556***	0.456***	0.479***	0.457***	0.338***	0.309***
		(0.053)	(0.053)	(0.053)	(0.053)	(0.048)	(0.051)
	N	6897	5820	5857	5820	6773	5857
	R^2	0.267	0.338	0.323	0.342	0.353	0.399
	adj. R^2	0.266	0.335	0.32	0.339	0.349	0.394
Extended sample (2*) - females	vmbo	-0.154**	-0.170***	-0.172***	-0.176***	-0.141***	-0.151***
		(0.061)	(0.064)	(0.062)	(0.064)	(0.045)	(0.045)
	havo/vwo	0.085	0.03	0.04	0.027	0.018	0.001
		(0.068)	(0.069)	(0.066)	(0.070)	(0.051)	(0.050)
	mbo	0.02	-0.025	0	-0.03	-0.046	-0.05
		(0.062)	(0.063)	(0.060)	(0.064)	(0.046)	(0.043)
	hbo	0.282***	0.212***	0.241***	0.206***	0.142***	0.120***
		(0.060)	(0.061)	(0.058)	(0.062)	(0.042)	(0.040)
	wo	0.520***	0.444***	0.463***	0.441***	0.306***	0.285***
		(0.065)	(0.066)	(0.062)	(0.066)	(0.049)	(0.047)
	N	6897	5820	5857	5820	6773	5857
	R^2	0.269	0.338	0.324	0.343	0.355	0.401
	adj. R^2	0.267	0.335	0.321	0.34	0.35	0.395

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The same models are estimated as in Table A. 6 in the appendix. The baseline results only includes full time workers (i.e. a minimum of 32 hours per week) aged 30 -55 years, either males or females. The extended sample (1) includes full time workers aged 20 – 65, either males or females. The extended sample (2) includes full time and part time workers (i.e. 12 - 31 hours per week), either males or females. The extended sample (2*) is identical to extended sample (2), however, all six models correct for part time workers by including the interaction term of part time * the level of education. If the interaction terms are significant, these are included. Generally, gross hourly wage as the dependent variable is sufficient to control for part time workers.

Table A. 22: Wage premium interacted with year dummies (full time male workers aged 20 – 65 years only)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Educational level - vmbo	0.153**	0.152**	0.150**	0.141**	0.122**	0.098*
	(0.068)	(0.069)	(0.069)	(0.069)	(0.056)	(0.057)
Educational level – havo/vwo	0.353***	0.297***	0.299***	0.290***	0.169***	0.140***
	(0.066)	(0.066)	(0.065)	(0.066)	(0.053)	(0.052)
Educational level – mbo	0.290***	0.248***	0.248***	0.237***	0.155***	0.123***
	(0.060)	(0.061)	(0.060)	(0.061)	(0.047)	(0.046)
Educational level – hbo	0.582***	0.520***	0.523***	0.508***	0.335***	0.296***
	(0.060)	(0.061)	(0.060)	(0.061)	(0.048)	(0.048)
Educational level – wo	0.780***	0.712***	0.702***	0.701***	0.497***	0.446***
	(0.064)	(0.066)	(0.064)	(0.066)	(0.053)	(0.053)
vmbo # year 2009	-0.067	-0.048	-0.070	-0.051	-0.048	-0.045
	(0.065)	(0.060)	(0.060)	(0.060)	(0.054)	(0.053)
vmbo # year 2010	-0.149**	-0.188***	-0.195***	-0.186***	-0.115**	-0.138**
	(0.065)	(0.065)	(0.064)	(0.066)	(0.055)	(0.056)
vmbo # year 2011	-0.102	-0.136*	-0.133*	-0.138*	-0.117*	-0.124*
	(0.076)	(0.078)	(0.078)	(0.078)	(0.063)	(0.066)
vmbo # year 2012	-0.157**	-0.136	-0.140	-0.126	-0.145**	-0.118
	(0.080)	(0.099)	(0.096)	(0.096)	(0.069)	(0.086)
vmbo # year 2013	-0.188**	-0.265***	-0.270***	-0.258***	-0.187***	-0.217***
	(0.088)	(0.094)	(0.093)	(0.093)	(0.071)	(0.077)
vmbo # year 2014	-0.080	-0.152	-0.127	-0.134	-0.111	-0.104
	(0.086)	(0.095)	(0.093)	(0.095)	(0.074)	(0.083)
vmbo # year 2015	-0.365	-0.124	-0.139	-0.108	-0.405	-0.107
	(0.302)	(0.127)	(0.117)	(0.122)	(0.305)	(0.091)
havo/vwo # year 2009	-0.045	-0.023	-0.022	-0.021	-0.010	-0.008
	(0.070)	(0.064)	(0.066)	(0.065)	(0.058)	(0.057)
havo/vwo # year 2010	-0.118*	-0.125*	-0.131**	-0.124*	-0.053	-0.069
	(0.064)	(0.066)	(0.065)	(0.066)	(0.053)	(0.053)
havo/vwo # year 2011	-0.087	-0.064	-0.067	-0.065	-0.042	-0.026
	(0.077)	(0.078)	(0.078)	(0.078)	(0.062)	(0.063)
havo/vwo # year 2012	-0.120	-0.079	-0.082	-0.068	-0.074	-0.039
	(0.085)	(0.103)	(0.100)	(0.100)	(0.072)	(0.088)
havo/vwo # year 2013	-0.218**	-0.246**	-0.254***	-0.240**	-0.150**	-0.179**
	(0.093)	(0.099)	(0.097)	(0.098)	(0.073)	(0.081)
havo/vwo # year 2014	-0.061	-0.087	-0.071	-0.071	-0.026	-0.029
	(0.086)	(0.094)	(0.094)	(0.094)	(0.072)	(0.083)
havo/vwo # year 2015	-0.400	-0.097	-0.110	-0.078	-0.357	-0.040
	(0.303)	(0.128)	(0.117)	(0.123)	(0.307)	(0.090)
mbo # year 2009	-0.028	-0.024	-0.037	-0.032	-0.009	-0.011
	(0.060)	(0.054)	(0.056)	(0.055)	(0.047)	(0.046)
mbo # year 2010	-0.104*	-0.153**	-0.162***	-0.157***	-0.070	-0.099**
	(0.059)	(0.060)	(0.058)	(0.060)	(0.046)	(0.047)
mbo # year 2011	-0.031	-0.049	-0.052	-0.058	-0.038	-0.045
	(0.069)	(0.071)	(0.071)	(0.072)	(0.054)	(0.057)
mbo # year 2012	-0.080	-0.077	-0.080	-0.073	-0.061	-0.048
	(0.073)	(0.092)	(0.089)	(0.090)	(0.061)	(0.079)
mbo # year 2013	-0.135*	-0.195**	-0.212**	-0.201**	-0.096	-0.130*
	(0.082)	(0.088)	(0.086)	(0.087)	(0.063)	(0.069)
mbo # year 2014	-0.068	-0.123	-0.103	-0.108	-0.050	-0.052
	(0.078)	(0.086)	(0.086)	(0.087)	(0.065)	(0.075)
mbo # year 2015	-0.342	-0.094	-0.104	-0.081	-0.333	-0.039
	(0.300)	(0.121)	(0.110)	(0.116)	(0.305)	(0.083)
hbo # year 2009	-0.032	-0.012	-0.028	-0.016	-0.004	0.001
	(0.059)	(0.053)	(0.055)	(0.054)	(0.046)	(0.045)
hbo # year 2010	-0.111*	-0.146**	-0.162***	-0.149**	-0.067	-0.092**
	(0.058)	(0.059)	(0.058)	(0.059)	(0.046)	(0.047)
hbo # year 2011	-0.062	-0.064	-0.070	-0.068	-0.038	-0.044
	(0.068)	(0.070)	(0.070)	(0.071)	(0.054)	(0.057)
hbo # year 2012	-0.084	-0.082	-0.092	-0.076	-0.065	-0.056
	(0.073)	(0.092)	(0.089)	(0.089)	(0.061)	(0.078)

hbo # year 2013	-0.150*	-0.206**	-0.223***	-0.206**	-0.112*	-0.150**
	(0.081)	(0.087)	(0.085)	(0.087)	(0.062)	(0.069)
hbo # year 2014	-0.057	-0.085	-0.082	-0.073	-0.044	-0.041
	(0.079)	(0.087)	(0.087)	(0.087)	(0.066)	(0.076)
hbo # year 2015	-0.353	-0.096	-0.121	-0.086	-0.353	-0.058
	(0.300)	(0.121)	(0.111)	(0.116)	(0.304)	(0.084)
wo # year 2009	-0.033	-0.016	-0.041	-0.024	-0.007	-0.010
	(0.061)	(0.056)	(0.057)	(0.057)	(0.049)	(0.048)
wo # year 2010	-0.052	-0.097	-0.109*	-0.101	-0.020	-0.050
	(0.065)	(0.067)	(0.065)	(0.067)	(0.056)	(0.056)
wo # year 2011	0.013	-0.043	-0.045	-0.053	0.004	-0.027
	(0.073)	(0.075)	(0.074)	(0.075)	(0.059)	(0.061)
wo # year 2012	-0.024	-0.044	-0.051	-0.045	-0.031	-0.031
	(0.076)	(0.095)	(0.092)	(0.092)	(0.064)	(0.082)
wo # year 2013	-0.087	-0.162*	-0.178**	-0.169*	-0.089	-0.134*
	(0.084)	(0.091)	(0.089)	(0.090)	(0.066)	(0.073)
wo # year 2014	-0.021	-0.088	-0.078	-0.081	-0.038	-0.046
	(0.084)	(0.091)	(0.091)	(0.092)	(0.071)	(0.080)
wo # year 2015	-0.302	-0.064	-0.085	-0.058	-0.324	-0.027
	(0.301)	(0.123)	(0.112)	(0.118)	(0.305)	(0.086)
N	7291	6483	6565	6483	7203	6565
R^2	0.399	0.451	0.456	0.457	0.532	0.559
adj. R^2	0.395	0.446	0.452	0.452	0.527	0.554

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All estimated models are identical to Table A. 7 in the appendix. However, only the variables of interest are presented. The reference year is 2008. The sample is based on male individuals aged 20 – 65 years working full time (i.e. at least 32 hours per week).

Table A. 23: Wage premium interacted with year dummies (full time female workers aged 20 – 65 years only)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Educational level - vmbo	-0.016	-0.051	-0.044	-0.026	-0.094	-0.074
	(0.092)	(0.099)	(0.100)	(0.101)	(0.090)	(0.090)
Educational level – havo/vwo	0.227**	0.110	0.116	0.134	0.071	0.064
	(0.097)	(0.106)	(0.105)	(0.107)	(0.099)	(0.098)
Educational level – mbo	0.218**	0.113	0.130	0.138	0.055	0.036
	(0.093)	(0.103)	(0.103)	(0.105)	(0.102)	(0.107)
Educational level – hbo	0.481***	0.362***	0.368***	0.377***	0.249***	0.208**
	(0.086)	(0.096)	(0.095)	(0.097)	(0.089)	(0.089)
Educational level – wo	0.732***	0.591***	0.591***	0.605***	0.434***	0.368***
	(0.090)	(0.099)	(0.098)	(0.101)	(0.093)	(0.092)
vmbo # year 2009	-0.127	-0.025	-0.014	-0.033	-0.025	0.006
	(0.082)	(0.098)	(0.098)	(0.095)	(0.074)	(0.089)
vmbo # year 2010	-0.100	-0.029	0.002	-0.032	-0.047	-0.004
	(0.100)	(0.118)	(0.118)	(0.119)	(0.095)	(0.107)
vmbo # year 2011	-0.242**	-0.201*	-0.162	-0.190	-0.121	-0.100
	(0.121)	(0.118)	(0.118)	(0.119)	(0.094)	(0.091)
vmbo # year 2012	-0.242**	-0.202	-0.189	-0.206	-0.116	-0.102
	(0.110)	(0.130)	(0.128)	(0.128)	(0.097)	(0.100)
vmbo # year 2013	-0.119	-0.139	-0.115	-0.136	-0.036	-0.046
	(0.140)	(0.148)	(0.145)	(0.146)	(0.111)	(0.115)
vmbo # year 2014	-0.261*	-0.239	-0.232	-0.259*	-0.116	-0.163
	(0.146)	(0.161)	(0.155)	(0.156)	(0.122)	(0.127)
vmbo # year 2015	-0.386***	-0.439***	-0.404***	-0.424***	-0.168	-0.220*
	(0.134)	(0.142)	(0.132)	(0.133)	(0.119)	(0.125)
havo/vwo # year 2009	-0.200**	-0.062	-0.045	-0.065	-0.087	-0.028
	(0.083)	(0.102)	(0.102)	(0.098)	(0.078)	(0.093)
havo/vwo # year 2010	-0.156	-0.040	-0.005	-0.040	-0.088	-0.021
	(0.099)	(0.120)	(0.118)	(0.119)	(0.094)	(0.106)
havo/vwo # year 2011	-0.224*	-0.134	-0.105	-0.133	-0.115	-0.082
	(0.127)	(0.130)	(0.128)	(0.129)	(0.103)	(0.104)
havo/vwo # year 2012	-0.249**	-0.120	-0.087	-0.110	-0.118	-0.051
	(0.115)	(0.133)	(0.131)	(0.130)	(0.101)	(0.103)
havo/vwo # year 2013	-0.166	-0.091	-0.061	-0.088	-0.070	-0.058
	(0.149)	(0.159)	(0.155)	(0.156)	(0.123)	(0.123)
havo/vwo # year 2014	-0.252*	-0.176	-0.147	-0.182	-0.141	-0.151
	(0.152)	(0.165)	(0.160)	(0.160)	(0.126)	(0.129)
havo/vwo # year 2015	-0.323**	-0.269**	-0.224*	-0.263**	-0.129	-0.100
	(0.128)	(0.133)	(0.129)	(0.131)	(0.114)	(0.116)
mbo # year 2009	-0.175**	-0.057	-0.039	-0.060	-0.072	-0.005
	(0.082)	(0.102)	(0.101)	(0.098)	(0.080)	(0.095)
mbo # year 2010	-0.172*	-0.073	-0.035	-0.072	-0.115	-0.035
	(0.094)	(0.114)	(0.113)	(0.114)	(0.088)	(0.100)
mbo # year 2011	-0.334***	-0.238**	-0.214*	-0.223*	-0.223**	-0.157
	(0.121)	(0.121)	(0.121)	(0.121)	(0.099)	(0.101)
mbo # year 2012	-0.360***	-0.198	-0.181	-0.190	-0.230**	-0.097
	(0.104)	(0.124)	(0.122)	(0.122)	(0.093)	(0.093)
mbo # year 2013	-0.246*	-0.135	-0.108	-0.127	-0.141	-0.062
	(0.142)	(0.151)	(0.149)	(0.150)	(0.116)	(0.118)
mbo # year 2014	-0.354**	-0.241	-0.211	-0.244	-0.210*	-0.162
	(0.142)	(0.157)	(0.152)	(0.152)	(0.119)	(0.130)
mbo # year 2015	-0.389***	-0.322**	-0.269**	-0.310**	-0.167	-0.088
	(0.119)	(0.128)	(0.123)	(0.125)	(0.109)	(0.121)
hbo # year 2009	-0.197***	-0.074	-0.049	-0.071	-0.067	0.001
	(0.076)	(0.096)	(0.094)	(0.091)	(0.069)	(0.085)
hbo # year 2010	-0.178**	-0.084	-0.041	-0.078	-0.113	-0.038
	(0.086)	(0.106)	(0.104)	(0.106)	(0.079)	(0.091)
hbo # year 2011	-0.321***	-0.234**	-0.194*	-0.226**	-0.188**	-0.125
	(0.114)	(0.113)	(0.112)	(0.113)	(0.086)	(0.084)
hbo # year 2012	-0.331***	-0.208*	-0.175	-0.198*	-0.199**	-0.086
	(0.096)	(0.116)	(0.114)	(0.114)	(0.082)	(0.083)

hbo # year 2013	-0.213	-0.140	-0.098	-0.121	-0.106	-0.038
	(0.133)	(0.142)	(0.139)	(0.140)	(0.105)	(0.105)
hbo # year 2014	-0.374***	-0.278*	-0.247*	-0.278*	-0.228**	-0.184
	(0.137)	(0.151)	(0.146)	(0.146)	(0.110)	(0.116)
hbo # year 2015	-0.372***	-0.310***	-0.270**	-0.298**	-0.140	-0.075
	(0.111)	(0.117)	(0.114)	(0.116)	(0.096)	(0.103)
wo # year 2009	-0.114	-0.009	0.007	-0.012	-0.012	0.056
	(0.077)	(0.097)	(0.096)	(0.093)	(0.069)	(0.086)
wo # year 2010	-0.185**	-0.086	-0.042	-0.081	-0.128	-0.034
	(0.092)	(0.111)	(0.109)	(0.110)	(0.085)	(0.096)
wo # year 2011	-0.328***	-0.236*	-0.193	-0.222*	-0.204**	-0.120
	(0.121)	(0.121)	(0.119)	(0.120)	(0.093)	(0.092)
wo # year 2012	-0.307***	-0.188	-0.147	-0.171	-0.179**	-0.047
	(0.103)	(0.123)	(0.120)	(0.121)	(0.087)	(0.090)
wo # year 2013	-0.250*	-0.159	-0.123	-0.146	-0.155	-0.063
	(0.138)	(0.146)	(0.143)	(0.144)	(0.108)	(0.109)
wo # year 2014	-0.373***	-0.256*	-0.217	-0.249*	-0.236**	-0.165
	(0.139)	(0.153)	(0.148)	(0.148)	(0.113)	(0.118)
wo # year 2015	-0.463***	-0.382***	-0.335***	-0.367***	-0.212**	-0.129
	(0.114)	(0.120)	(0.116)	(0.118)	(0.100)	(0.106)
N	3258	2769	2789	2769	3196	2789
R^2	0.389	0.443	0.454	0.459	0.502	0.542
adj. R^2	0.380	0.432	0.443	0.447	0.490	0.528

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All estimated models are identical to Table A. 7 in the appendix. However, only the variables of interest are presented. The sample is based on female individuals aged 20 – 65 years working full time (i.e. at least 32 hours per week).

Table A. 24: Interaction of the tenure dummy and years of education (full time male workers aged 20 – 65 years only)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.078***	0.068***	0.068***	0.067***	0.036***	0.033***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tenure dummy	-0.389***	-0.409***	-0.390***	-0.397***	-0.291***	-0.296***
	(0.133)	(0.110)	(0.110)	(0.110)	(0.097)	(0.092)
Tenure dummy # years of education	0.025***	0.027***	0.026***	0.027***	0.020***	0.021***
	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
N	7291	6536	6565	6536	7203	6565
R^2	0.304	0.369	0.376	0.374	0.497	0.529
adj. R^2	0.302	0.368	0.374	0.372	0.495	0.525
Years of education	0.075***	0.064***	0.065***	0.064***	0.034***	0.030***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year 2009 # years of education	0.005	0.005	0.004	0.004	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year 2010 # years of education	0.000	-0.001	-0.002	-0.002	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year 2011 # years of education	0.008	0.007	0.007	0.007	0.009*	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Year 2012 # years of education	0.009	0.007	0.006	0.006	0.006	0.005
	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)	(0.006)
Year 2013 # years of education	0.005	0.007	0.005	0.005	0.005	0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Year 2014 # years of education	0.007	0.009	0.008	0.008	0.007	0.007
	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)	(0.007)
Year 2015 # years of education	-0.010	0.006	0.005	0.006	-0.011	0.008
	(0.018)	(0.008)	(0.008)	(0.008)	(0.018)	(0.007)
Tenure dummy	0.183*	0.230	0.233	0.210	0.187	0.331***
	(0.108)	(0.174)	(0.174)	(0.179)	(0.138)	(0.120)
Tenure dummy # years of education	-0.055***	-0.053***	-0.055***	-0.053***	-0.042***	-0.054***
	(0.007)	(0.015)	(0.015)	(0.016)	(0.011)	(0.009)
Year 2009 # tenure dummy	-0.611**	-0.642**	-0.652**	-0.624**	-0.527**	-0.599***
	(0.290)	(0.301)	(0.296)	(0.300)	(0.238)	(0.231)
Year 2010 # tenure dummy	-0.553***	-0.503**	-0.494**	-0.478*	-0.501***	-0.624***
	(0.181)	(0.244)	(0.244)	(0.248)	(0.181)	(0.193)
Year 2011 # tenure dummy	-0.440**	-0.523*	-0.507*	-0.492*	-0.327*	-0.506***
	(0.220)	(0.274)	(0.277)	(0.279)	(0.195)	(0.196)
Year 2012 # tenure dummy	-0.620**	-0.808***	-0.782***	-0.769***	-0.557***	-0.847***
	(0.243)	(0.268)	(0.270)	(0.272)	(0.215)	(0.223)
Year 2013 # tenure dummy	-0.668***	-0.897***	-0.883***	-0.857***	-0.536**	-0.812***
	(0.227)	(0.283)	(0.288)	(0.290)	(0.221)	(0.255)
Year 2014 # tenure dummy	-0.374*	-0.460*	-0.457*	-0.439*	-0.306	-0.490**
	(0.206)	(0.254)	(0.253)	(0.254)	(0.203)	(0.198)
Year 2015 # tenure dummy	-0.741**	-0.598**	-0.571**	-0.549**	-0.647***	-0.518***
	(0.304)	(0.256)	(0.253)	(0.256)	(0.230)	(0.200)
Year 2009 # tenure dummy # years of education	0.080***	0.078***	0.081***	0.078***	0.064***	0.072***
	(0.021)	(0.023)	(0.023)	(0.023)	(0.018)	(0.017)
Year 2010 # tenure dummy # years of education	0.080***	0.071***	0.073***	0.071***	0.064***	0.075***
	(0.013)	(0.020)	(0.020)	(0.020)	(0.014)	(0.015)
Year 2011 # tenure dummy # years of education	0.072***	0.075***	0.075***	0.074***	0.054***	0.070***
	(0.015)	(0.021)	(0.021)	(0.022)	(0.015)	(0.014)
Year 2012 # tenure dummy # years of education	0.082***	0.090***	0.089***	0.088***	0.066***	0.087***
	(0.017)	(0.021)	(0.021)	(0.021)	(0.016)	(0.016)
Year 2013 # tenure dummy # years of education	0.086***	0.097***	0.098***	0.095***	0.066***	0.086***
	(0.016)	(0.022)	(0.022)	(0.022)	(0.017)	(0.018)
Year 2014 # tenure dummy # years of education	0.067***	0.068***	0.070***	0.067***	0.050***	0.066***
	(0.015)	(0.020)	(0.020)	(0.020)	(0.016)	(0.015)
Year 2015 # tenure dummy # years of education	0.093***	0.079***	0.079***	0.077***	0.074***	0.067***
	(0.021)	(0.020)	(0.020)	(0.020)	(0.016)	(0.015)
N	7291	6536	6565	6536	7203	6565
R^2	0.305	0.371	0.378	0.376	0.499	0.530
adj. R^2	0.302	0.367	0.374	0.372	0.494	0.525

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table is a combination of Table 7 and Table 8 where the thick horizontal line separates the two tables. However, the results of this table are based on the extended sample of full time male workers aged 20 – 65 years

Table A. 25: Interaction of the tenure dummy, years of education and year dummies (full time female workers aged 20 – 65 years only)

Dep Var: (Log of) gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	0.075***	0.065***	0.068***	0.066***	0.041***	0.040***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)
Tenure dummy	0.205	0.192	0.162	0.160	0.193	0.167
	(0.173)	(0.154)	(0.149)	(0.147)	(0.125)	(0.114)
Tenure dummy # years of education	-0.015	-0.013	-0.011	-0.010	-0.014	-0.011
	(0.012)	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)
N	3258	2785	2789	2785	3196	2789
R^2	0.239	0.324	0.345	0.348	0.433	0.492
adj. R^2	0.236	0.321	0.341	0.343	0.426	0.484
Years of education	0.085***	0.070***	0.072***	0.069***	0.048***	0.040***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Year 2009 # years of education	-0.005	-0.000	-0.000	-0.000	-0.001	0.005
	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)
Year 2010 # years of education	-0.014	-0.006	-0.005	-0.005	-0.015**	-0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)
Year 2011 # years of education	-0.025**	-0.021*	-0.020*	-0.021**	-0.017**	-0.013
	(0.011)	(0.011)	(0.011)	(0.010)	(0.008)	(0.008)
Year 2012 # years of education	-0.017	-0.007	-0.004	-0.005	-0.010	0.004
	(0.012)	(0.013)	(0.013)	(0.013)	(0.009)	(0.010)
Year 2013 # years of education	-0.020	-0.010	-0.009	-0.008	-0.009	-0.000
	(0.013)	(0.013)	(0.013)	(0.013)	(0.009)	(0.010)
Year 2014 # years of education	-0.016	-0.001	-0.000	0.000	-0.011	-0.000
	(0.016)	(0.018)	(0.017)	(0.017)	(0.012)	(0.013)
Year 2015 # years of education	0.006	0.025	0.028*	0.026*	0.004	0.025*
	(0.014)	(0.016)	(0.016)	(0.015)	(0.011)	(0.014)
Tenure dummy	1.280***	1.300***	1.233***	1.254***	1.021***	0.921***
	(0.402)	(0.372)	(0.324)	(0.333)	(0.218)	(0.181)
Tenure dummy # years of education	-0.105**	-0.107**	-0.103***	-0.104***	-0.074***	-0.069***
	(0.047)	(0.043)	(0.038)	(0.040)	(0.025)	(0.020)
Year 2009 # tenure dummy	-0.865*	-0.953**	-0.934**	-0.970**	-0.739***	-0.681***
	(0.458)	(0.434)	(0.386)	(0.397)	(0.262)	(0.234)
Year 2010 # tenure dummy	-0.969**	-0.933**	-0.908**	-0.930**	-0.936***	-0.811***
	(0.425)	(0.416)	(0.373)	(0.382)	(0.257)	(0.223)
Year 2011 # tenure dummy	-2.039***	-2.062***	-2.045***	-2.062***	-1.376***	-1.372***
	(0.521)	(0.489)	(0.454)	(0.459)	(0.342)	(0.327)
Year 2012 # tenure dummy	-1.222**	-1.496***	-1.450***	-1.474***	-0.762**	-0.760**
	(0.491)	(0.499)	(0.450)	(0.454)	(0.309)	(0.309)
Year 2013 # tenure dummy	-1.209**	-1.090**	-1.068**	-1.081**	-0.731***	-0.586**
	(0.473)	(0.471)	(0.432)	(0.437)	(0.282)	(0.270)
Year 2014 # tenure dummy	-1.056**	-0.942*	-0.924**	-0.930**	-0.758**	-0.630**
	(0.495)	(0.480)	(0.439)	(0.444)	(0.303)	(0.289)
Year 2015 # tenure dummy	-0.805	-0.728	-0.611	-0.659	-0.853**	-0.534*
	(0.510)	(0.515)	(0.460)	(0.463)	(0.341)	(0.323)
Year 2009 # tenure dummy # years of education	0.071	0.081*	0.080**	0.082*	0.054**	0.053**
	(0.049)	(0.046)	(0.041)	(0.042)	(0.027)	(0.022)
Year 2010 # tenure dummy # years of education	0.080*	0.080*	0.079**	0.080*	0.068**	0.062***
	(0.047)	(0.045)	(0.040)	(0.041)	(0.027)	(0.022)
Year 2011 # tenure dummy # years of education	0.154***	0.158***	0.157***	0.158***	0.096***	0.099***
	(0.052)	(0.048)	(0.044)	(0.045)	(0.031)	(0.027)
Year 2012 # tenure dummy # years of education	0.101**	0.120**	0.118***	0.119***	0.056*	0.059**
	(0.050)	(0.049)	(0.044)	(0.045)	(0.029)	(0.026)
Year 2013 # tenure dummy # years of education	0.101**	0.095**	0.094**	0.094**	0.054*	0.049**
	(0.050)	(0.048)	(0.043)	(0.044)	(0.028)	(0.024)
Year 2014 # tenure dummy # years of education	0.089*	0.083*	0.083*	0.083*	0.054*	0.050**
	(0.051)	(0.048)	(0.043)	(0.044)	(0.029)	(0.025)
Year 2015 # tenure dummy # years of education	0.074	0.070	0.062	0.065	0.064**	0.045*
	(0.051)	(0.050)	(0.044)	(0.045)	(0.031)	(0.027)
N	3258	2785	2789	2785	3196	2789
R^2	0.246	0.332	0.353	0.355	0.436	0.496
adj. R^2	0.238	0.323	0.343	0.345	0.426	0.484

Note: Robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
This table is a combination of Table 7 and Table 8 where the thick horizontal line separates the two tables. However, the results of this table are based on the extended sample of full time female workers aged 20 – 65 years.

Table A. 26: Overview IV results extended sample (male workers only)

Dep Var: (Log of) gross hourly wage		(1)	(2)	(3)	(4)	(5)	(6)
Baseline IV - Father	Years of education	0.129***	0.119***	0.116***	0.123***	0.067*	0.058
		(0.023)	(0.026)	(0.025)	(0.026)	(0.037)	(0.038)
	N	3429	3123	3149	3123	3406	3149
Extended IV (1) - Father	Years of education	0.137***	0.130***	0.125***	0.134***	0.107***	0.097***
		(0.021)	(0.025)	(0.023)	(0.024)	(0.036)	(0.036)
	N	4753	4296	4342	4296	4722	4342
Extended IV (2) - Father	Years of education	0.142***	0.142***	0.135***	0.144***	0.125***	0.121***
		(0.021)	(0.025)	(0.023)	(0.024)	(0.035)	(0.036)
	N	5030	4556	4606	4556	4998	4606
Extended IV (2*) - Father	Years of education	0.140***	0.137***	0.130***	0.140***	0.120***	0.113***
		(0.020)	(0.024)	(0.022)	(0.024)	(0.034)	(0.034)
	N	5030	4556	4606	4556	4998	4606
Baseline IV - Father & Mother	Years of education	0.149***	0.135***	0.132***	0.139***	0.092**	0.087*
		(0.028)	(0.030)	(0.029)	(0.030)	(0.046)	(0.047)
	N	3233	2957	2982	2957	3213	2982
Extended IV (1) - Father & Mother	Years of education	0.158***	0.151***	0.145***	0.153***	0.143***	0.138***
		(0.025)	(0.028)	(0.026)	(0.028)	(0.044)	(0.043)
	N	4512	4098	4141	4098	4484	4141
Extended IV (2) - Father & Mother	Years of education	0.159***	0.158***	0.150***	0.160***	0.153***	0.149***
		(0.024)	(0.028)	(0.025)	(0.027)	(0.041)	(0.041)
	N	4779	4350	4396	4350	4750	4396
Extended IV (2*) - Father & Mother	Years of education	0.158***	0.155***	0.147***	0.157***	0.150***	0.145***
		(0.023)	(0.027)	(0.024)	(0.026)	(0.040)	(0.040)
	N	4779	4350	4396	4350	4750	4396

Note: robust clustered standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
The same IV models are estimated as in Table 9 and Table A. 15. The models are estimated for all samples, both with the inclusion of father's years of education and also mother's years of education. The baseline IV result is based on the baseline sample (male workers aged 30 – 55 years working at least 32 hours per week). The extended IV (1) sample is based on male individuals working full time (at least 32 hours per week) aged 20 – 65 years. The extended IV (2) sample is based on male individuals working full time or part time (at least 12 hours per week) aged 20 – 65 years. The extended IV (2*) sample is identical to the extended IV (2) sample, however, all models include a dummy for part time workers.

Table A. 27: Heckman results full time male workers in extended sample 1 (years of education)

Dep Var: (Log of) gross hourly wage		2008	2009	2010	2011	2012	2013	2014	2015	pooled
Baseline results	Years of education	0.074***	0.082***	0.081***	0.086***	0.089***	0.087***	0.085***	0.078***	0.082***
		(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.011)	(0.004)
	N	1176	937	948	761	884	818	919	848	7291
	r2	0.268	0.287	0.297	0.369	0.359	0.349	0.307	0.22	0.3
Non-response	Years of education	0.089***	0.098***	0.097***	0.099***	0.099***	0.096***	0.097***	0.096***	0.096***
		(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.005)
	N (uncensored)	1630	1270	1293	1040	1187	1067	1232	1173	9892
	N (censored)	455	334	349	283	307	254	326	337	2645
	lambda	0.353	0.302	0.384	0.281	0.203	0.196	0.313	0.433	0.326
	chi2 (comparison test)	27.72	12.11	44.349	53.98	8.077	4.271	24.369	18.746	57.561
	p-value	0.000	0.001	0.000	0.000	0.004	0.039	0.000	0.000	0.000
Non-employment (1)	Years of education	0.074***	0.082***	0.081***	0.085***	0.088***	0.086***	0.084***	0.083***	0.081***
		(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.010)	(0.004)
	N (uncensored)	1216	962	1012	805	923	852	971	869	7602
	N (censored)	41	26	64	44	43	39	65	33	355
	lambda	-0.008	-0.002	-0.012	-0.022	-0.133	-0.155	-0.054	0.341	-0.013
	chi2 (comparison test)	0.257	0.002	0.389	0.323	4.427	6.244	5.763	8.858	1.181
	p-value	0.612	0.964	0.533	0.570	0.035	0.012	0.016	0.003	0.277
Non-employment (2)	Years of education	0.074***	0.082***	0.083***	0.085***	0.088***	0.086***	0.083***	0.086***	0.081***
		(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.010)	(0.004)
	N (uncensored)	1516	1080	1125	895	987	894	1035	900	8432
	N (censored)	341	144	181	138	107	81	129	64	1185
	lambda	0.007	0.005	0.316	-0.027	-0.083	-0.107	-0.076	0.356	0.004
	chi2 (comparison test)	0.057	0.127	18.916	0.421	1.104	2.185	7.139	9.699	0.068
	p-value	0.811	0.722	0.000	0.516	0.293	0.139	0.008	0.002	0.795

Note: robust (clustered) standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The standard errors are clustered when the regression is pooled. The extended sample 1 is composed of male individuals working full time (i.e. at least 32 hours per week) aged 20 – 65 years. In total eight separate year regressions and one pooled regressions is estimated for each type of model. The dependent variable is the (log of) gross hourly wage and the independent variables are years of education, experience and experience squared. In the pooled regression, also year dummies are included. With the exception of the baseline results, all selection equations are based on the explanatory variables, the civil status (*burgstat*), urban character of the place of residence (*sted*) and the number of household members (*aantalhh*). All heckman selection models are based on the maximum likelihood estimation procedure. N is the total number of observations in the wage equation. N (censored) is the number of observations in the selection equation. Lambda is the inverse Mills ratio and represents the selection term. The chi^2 and its corresponding p-value are used to indicate the presence of sample selectivity. Non-employment (1) only includes individuals who lost their job, non-employment (2) also includes all other individuals who are not employed. The non-employment (1) regression for the year 2011 does not contain the variable *sted* in the selection equation due to an otherwise infinite number of iterations.

Table A. 28: Heckman results full time male workers in extended sample 1 (level of education)

Dep Var: (Log of) gross hourly wage		2008	2009	2010	2011	2012	2013	2014	2015	pooled
Baseline results	vmbo	0.142**	0.081	0.013	0.033	-0.003	-0.03	0.078	-0.188	0.034
		(0.069)	(0.108)	(0.070)	(0.062)	(0.067)	(0.079)	(0.067)	(0.279)	(0.056)
	havo/vwo	0.331***	0.298***	0.247***	0.247***	0.236***	0.142	0.297***	-0.018	0.241***
		(0.069)	(0.107)	(0.064)	(0.071)	(0.076)	(0.088)	(0.071)	(0.276)	(0.058)
	mbo	0.264***	0.250**	0.199***	0.236***	0.212***	0.163**	0.227***	-0.019	0.207***
		(0.062)	(0.102)	(0.059)	(0.061)	(0.065)	(0.078)	(0.065)	(0.271)	(0.053)
	hbo	0.557***	0.538***	0.486***	0.503***	0.501***	0.441***	0.530***	0.264	0.493***
		(0.063)	(0.102)	(0.060)	(0.060)	(0.067)	(0.079)	(0.066)	(0.270)	(0.054)
	wo	0.755***	0.734***	0.743***	0.780***	0.760***	0.705***	0.761***	0.509*	0.732***
		(0.066)	(0.107)	(0.072)	(0.069)	(0.071)	(0.084)	(0.069)	(0.273)	(0.058)
	N	1176	937	948	761	884	818	919	848	7291
	r2	0.344	0.362	0.396	0.475	0.468	0.465	0.419	0.329	0.396
Non-response	vmbo	0.150**	0.09	-0.061	0.03	0.011	-0.021	0.109	-0.115	0.039
		(0.075)	(0.116)	(0.069)	(0.068)	(0.070)	(0.081)	(0.074)	(0.225)	(0.060)
	havo/vwo	0.422***	0.391***	0.290***	0.325***	0.295***	0.194**	0.370***	0.129	0.320***
		(0.078)	(0.122)	(0.075)	(0.079)	(0.086)	(0.096)	(0.080)	(0.207)	(0.062)
	mbo	0.326***	0.323***	0.208***	0.279***	0.252***	0.194**	0.300***	0.098	0.261***
		(0.070)	(0.114)	(0.067)	(0.067)	(0.071)	(0.083)	(0.073)	(0.208)	(0.057)
	hbo	0.677***	0.649***	0.541***	0.595***	0.561***	0.497***	0.625***	0.427**	0.589***
		(0.072)	(0.117)	(0.070)	(0.068)	(0.077)	(0.088)	(0.078)	(0.198)	(0.058)
	wo	0.882***	0.858***	0.814***	0.871***	0.827***	0.771***	0.875***	0.711***	0.839***
		(0.076)	(0.123)	(0.083)	(0.077)	(0.082)	(0.095)	(0.082)	(0.194)	(0.062)
	N (uncensored)	1630	1270	1293	1040	1187	1067	1232	1173	9892
	N (censored)	455	334	349	283	307	254	326	337	2645
	lambda	0.334	0.276	0.345	0.251	0.14	0.142	0.268	0.39	0.292
	chi2 (comparison test)	26.999	9.795	38.118	59.631	4.068	3.395	16.084	17.731	45.245
	p-value	0.000	0.002	0.000	0.000	0.044	0.065	0.000	0.000	0.000
Non-employment (1)	vmbo	0.141**	0.079	0.013	0.038	0.001	-0.053	0.08	-0.205	0.027
		(0.069)	(0.108)	(0.070)	(0.062)	(0.067)	(0.081)	(0.067)	(0.292)	(0.056)
	havo/vwo	0.331***	0.298***	0.245***	0.253***	0.224***	0.114	0.301***	-0.039	0.229***
		(0.068)	(0.106)	(0.064)	(0.071)	(0.077)	(0.091)	(0.071)	(0.289)	(0.058)
	mbo	0.263***	0.248**	0.196***	0.239***	0.208***	0.151*	0.227***	-0.036	0.195***
		(0.062)	(0.102)	(0.059)	(0.060)	(0.066)	(0.080)	(0.065)	(0.284)	(0.053)
	hbo	0.556***	0.535***	0.481***	0.501***	0.498***	0.419***	0.529***	0.244	0.481***
		(0.062)	(0.102)	(0.060)	(0.060)	(0.067)	(0.082)	(0.065)	(0.283)	(0.053)
	wo	0.754***	0.731***	0.741***	0.783***	0.752***	0.683***	0.759***	0.496*	0.719***
		(0.066)	(0.106)	(0.072)	(0.069)	(0.072)	(0.086)	(0.069)	(0.286)	(0.057)
	N (uncensored)	1216	962	1008	801	923	852	984	869	7602
	N (censored)	41	26	64	44	43	39	65	33	355
	lambda	-0.013	-0.024	-0.031	-0.068	-0.138	-0.139	-0.062	-0.008	-0.019
	chi2 (comparison test)	1.168	2.054	4.546	2.843	7.308	4.624	14.66	0.367	3.943
	p-value	0.280	0.152	0.033	0.092	0.007	0.032	0.000	0.545	0.047
Nonemployment (2)	vmbo	0.142**	0.081	0.015	0.035	0.002	-0.025	0.08	-0.205	0.028
		(0.068)	(0.107)	(0.070)	(0.062)	(0.068)	(0.080)	(0.067)	(0.292)	(0.056)
	havo/vwo	0.332***	0.299***	0.249***	0.249***	0.233***	0.145*	0.301***	-0.038	0.231***
		(0.068)	(0.106)	(0.064)	(0.071)	(0.076)	(0.088)	(0.072)	(0.288)	(0.058)
	mbo	0.264***	0.250**	0.200***	0.236***	0.209***	0.169**	0.225***	-0.035	0.197***
		(0.062)	(0.102)	(0.058)	(0.060)	(0.065)	(0.079)	(0.065)	(0.284)	(0.053)
	hbo	0.557***	0.538***	0.485***	0.502***	0.501***	0.442***	0.527***	0.244	0.483***
		(0.062)	(0.102)	(0.060)	(0.060)	(0.067)	(0.080)	(0.066)	(0.283)	(0.054)
	wo	0.755***	0.734***	0.746***	0.784***	0.756***	0.703***	0.751***	0.496*	0.720***
		(0.066)	(0.106)	(0.072)	(0.069)	(0.071)	(0.084)	(0.070)	(0.286)	(0.057)
	N (uncensored)	1516	1080	1125	895	987	894	1035	900	8432
	N (censored)	341	144	181	138	107	81	129	64	1185
	lambda	-0.007	-0.007	-0.014	-0.019	-0.082	-0.104	-0.074	-0.004	-0.009
	chi2 (comparison test)	0.12	0.273	1.072	0.379	1.735	2.264	10.854	0.148	0.768
	p-value	0.729	0.601	0.300	0.538	0.188	0.132	0.001	0.700	0.381

Note: robust (clustered) standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The standard errors are clustered when the regression is pooled. The extended sample 1 is composed of male individuals working full time (i.e. at least 32 hours per week) aged 20 – 65 years. In total eight separate year regressions and one pooled regressions is estimated for each type of model. The dependent variable is the (log of) gross hourly wage and the independent variables are years of education, experience and experience squared. In the pooled regression, also year dummies are included. With the exception of the baseline results, all selection equations are based on the explanatory variables, the civil status (*burgstat*), urban character of the place of residence (*sted*) and the number of household members (*aantalhh*). All heckman selection models are based on the maximum likelihood estimation procedure. N is the total number of observations in the wage equation. N (censored) is the number of observations in the selection equation. Lambda is the inverse Mills ratio and represents the selection term. The chi^2 and its corresponding p-value are used to indicate the presence of sample selectivity. Non-employment (1) only includes individuals who lost their job, non-employment (2) also includes all other individuals who are not employed. The non-employment (1) regression for the year 2014 does not contain the variable *sted* in the selection equation due to an otherwise infinite number of iterations.

SECTION 9: BIBLIOGRAPHY

Acemoglu, D., & Autor, D. (2012). What Does Human Capital Do? A Review of Goldin and Katz's The Race between Education and Technology. *Journal of Economic Literature*, *50*(2), 426–463.

Angrist, J. D., & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives*, *15*(4), 69–85.

Ashenfelter, O., Harmon, C., & Oosterbeek, H. (1999). A Review of Estimates of the Schooling/Earnings Relationship, with Tests for Publication Bias. *Labour Economics*, *6*(4), 453–470.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2010). ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression. Retrieved from http://ideas.repec.org/c/boc/bocode/s425401.html

Becker, G. S. (1962). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, *70*(5), 9–49.

Becker, G. S. (1964). *Human Capital: a Theoretical and Empirical Analysis, with Special References to Education*. New York: National Bureau of Economic Research and Columbia University Press.

Blundell, R., Dearden, L., & Sianesi, B. (2001). *Estimating the Returns to Education: Models, Methods and Results*. London: Centre for the Economics of Education, London School of Economics.

Card, D. (1999). The Causal Effect of Education on Earnings. In *Handbook of Labor Economics* (Vol. 3, pp. 1801–1863). Amsterdam: Elsevier B.V.

Card, D. (2001). Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems. *Econometrica*, *69*(5), 1127–1160.

CBS. (2015). StatLine - Arbeidsdeelname: kerncijfers. Retrieved from http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=82309NED&D1=19-20&D2=a&D3=0&D4=0-3&D5=14,19,24,29,34,39,44,49,54,59&HDR=T,G2,G1&STB=G3,G4&VW=T

CBS. (2016). Bbp, productie en bestedingen; kwartalen, mutaties, nationale rekeningen. Retrieved from http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=82602NED&D1=0-17&D2=0-1&D3=54,59,64,69,74,79,84,89,94,99,l&HDR=G1,G2&STB=T&VW=T

Deelen, A., & Verbeek, W. (2015). Measuring Downward Nominal and Real Wage Rigidity - Why Methods Matter. *CPB Discussion Paper 315*, 1–33.

Doran, J., & Fingleton, B. (2015). Resilience from the micro perspective. *Cambridge Journal of Regions, Economy and Society*, *8*(2), 205–223.

Farber, H. S. (2005). What do we know about job loss in the United States? Evidence from the Displaced Workers Survey, 1984-2004. *Federal Reserve Bank of Chicago, Economic P*(2Q), 13–28.

Farber, H. S. (2011). Job Loss in the Great Recession: Historical Perspective from the Displaced Workers Survey, 1984-2010. *NBER Working Paper Series*, *17040*, 1–41.

FD. (2015a, March 5). CPB verhoogt raming groei Nederlandse economie. *Financieel Dagblad*. Retrieved from http://fd.nl/economie-politiek/1095404/cpb-verhoogt-raming-groei-nederlandse-economie

FD. (2015b, May 15). Nederlandse economie groeit opnieuw. *Financieel Dagblad*. Retrieved from http://fd.nl/economie-politiek/1103900/duitse-economie-groeit-minder-dan-verwacht

FD. (2015c, June 10). CPB: herstel Nederlandse economie zet door. *Financieel Dagblad*. Retrieved from http://fd.nl/economie-politiek/1107159/cpb-herstel-nederlandse-economie-zet-door

FD. (2015d, November 5). Nederland is op niveau van voor de crisis. *Financieel Dagblad*. Retrieved from http://fd.nl/economie-politiek/1125998/nederland-zit-op-een-stabiel-groeipad

FD. (2015e, November 19). CBS: werkloosheid neemt toe doordat meer mensen werk zoeken. *Financieel Dagblad*. Retrieved from http://fd.nl/ondernemen/1127935/werkloosheid-iets-hoger

FD. (2015f, December 7). Nederlandse economie groeit op eigen kracht door. *Financieel Dagblad*. Retrieved from http://fd.nl/economie-politiek/1130319/nederlandse-economie-groeit-op-eigen-kracht-door

Fersterer, J., & Winter-Ebmer, R. (2003). Are Austrian Returns to Education Falling Over Time? *Labour Economics*, *10*(1), 73–89.

Gielen, A. C., & van Ours, J. C. (2006). Age-specific cyclical effects in job reallocation and labor mobility. *Labour Economics*, *13*(4), 493–504.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review*, *73*(1), 103–130.

Harmon, C., Oosterbeek, H., & Walker, I. (2000). *The Returns to Education: A Review of Evidence , Issues and Deficiencies in the Literature*. *London School of Economics and Political Science*.

Harmon, C., Oosterbeek, H., & Walker, I. (2003). The Returns to Education: Microeconomics. *Journal of Economic Surveys*, *17*(2), 115–155.

Hawley, J. D. (2004). Changing returns to education in times of prosperity and crisis, Thailand 1985-1998. *Economics of Education Review*, *23*(3), 273–286.

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2008). Earnings Functions and Rates of Return. *Journal of Human Capital*, *2*(1), 1–31.

Henderson, D. J., Polachek, S. W., & Wang, L. (2011). Heterogeneity in Schooling Rates of Return. *Economics of Education Review*, *30*(6), 1202–1214.

Hinrichs, J. (2014, November 20). Werkzoekende durft zich weer op de arbeidsmarkt te vertonen. *Financieel Dagblad*, p. 6. Retrieved from http://fd.nl/frontpage/economie-politiek/903480/nederlander-durft-de-arbeidsmarkt-weer-op

Hoogerheide, L., Block, J. H., & Thurik, R. (2012). Family background variables as instruments for education in income regressions: A Bayesian analysis. *Economics of Education Review*, *31*(5), 515–523.

Hoynes, H., Miller, D. L., & Schaller, J. (2012). Who Suffers During Recessions. *Journal of Economic Perspectives*, *26*(3), 27–48.

Kalwij, A. S. (2000). Estimating the economic return to schooling on the basis of panel data. *Applied Economics*, *32*(1), 61–71.

Leigh, A., & Ryan, C. (2008). Estimating returns to education using different natural experiment techniques. *Economics of Education Review*, *27*(2), 149–160.

Levin, J., & Plug, E. (1999). Instrumenting education and the returns to schooling in the Netherlands. *Labour Economics*, *6*(4), 521–534.

López Bóo, F. (2010). Returns to Education and Macroeconomic Shocks: Evidence from Argentina. *IZA Discussion Paper No. 4753*, 1–43.

McGuinness, S., McGinnity, F., & O'Connell, P. J. (2009). Changing Returns to Education During a Boom? The Case of Ireland. *LABOUR*, *23*(Supplement s1), 197–221.

Meghir, C., & Palme, M. (2005). Educational Reform, Ability, and Family Background. *American Economic Review*, *95*(1), 414–424.

Milne, R., & Oakley, D. (2011, April 18). Greek bond fears intensify debt debate. *Financial Times*. Retrieved from http://www.ft.com/intl/cms/s/0/9f5474f0-69e7-11e0-89db-00144feab49a.html#axzz41Ia43wWP

Mincer, J. A. (1974). *Schooling, Experience, and Earnings*. *Human Behavior and Social Institutions No. 2* (1st ed.). New York: National Bureau of Economic Research and Columbia University Press.

Motellón, E., & López-Bazo, E. (2015). Job Loss Among Immigrant and Native Workers: Evidence from Spain's Economic Downturn. *Social Indicators Research*, *120*(2), 345–371.

OECD. (2013). Back to Work: Re-employment, Earnings and Skill Use after Job Displacement. *OECD*, *OECD Emplo*, 2–65.

Oreopoulos, P., & Salvanes, K. G. (2011). Priceless: The Nonpecuniary Benefits of Schooling. *Journal of Economic Perspective*, *25*(1), 159–184.

Park, S. (2011). Returning to school for higher returns. *Economics of Education Review*, *30*(6), 1215–1228.

Plug, E. J. S. (2001). Season of birth, schooling and earnings. *Journal of Economic Psychology*, *22*(5), 641–660.

Plug, E., & Vijverberg, W. (2003). Schooling, Family Background, and Adoption: Is It Nature or Is It Nurture? *Journal of Political Economy*, *111*(3), 611–641.

Scherpenzeel, A. C., & Das, M. (2010). "True" Longitudinal and Probability-Based Internet

Panels: Evidence From the Netherlands. In M. Das, P. Ester, & L. Kaczmirek (Eds.), *Social and Behavioral Research and the Internet: Advances in Applied Methods and Research Strategies* (pp. 77–104). Boca Raton: Taylor & Francis.

Schultz, T. W. (1975). The Value of the Ability to Deal with Disequilibria. *Journal of Economic Literature*, *13*(3), 827–846.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics*, *15*(2), 127–148.

Strauss, H., & De La Maisonneuve, C. (2009). The Wage Premium on Tertiary Education: New Estimates for 21 OECD countries. *OECD Journal: Economic Studies*, *2009*(1), 1–29.

Trostel, P., Walker, I., & Woolley, P. (2002). Estimates of the economic return to schooling for 28 countries. *Labour Economics*, *9*(1), 1–16.

van den Berge, W., & ter Weel, B. (2015). *Berekeningen en achtergrondinformatie over baanpolarisatie in Nederland*. Den Haag.

van der Meer, H. (2015, June 8). UWV ziet een voorzichtig herstel van de werkgelegenheid. *Financieel Dagblad*. Retrieved from http://fd.nl/economie-politiek/1106251/uwv-voorzichtig-herstel-arbeidsmarkt

Vilerts, K., Krasnopjorovs, O., & Brēķis, E. (2015). Does Education Affect Wages During and After Economic Crisis? Evidence from Latvia 2006-2012. *Latvijas Banka Working Paper 3/2015*, 1–50.

Webbink, D. (2007). Returns to University Education: Evidence from a Dutch Institutional Reform. *Economica*, *74*(293), 113–134.