Returns to Schooling in a Dynamic Mincerian Model with Individual Unobserved Heterogeneity

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ABSTRACT

Mincer (1974) assumes that the observed wage of an individual is equal to the monetary value of his human-capital productivity, i.e. his potential wage, at any point in time. We test this hypothesis by estimating a dynamic adjustment model which controls for individual unobserved heterogeneity. The results suggest that Mincer's assumption is rejected. The implication is that a dynamic approach should be used to compute the return to schooling in terms of observed earnings. This return is found to be lower than its potential level at the beginning of the working life.

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1. Introduction

In 1974, Jacob Mincer published a seminal book that has been the starting point of a large body of literature dealing with the estimation of a model where the logarithm of the hourly wage of an individual is explained by his schooling years, labor-market experience, experience squared, and the monetary value of the individual ability at birth, which is not observable.

In spite of its wide acceptance within the profession, the spread of the framework developed by Mincer (1974) over the last forty years has not been uncontroversial. Some authors criticized the framework by arguing that it is not able to provide a good fit of empirical data; some stressed that the average effect of schooling on earnings is likely to be non-linear in schooling; some suggested that education levels should replace schooling years in the wage equation; other authors proposed other arguments questioning the original Mincer model. As a matter of example, Murphy and Welch (1990) maintained that the standard Mincer equation provides a very poor approximation of the true empirical relationship between earnings and experience, Trostel (2005) argued that the average impact of an additional year of schooling on earnings varies with the number of completed years of education, while Belzil (2007) argued that schooling and experience are not separable in a wage equation.

Looking at the big picture, however, besides some critical voices, the history of human-capital regressions has been characterized by a generalized attempt of consistently estimating the coefficients of the Mincer equation, under an implicit acceptance of the theoretical setup of the model.

As stressed by Polachek (2007), at present, several survey articles have been written on the Mincer earnings function. Perhaps three of the most popular have been authored by Card (1999), Heckman, Lochner and Todd (2003), and Lemieux (2006). One common feature of the reviewed works is that the empirical models have a static nature. Putting it differently, as shall be seen in the next section, they implicitly assume that the observed wage of an individual is equal to the monetary value of the individual human-capital productivity at any point in time. What actually changes from one study to another is the way the monetary value of the individual human-capital productivity is modeled. This paper tackles the issue of the estimation of the Mincer model from a different, dynamic perspective. Let us focus on it.

The monetary value of the individual human-capital productivity defines what an individual may potentially earn because of his observed human-capital skills and his unobserved ability, and is usually referred as potential wage. In the basic specification, it is conceived as a linear function of ability, schooling, experience and its square. In more complex specifications, it is modeled using additional variables[1] or combinations of these variables, for instance due to complementarities between schooling and experience. As we will see in the next section, the assumption of equality between potential wage and observed wage directly follows from the Mincer's theory and, with the exception of very few articles supporting a dynamic approach (see Andini 2007, 2009 and 2010), it has been always made in Mincerian studies so far.

In this paper, following earlier studies on the dynamic approach, we relax the above-mentioned assumption of equality by allowing an adjustment between observed and potential wages to take place over time. This leads to a dynamic Mincer equation where past wages play the role of additional explanatory variable. This equation allows us to measure the adjustment speed of wages to human-capital productivity and also to analyze the implications of this adjustment for the estimation of the return to schooling.

[1] These variables typically include individual observed characteristics such as birth cohort, industry, occupation, sector of activity, marital status, gender, health, race, residence, etc… Sometimes these variables include indicators of labor-market mismatch, over-education or other factors affecting the individual potential wage.

As stressed before, a dynamic Mincer equation has been already estimated by Andini (2007, 2009, and 2010) using data from the United States, Spain and Portugal. His models controlled for observed heterogeneity and used quantile-regression techniques to inspect the impact of schooling not only on the mean but also on the shape of the conditional wage distribution. Andini (forthcoming) is, to the best of our knowledge, the first attempt to estimate a dynamic model just focusing on the mean but controlling for *both observed and unobserved* heterogeneity. Yet, Andini (forthcoming) does not discuss the implication of his approach for the computation of the return to schooling. In this paper, we build on Andini (forthcoming) by providing the first attempt to estimate the average wage return to schooling in a dynamic model with both observed and unobserved heterogeneity.

To discuss our main point, we use a limited set of observed controls, namely the past wage of the individual and the three classical human-capital variables: schooling, experience and experience squared. The main reason is that, as shall be seen in Section 3, we want to test *one specific* assumption of the original Mincer's theory: the above-referred assumption of equality. Nevertheless, in using a simple specification, we follow important contributions to the literature such as those of Buchinsky (1994) and Martins and Pereira (2004) among others, and we extend their sets of observed controls using one lagged wage. The rationale for a simple specification is discussed in Andini (2007) and is consistent with the main argument of Pereira and Martins (2004) in favor of the estimation of *total* returns to schooling[2]. Yet, to reduce skepticism about the significance of estimation results obtained using a simplified model, we also provide some robustness checks using additional control variables.

The empirical analysis presented in this paper will explore data for Belgium, Denmark and Finland extracted from the European Community Household Panel (ECHP) because the data for these three countries allow to test a number of issues. First, Andini (2009) has shown that a dynamic Mincer equation can be seen as the result of a simple wage-bargaining model where the outside option of the worker depends on the level of the unemployment benefit which, in turn, depends on the past wage of the worker. Hence, Andini (2009) predicts that a dynamic Mincer equation should fit the data well in countries where unemployment-benefit policies exist, cover a large share of the labor force, and the benefits depend on past earnings. Since Belgium, Denmark and Finland have the highest generosity index of unemployment benefit adjusted for coverage in a sample of 12 European countries (Boeri and van Ours, 2008, p. 283) and unemployment benefits are based on past wages and contributions, using data for Belgium, Denmark and Finland allows to test the prediction of Andini (2009). Second, using data for these three countries, it is possible to test whether the time span of the sample matters (6 years for Finland vs. 8 years for Belgium and Denmark). Third, using data for these three countries allows to test whether the choice of the sample period is relevant (1996-2001 for Finland vs. 1994-2001 for Belgium and Denmark). Fourth, it is possible to test whether the amplitude of the sample matters (roughly 6800 observations in Belgium vs. 2300 or less in Denmark and Finland). Finally, using data for three different countries

[2] Martins and Pereira (2004) argued in favor of a simple Mincer specification for estimating the total return to schooling. Since many variables that are normally used as controls, such as industry or occupational dummies, are choice variables that depend on education, controlling for these variables implies that a share of the impact of education on wages is captured by the coefficient of these education-dependent covariates. Of course, downsizing the wage equation is a risky exercise because the lower is the number of regressors, the likelier is the possibility that the coefficients are inconsistently estimated due to omitted-variable bias. Andini (2007) proposed a method for the estimation of the total return to schooling when longitudinal data are available. The introduction of past earnings as additional explanatory variable increases the explained variability of wages and reduces the risk of inconsistency *without* implying any additional difficulty for the issue of recovering the total return to education.

allows to test whether there are significant country-level differences in the estimation results.
As shall be seen further below, the empirical evidence presented in this paper does not reject Andini (2009)'s prediction. In addition, it appears be robust to country heterogeneity, time span of the sample, number of observations and choice of the sample period.
The structure of the paper is as follows. Section 2 reviews the static Mincer's theory. Section 3 presents our adjustment model. Section 4 discusses issues and problems related to the estimation of our adjustment model when controlling for both observed and unobserved individual heterogeneity. Section 5 describes the dataset and the variables used in the empirical analysis. Estimation results are also presented. Section 6 provides a numerical example of how our adjustment model should be used to compute returns to schooling. Sensitivity analysis is also performed. Section 7 concludes.

2. Mincer's static model

This section presents the theoretical foundations of the standard Mincer equation as reported by Heckman et al. (2003). Therefore, we make no claim of originality at this stage and mainly aim at helping the reader with notations and terminology adopted in the next sections.
Mincer argues that potential earnings today depend on investments in human capital made yesterday. Denoting potential earnings at time t as E_t, Mincer assumes that an individual invests in human capital a share k_t of his potential earnings with a return of r_t in each period t. Therefore we have:

(1) $$E_{t+1} = E_t(1 + r_t k_t)$$

which, after repeated substitution, becomes:

(2) $$E_t = \prod_{j=0}^{t-1}(1 + r_j k_j)E_0$$

or alternatively:

(3) $$\ln E_t = \ln E_0 + \sum_{j=0}^{t-1}\ln(1 + r_j k_j) .$$

Under the assumptions that:

- schooling is the number of years s spent in full-time investment in human capital ($k_0 = ... = k_{s-1} = 1$),
- the return to the schooling investment in terms of potential earnings is constant over time ($r_0 = ... = r_{s-1} = \beta$),
- the return to the post-schooling investment in terms of potential earnings is constant over time ($r_s = ... = r_{t-1} = \lambda$),

we can write expression (3) as follows:

(4) $$\ln E_t = \ln E_0 + s\ln(1+\beta) + \sum_{j=s}^{t-1} \ln(1+\lambda k_j)$$

which yields:

(5) $$\ln E_t \approx \ln E_0 + \beta s + \lambda \sum_{j=s}^{t-1} k_j$$

for small values of β, λ and k[3].

In order to build up a link between potential earnings and labor-market experience z, Mincer assumes that the post-schooling investment linearly decreases over time, that is:

(6) $$k_{s+z} = \eta\left(1 - \frac{z}{T}\right)$$

where $z = t - s \geq 0$, T is the last year of the working life and $\eta \in (0,1)$.

Therefore, using (6), we can re-arrange expression (5) and get:

(7) $$\ln E_t \approx \ln E_0 - \eta\lambda + \beta s + \left(\eta\lambda + \frac{\eta\lambda}{2T}\right)z - \left(\frac{\eta\lambda}{2T}\right)z^2 .$$

Then, by subtracting (6) from (7), we obtain an expression for net potential earnings, i.e. potential earnings net of post-schooling investment costs[4]:

(8) $$\ln E_t - \eta\left(1 - \frac{z}{T}\right) \approx \ln E_0 - \eta\lambda - \eta + \beta s + \left(\eta\lambda + \frac{\eta\lambda}{2T} + \frac{\eta}{T}\right)z - \left(\frac{\eta\lambda}{2T}\right)z^2$$

which can also be written as:

(9) $$\ln npe_t \approx \alpha + \beta s + \delta z + \phi z^2 + \ln E_0$$

where $\ln npe_t = \ln E_t - \eta\left(1 - \frac{z}{T}\right)$, $\alpha = -\eta\lambda - \eta$, $\delta = \eta\lambda + \frac{\eta\lambda}{2T} + \frac{\eta}{T}$ and $\phi = -\frac{\eta\lambda}{2T}$.

Assuming that observed earnings are equal to net potential earnings at any time $t \geq s$ (a key-assumption, as shall be seen in the next section):

(10) $$\ln w_t = \ln npe_t$$

and, using expression (9), we get:

[3] Note that the symbol of equality $(=)$ in expression (4) becomes a symbol of rough equality $(\approx)$ in expression (5). It happens because, if a number x is close to zero, then $\ln(1+x) \approx x$.

[4] Note the post-schooling investment costs are given by $k_t E_t$ with $t \geq s$. Therefore, net potential earnings in levels are given by $E_t - k_t E_t$, or $E_t(1-k_t)$ which, after taking logarithms, if k is small, is equal to $\ln E_t - k_t$, i.e. the left-hand side of expression (8).

(11) $\ln w_t \approx \alpha + \beta s + \delta z + \phi z^2 + \ln E_0$

By adding subscripts where necessary, we get:

(12) $\ln w_{it} \approx \alpha + \beta s_i + \delta z_{it} + \phi z_{it}^2 + \ln E_{0i}$

By making the model stochastic, we obtain:

(13) $\ln w_{it} = \alpha + \beta s_i + \delta z_{it} + \phi z_{it}^2 + \ln E_{0i} + e_{it}$

Normally, the error e_{it} is assumed to be a pure well-behaved individual wage shock, uncorrelated with the explanatory variables. Instead, as $\ln E_{0i}$ represents the value of the individual potential earnings at birth, it is usually interpreted as the value of the individual unobserved ability and is therefore assumed be correlated with s_i and z_{it}. Hence, the estimation of model (13) is non-trivial.

To conclude this section, it is important to stress that the total return to schooling in the static model (13) is given by the following expression:

(14) $\frac{\partial \ln w_{it}}{\partial s_i} = \beta$

and is constant over the working life, meaning *independent* of labor-market experience z. Further, because of assumption (10), the return to schooling in terms of observed earnings and the one in terms of net potential earnings coincide.

We label β as ‘the static return to schooling in terms of net potential earnings’ and show, in Section 6, that our interpretation of β in terms of *net potential* rather than *observed* earnings is appropriate.

3. Adjustment model

If one takes as a starting point the presentation of the Mincer’s model made in the previous section, it is possible to argue that the model is characterized by two main features. First, it provides an explanation why the logarithm of the net potential earnings of an individual at time $t = s + z$ can be approximately represented as a function of s, z and $\ln E_0$, i.e. expression (9). This expression can be seen as ‘the building block’ of the Mincer’s model. Second, it is based on the assumption that, at any time $t \geq s$, the logarithm of the observed wage of an individual is equal to the monetary value of his net human-capital productivity, measured by his net potential wage, i.e. assumption (10).

As anticipated in Section 1, there are three popular surveys on the Mincer equation: Card (1999), Heckman, Lochner and Todd (2003), and Lemieux (2006).

Card concentrated on econometric issues regarding the identification of the causal relationship between schooling and earnings, and therefore he only marginally discussed whether the theory proposed by Mincer was able to provide a good fit of the real data. In contrast, Heckman et al. concentrated on the empirical support to the theory using past and current data (and on how to best incorporate future earnings uncertainty into the Mincer framework). Analogously, Lemieux focused on how well the most common version of the Mincer earnings function fits current data. Hence, for the purpose of this paper, the surveys by Heckman et al. and Lemieux deserve special consideration.

On the one hand, Heckman et al. tested three implications of the Mincer model: i) log-earnings experience profiles are parallel across schooling level (i.e. the return to schooling is independent of labor-market experience); ii) log-earnings age profiles diverge across schooling levels (i.e. the return to labor-market experience increases as age increases); iii) the variance of earnings over the life-cycle has a U-shaped pattern. Using Census data on white and black males, they found mixed evidence of these predictions. In general, it seems that more recent data are supporting Mincer's predictions less.
On the other hand, Lemieux found that the Mincer equation remains an accurate benchmark for estimating wage equations provided that it is adjusted by i) including a quartic function of potential experience instead of a quadratic one; ii) allowing for a quadratic term in years of schooling to capture the growing convexity in the relationship between schooling and wages; and 3) allowing for cohort effects to capture the dramatic growth in returns to schooling among cohorts born after 1950.
Summing up, these influential authors basically argued that equation (11) may have some problems to fit the most recent data and, in order to solve these problems, they suggested to modify (9) instead of relaxing (10). The aim of this paper is to show that *relaxing (10) is a possibility that is worth exploring more* as it allows to 'save Mincer', at least in the long run.
Hence, unlike previous studies, this paper does not question the building block of the Mincer's theory, i.e. expression (9). Although expression (9) can be criticized, and has been criticized in the past, it has a feature that is very appreciated by the applied economist: it allows the estimation of a wage model that is linear in parameters (see model (13)). In addition, and most importantly, expression (9) is theoretically well-grounded while many departures from it are not (i.e. they are justified on empirical grounds). In this paper, we show that, assuming that (9) holds (an assumption made in hundreds of studies), one can actually obtain a better estimate of the return to schooling in terms of observed earnings by relaxing assumption (10) in a simple and flexible way.
The main argument to relax assumption (10) is as follows. As we have seen, Mincer suggested that, by investing in human capital, an individual can increase the monetary value of his productivity and achieve a certain level of net potential earnings. If the labor market were characterized by perfect competition at any point in time, the net potential earnings of an individual and his observed earnings would coincide at any point in time, as in assumption (10). That is, an individual would always earn the net monetary value of his human-capital productivity. However, without departing from the perfect-competition hypothesis in the long run, there may be frictions in the labor market in the short run that may cause the observed wages to adjust to the potential wages *with some lag*. In this case, the return to the individual human-capital investment measured in terms of observed earnings - say the observed return - may be different, at some point in time, from the return to the same investment measured in terms of net potential earnings - say the potential return.
This paper investigates the above hypothesis and shows that the observed return to schooling is substantially lower than its potential level at the beginning of the working life. Andini (2009) discusses one possible source of the above-referred frictions in the labor market, namely the existence of wage bargaining at worker-employer level in a world where unemployment benefits depend on past wages, but his empirical model does not control for individual unobserved heterogeneity. In this paper, we want to document that observed wages adjust to potential wages with some lag even after controlling for individual unobserved heterogeneity. In addition, we aim to discuss the consequences of this adjustment for the calculation of the return to schooling.
On the lines of Flannery and Rangan (2006) among others, we argue that assumption (10) can be replaced by a more flexible assumption. Particularly, observed earnings can

be seen as dynamically adjusting to net potential earnings, according to the following simple adjustment model:

$$(15) \qquad \ln w_t - \ln w_{t-1} = \rho(\ln npe_t - \ln w_{t-1})$$

where $\rho \in [0,1]$ measures the speed of adjustment.

If $\rho = 1$, then assumption (10) holds, observed earnings are equal (adjust) to net potential earnings at time t (within period t), and the standard Mincerian model (11) holds. If instead $\rho = 0$, then observed earnings are constant over time, always equal to the labor-market entry earnings $\ln w_s$, and do not adjust at all to variations of net potential earnings. In general, when the speed of adjustment is neither zero nor one, by replacing expression (9) into (15), we get:

$$(16) \qquad \ln w_t \approx (1-\rho)\ln w_{t-1} + \rho(\alpha + \beta s + \delta z + \phi z^2 + \ln E_0)$$

or alternatively:

$$(17) \qquad \ln w_t \approx \upsilon_0 + \upsilon_1 \ln w_{t-1} + \upsilon_2 s + \upsilon_3 z + \upsilon_4 z^2 + \rho \ln E_0$$

where $\upsilon_0 = \rho\alpha$, $\upsilon_1 = 1-\rho$, $\upsilon_2 = \rho\beta$, $\upsilon_3 = \rho\delta$ and $\upsilon_4 = \rho\phi$.

By adding subscripts where necessary, we get:

$$(18) \qquad \ln w_{it} \approx \upsilon_0 + \upsilon_1 \ln w_{it-1} + \upsilon_2 s_i + \upsilon_3 z_{it} + \upsilon_4 z_{it}^2 + \upsilon_i$$

where $\upsilon_i = \rho \ln E_{0i}$.

By making the model stochastic, we get:

$$(19) \qquad \ln w_{it} = \upsilon_0 + \upsilon_1 \ln w_{it-1} + \upsilon_2 s_i + \upsilon_3 z_{it} + \upsilon_4 z_{it}^2 + \upsilon_i + e_{it}$$

Expression (19) is a dynamic version of the Mincer equation, which we label as the 'adjustment model'. When individual-level longitudinal data are available, the complement to one of the speed of adjustment $(1-\rho)$ can be estimated and the theory underlying (19) can be tested. The minimum requirement for the theory to be consistent with the data is to find that the coefficient υ_1 is significantly different from zero.

4. Methods

To explore wage dynamics as those described in model (19), due to the presence of initial potential earnings $\ln E_{0i}$, we need to estimate a dynamic panel-data model with individual unobserved heterogeneity of the following type:

$$(20) \qquad Y_{it} = \upsilon_i + \upsilon_1 Y_{it-1} + \upsilon_2 X_{it} + \upsilon_3 S_i + e_{it}$$

where υ_i is correlated with S_i and X_{it} by assumption, while e_{it} is a pure wage shock (white noise), orthogonal to the explanatory variables.

Since $Y_{it-1} = \upsilon_i + \upsilon_1 Y_{it-2} + \upsilon_2 X_{it-1} + \upsilon_3 S_i + e_{it-1}$, then υ_i is also correlated with Y_{it-1}. Therefore, as the OLS estimator assumes the orthogonality of the composite error term

$\upsilon_i + e_{it}$ with the explanatory variables, and this condition is violated, the OLS estimates of model (20) are inconsistent.
A transformation that eliminates υ_i is the first-difference transformation:

$$(21) \qquad Y_{it} - Y_{it-1} = \upsilon_1 \left(Y_{it-1} - Y_{it-2} \right) + \upsilon_2 (X_{it} - X_{it-1}) + (e_{it} - e_{it-1})$$

Based on model (21), Anderson and Hsiao (1981) propose to use Y_{it-2} as instrument for $Y_{it-1} - Y_{it-2}$. This instrument is mathematically linked to (hence correlated with) $Y_{it-1} - Y_{it-2}$ and uncorrelated with $e_{it} - e_{it-1}$, as long as e_{it} is not serially correlated.
Arellano and Bond (1991) provide a useful test for autocorrelation in the errors. The test has a null hypothesis of 'no autocorrelation' and is applied to the differenced residuals $\Delta e_{it} = \vartheta_1 \Delta e_{it-1} + \vartheta_2 \Delta e_{it-2} + \omega_{it}$. The test of $\vartheta_1 = 0$ (ABAR1) should reject the null hypothesis as Δe_{it-1} is mathematically linked to Δe_{it} through e_{it-1}. Instead, the test of $\vartheta_2 = 0$ (ABAR2) should not reject the null. That is, we should have $\vartheta_2 = 0$ otherwise the residuals in levels would be serially correlated of order one. This would make Y_{it-2} an invalid instrument since Δe_{it} would be correlated with it. In this case, one may test Y_{it-3} and so on.
The procedure suggested by Anderson and Hsiao (1981) provides consistent but not efficient estimates because it does not exploit all the available moment conditions. Arellano and Bond (1991) provide a more efficient GMM procedure that uses *all* the orthogonality conditions between the lagged values of both Y_{it} and X_{it} and the first differences of e_{it}. Their estimator is usually called the Difference GMM estimator (GMM-DIF).
A problem with the estimator of both Arellano and Bond (1991) and Anderson and Hsiao (1981) is that time-invariant variables are eliminated by the first-difference transformation. Since the major issue in this paper is to investigate how well model (19) fits the data and therefore to estimate the impact of all the explanatory variables on wages, including schooling which is time-invariant, we use the estimator proposed by Blundell and Bond (1998) who (building on Arellano and Bover, 1995) suggest to instrument the variables in levels in model (20) with their lagged first differences. The estimator of Blundell and Bond is usually called the System GMM estimator (GMM-SYS) because both (20) and (21) are used as a system.
The validity of the GMM-SYS additional moment conditions depends on the validity of initial-condition restrictions which, as argued by Blundell and Bond (1998, 2000) and Bond (2002), hold under (sufficient but not necessary) assumptions of mean stationarity of the Y and X series. In our specific case, since only lagged wage differences are used as instruments for model (20), the key condition to identify the schooling parameter is the mean stationarity of the stochastic process that generates the logarithm of the hourly wage for each individual i at each time t.
We simply test this hypothesis by estimating an AR1 process (with a constant) for the wage logarithm using the OLS estimator. In presence of individual unobserved heterogeneity, the OLS estimator is biased upward and therefore provides an *upper-bound* estimate of the true autoregressive coefficient. In particular, we find that the OLS estimate of the autoregressive coefficient is 0.824, 0.819 and 0.742 (all significant at 1% level) for Belgium, Denmark and Finland respectively. These values are well below the critical value of 1, thus providing evidence that the logarithm of the hourly wage is mean stationary in all the three countries.
Summing up, in this paper, model (19) is estimated in both levels and difference using equations (20) and (21) as a system. The explanatory variables, i.e. past wages,

schooling years, experience and experience squared, are all considered endogenous because they are all correlated with individual unobserved heterogeneity. The instruments for the equation in levels are the lagged differences in the logarithm of the hourly wage ($\Delta \ln w_{it-1}, \Delta \ln w_{it-2}$, …). The instruments for the difference equation are the lagged levels of all the time-varying explanatory variables ($\ln w_{it-2}$, $\ln z_{it-2}$, $\ln z^2_{it-2}$, $\ln w_{it-3}$, …).

The null hypothesis of 'the instruments as a group are exogenous' is tested using the Hansen J test. As the GMM-SYS method can generate a very high number of instruments, the evidence can suffer a problem of instruments proliferation, meaning that the endogenous variables can be over-fitted, and the power of the Hansen test to detect instruments joint-validity can be weakened. Hansen test p-values equal to 1, or very close to 1, should be seen as a warning (Roodman, 2006). Yet, as shall be seen further below, the latter does not seem to be an issue in this paper.

5. Data and estimates

The empirical application proposed in this section is based on data on male workers, aged between 18 and 65, for Belgium, Denmark and Finland. The data are extracted from the European Community Household Panel (ECHP) and cover the period of 1994-2001 for Belgium and Denmark while only 1996-2001 for Finland. Table 1 contains a description of the sample statistics. We restrict the analysis to males in order to minimize the classical sample-selection problems that would arise with females.

To obtain the variables for years of schooling (s), potential labor-market experience (z) and logarithm of gross hourly wage (lnw), which are not directly observable in our dataset, we use the following ECHP variables:

- pt023. Age when the highest level of general or higher education was completed
- pe039. How old were you when you began your working life, that is, started your first job or business?
- pd003. Age
- pi211mg. Current wage and salary earnings – gross (monthly)
- pe005. Total number of hours per week (in main + additional jobs)

Specifically, to be consistent with the standard Mincerian model where the representative agent first stops schooling and then starts working, we select a sample of individuals whose age at the completion of the highest level of education was not higher than the age at the start of the working life (pt023 ≤ pe039) and define the human-capital variables as follows:

- $s = pt023 - 6$
- $z = pd003 - s - 6$

It is worth stressing that the variable s does not necessarily reflect successfully completed years of schooling. This is a compromise that allows us to obtain homogenous measures of schooling years (and potential labor-market experience) across three countries that are different in many aspects including educational systems.

An alternative would have been that of imputing a given number of schooling years to each completed degree. Yet, we believe that the latter is not the correct way to proceed because in the classical Mincer model the human-capital accumulation is potential in nature (indeed there is an explicit reference to potential rather than actual labour-market experience) but, most importantly, because completing a degree in 5 or 6 years - rather than the regular 4 or 5 years - does not necessarily mean that an individual has not accumulated human capital at school during those years that were not successfully completed. In addition, as we control for individual unobserved heterogeneity in our empirical models, we implicitly take into account that individuals have different abilities and that the explanatory variables can be measured with error. Therefore, we believe that the way we measure the human-capital variables in the context of this paper is the best available option.

The variable lnw represents the natural logarithm of the individual gross hourly wage. From the gross monthly wage (pi211mg), we obtain the daily (dividing the monthly wage by 30) and the weekly wage (multiplying the daily wage by 7). Dividing the latter by the number of weekly hours of work (pe005), we obtain the hourly wage.

Table 2 presents estimates of model (19) based on both OLS and GMM techniques. Our preferred estimates are the GMM-SYS estimates, accounting for endogeneity, individual heterogeneity and time effects. Specifically, as referred in Section 4, these estimates are obtained using the estimator of Blundell and Bond (1998). In our preferred estimates, the coefficient $\upsilon_1 = 1-\rho$ is statistically different from zero and estimated at 0.218, 0.335 and 0.420 in Finland, Belgium and Denmark, respectively. This implies that the speed of adjustment ρ is statistically different from one and estimated at 0.782, 0.665 and 0.580 in Finland, Belgium and Denmark, respectively. In addition, the standard Mincerian covariates, related to the individual human capital, are generally found to be significant. Note that all the standard specification tests are passed.

In sum, our preferred estimates in Table 2 provide evidence that model (19) fits the data well and that the Mincer assumption (10) or $\rho = 1$ is rejected.

As expected, the OLS estimator over-estimates the autoregressive coefficient[5] while the GMM-SYS estimates without year effects are not reliable because the model without time effects that does not pass the Hansen J test in the case of Finland, the Arellano-Bond 2nd order autocorrelation test in the case of Denmark, both these tests in the case of Belgium.

6. Computation of returns to schooling and sensitivity analysis

Using model (19), it can be easily shown that 'the return to schooling in terms of observed earnings' is given by the following expression:

$$(22) \qquad \beta(z) = \frac{\partial \ln w_{it}}{\partial s_i} = \upsilon_2(1+\upsilon_1+\upsilon_1^2+...+\upsilon_1^Z) = \rho\beta\left[1+(1-\rho)+(1-\rho)^2+....+(1-\rho)^Z\right]$$

and is, in general, dependent of labor-market experience z.

The return in expression (22) is, in general, lower than the return in expression (14), although the former converges to the latter as z increases. Indeed, for a value of $\rho \in (0,1)$, the following expression holds:

$$(23) \qquad \beta(\infty) = \lim_{z\to\infty} \beta(z) = \frac{\upsilon_2}{1-\upsilon_1} = \frac{\rho\beta}{1-(1-\rho)} = \beta\,.$$

Therefore, the adjustment model (19) is able to provide a measure of β comparable with expression (14). We label $\beta(\infty) = \frac{\upsilon_2}{1-\upsilon_1}$ as 'the dynamic return to schooling in terms of net potential earnings' to distinguish it from the 'the static return to schooling in terms of net potential earnings' defined in Section 2.

5 Although not reported in Table 2, as one would expect, the FE estimator under-estimates the autoregressive coefficient (0.112 in Belgium, -0.045 in Denmark, and -0.104 in Finland).

Expression (23) helps to show that the interpretation of β in terms of *net potential* rather than *observed* earnings, made in Section 2, is appropriate because nobody can live and work forever. To the extent of T being a finite number, the return to schooling in terms of observed earnings $\beta(z)$ can never be equal to β, but in the very special case of $\rho = 1$ (which is rejected in our empirical application).

As a matter of example, we use the adjustment model (19) to compute returns to schooling in terms of both net potential and observed earnings, using our preferred estimates in Table 1 (GMM-SYS, controlling for year effects).

Using expression (23), one can easily calculate that the return to schooling in terms of potential earnings $\beta(\infty)$, the equivalent of the static β return in the standard Mincer model[6], is equal to 0.093, 0.053 and 0.089 in Belgium, Denmark and Finland, respectively. For comparison, Figure 1 also reports the standard coefficients of the static Mincer equation (see expression (14)), as reported in column (6) of Table 3.

In addition, we can use expression (22) to calculate the return to schooling in terms of observed earnings over the working life $\beta(z)$. As shown in Figure 1 (the horizontal axis measures potential labor-market experience z), the standard static Mincerian model would not capture the fact that the return to schooling is increasing over time at the beginning of the working life and that the observed return to schooling at labor-market entry $\beta(0)$ (estimated at 0.031, 0.062 and 0.070 in Denmark, Belgium and Finland, respectively) is well below the potential one ($\beta(\infty)$).

The reminder of this section is devoted to the discussion of potential weaknesses of the analysis presented so far. In particular, we focus on the use of a simplified model which, we believe, is the major issue here. In Section 1, we discussed the rationale behind the use of a simple specification. In this section, we present some estimates supporting the arguments proposed in Section 1. In particular, the argument here is that using an extended model *does not allow* to recover the total return to schooling.

Specifically, Table 4 presents estimates of model (19) using the GMM-SYS estimator, controlling not only for individual unobserved heterogeneity, year effects, past wage and human-capital variables but also for other observed individual characteristics. This implies assuming that expression (9) does not hold, which may be reasonable but is not consistent with the original aim of this paper.

For identification purposes, we limit our control set to variables that exhibit time variation over the sample period. This allows us to treat these variables as endogenous and to instrument them using their lagged levels or lagged differences. This point is important because all the additional explanatory variables considered in this section are actually endogenous as they are choice variables that depend on individual unobserved characteristics.

A more elegant treatment of this type of endogeneity in a dynamic panel-data framework would require the specification and the estimation of several first-stage discrete-choice models (for instance, modeling the decision to work in the private rather than in the public sector) to produce fitted probabilities which can be used as instruments (see Wooldridge 2002, p. 625) in a GMM-SYS setting. However, this method would complicate a lot in presence of multiple-choice models, such as occupational choice-models[7], and the results would strongly depend on how the first-stage models are specified.

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[6] This does not mean that the two models, the dynamic one and the static one, must give the same estimates. The argument here is that the dynamic model allows a better estimate of the coefficient because the adjustment process is taken into account.

[7] The choice of the occupation is not just between 0 and 1 but among 0, 1, 2 or 3, etc…

We focus on the case of Belgium as this country has the highest number of observations among the three analyzed in the paper. The extension of the control set implies a substantial loss of observations (from 4787 to 1581), after excluding not-applicable or missing values (categories -8 and -9 in the ECHP dataset). If the same procedure is applied to Denmark and Finland, the already small number of observations for these two countries (1227 and 1192 respectively) becomes very small making the analysis not reliable.

In particular, the control set for Belgium includes information on occupations[8], job status (whether the individual is supervisor or not), marital status (whether the individual is married or not), health (whether the individual has chronic health problems or not), sector of production (whether the individual works in agriculture or not), migration status (whether the individual is immigrant or not), and finally sector of activity (whether the individual works in the private sector or not).

Columns from 1 to 8 gradually extend the model using a sequence of additional controls. The first model, in column 1, is model (19) estimated with the restricted sample (1581 observations) and hence with no additional controls (besides year effects). The last model, in column 8, includes the whole control set.

As one would reasonably expect, the results are consistent with the predictions of Martins and Pereira (2004). Since all the control variables are choice variables that are somehow dependent on education, the insertion of these variables into a human-capital regression model implies that a share of the impact of education on wages is captured by the coefficients of these education-dependent covariates. Typically, when the correlation between a schooling-dependent covariate and schooling is positive (negative), controlling for this schooling-dependent covariate lowers (increases) the coefficient of schooling. The latter seems to happen in Table 4 where the coefficient of schooling lowers. The issue is even clearer if one compares the estimate of the return to schooling in terms of potential earnings $\beta(\infty)$ based on column 1 (0.088) with the one based on column 8 (0.058).

In addition, the extension of the control set also affects the coefficients of the potential-experience variables, which become less statistically significant, and the coefficient of the past wage, which lowers. This is again consistent with the predictions of Martins and Pereira (2004) as past wage and experience are education-dependent covariates themselves.

Finally, the extension of the control set does not notably improve the explanatory power of the regression model in Belgium. In column 8, the only variables that are statistically significant are the indicator variables for the occupation as a clerk, the role of supervisor, and the private sector (the latter at 10% level), suggesting that individuals who work in the private sector, are clerks and supervisors earn on average more than their colleagues with the same observed and unobserved characteristics who work in the public sector, have a different occupation or are not supervisors.

From an empirical point of view, the latter suggests that individual wages are well explained by model (19) even if the dataset does not allow to control for a large set of covariates. We interpret this as another major result in the paper. Yet, the most important result in this section is that, again, the hypothesis of $\rho = 1$ is rejected, implying the need of using dynamic-Mincer-equation estimates for the calculation of the return to schooling in terms of both potential and observed earnings.

[8] The occupation categories are nine: 1) legislators, senior officials and managers; 2) professionals; 3) technicians and associate professionals; 4) clerks; 5) service workers and shop and market sales workers; 6) skilled agricultural and fishery workers; 7) craft and related trades workers; 8) plant and machine operators and assemblers; 9) elementary occupations.

7. Conclusions

To the best of our knowledge, there are two alternative approaches to modelling income dynamics in the literature (Guvenen, 2009). Both these approaches rely on the following specification of the income model:

$$(24) \qquad \ln w_{it} = \varphi_i + \upsilon_2 X_{it} + u_{it}$$

$$(25) \qquad u_{it} = \upsilon_1 u_{it-1} + e_{it}$$

where u_{it} is an autoregressive income shock, φ_i captures individual unobserved heterogeneity and X_{it} is a set of time-varying regressors.

These two approaches differ for how they perform the estimation of the parameters. The first, based on the hypothesis of no unobserved individual heterogeneity ($\varphi_i = \varphi \;\; \forall i$), finds that income shocks are highly persistent and is called the Restricted Income Profiles (RIP) hypothesis. The second, allowing for the presence of heterogeneity, finds modest persistence of income shocks and is called the Heterogeneous Income Profiles (HIP) hypothesis.

In the RIP specification, individuals are subject to extremely persistent - near random walks - shocks while facing similar life-cycle income profiles (conditional of the observed characteristics). In the HIP specification, individuals are subject to shocks with modest persistence, while facing life-cycle profiles that are individual-specific.

Guvenen (2009) found that disregarding individual unobserved heterogeneity, when in fact is present (as in the Mincer model), implies an overestimation of the persistence estimates. In addition, heterogeneity is estimated to be substantial.

It is easy to show that expressions (24) and (25) lead to the following dynamic specification, usually called common-factor restricted form:

$$(26) \qquad \ln w_{it} = \upsilon_i + \upsilon_1 \ln w_{it-1} + \upsilon_2 X_{it} + \upsilon_3 X_{it-1} + e_{it}$$

where $\upsilon_i = (1 - \upsilon_1)\varphi_i$ and $\upsilon_3 = -\upsilon_1 \upsilon_2$ is the common-factor restriction

The main improvement of the model proposed in this paper with respect to the literature on income profiles is that education is explicitly controlled for. For example, Guvenen (2009)'s analysis just uses subsamples of individuals by education level but education (or schooling) never enters the regression model as an additional explanatory variable. Controlling for schooling, we still find evidence in favour of the HIP hypothesis. In addition, model (26) is not suitable to be applied to Mincerian equations because of the presence of both X_{it} and X_{it-1}, which implies multicollinearity among current and lagged experience variables. Finally, while model (19) is the result of combining the Mincerian theory of potential earnings with a simple and flexible (adjustment) assumption, model (26) is the result of two assumptions, (24) and (25), which can be theoretically justified but still imply a common-factor restriction uneasy to be explained in a Mincerian context.

Consistently with the original Mincer's model, the adjustment model presented in this paper suggests that the potential return to schooling and the observed return coincide in the long-run equilibrium because the latter converges to the former as time increases. However, unlike the static Mincer equation, the model presented here allows to characterize the adjustment process toward the long-run equilibrium and highlights that, at the beginning of the working life, there may be a difference between the potential and the observed return whose size depends on the magnitude of the adjustment speed. In addition, our adjustment model is also able to provide a measure of the potential return, alternative to the standard Mincerian beta.

Under the assumption that the Mincerian theory of the individual human-capital productivity (or potential wage) holds, we have shown that the return to schooling in terms of observed earnings can be better estimated by allowing a dynamic wage adjustment process to take place rather than imposing an equality between observed and potential earnings at any point in time.

An interesting implication of a dynamic adjustment model is that it allows to take into account the argument, proposed by Heckman et al. (2003 and 2005), that the observed return to schooling may be not independent of labor-market experience. In particular, the model allows to estimate the observed return at several stages of the working life, including labor-market entry.

The estimation exercise has been conducted using micro data for Belgium, Denmark and Finland extracted from the European Community Household Panel. The results show that the observed return to schooling is substantially lower than its potential level at the beginning of the working life.

The empirical evidence supports previous results by Andini (2007, 2009 and 2010) in favor of dynamic Mincerian specifications but improves 'the state of the art' by keeping individual unobserved heterogeneity into account. It is shown that disregarding individual fixed effects (using OLS) implies an over-estimation of the autoregressive coefficient and, therefore, an under-estimation of the adjustment speed, which in turn affects the estimation of schooling returns, in terms of both observed and potential earnings.

Summing up, in this paper, we make the following contributions:

- We estimate a dynamic Mincer equation (DME) controlling for both observed and unobserved individual heterogeneity

- We find that observed earnings do not adjust to human-capital productivity as rapidly as assumed by Mincer (1974)

- We provide an expression to compute the return to schooling in terms of observed earnings using DME estimates

- This return is found to be lower that its potential level at the beginning of the working life

- Individual wages are well explained by a simple DME even if the dataset does not allow to control for a large set of covariates

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Table 1. Sample statistics

Belgium, 1994-2001	Obs.	Mean	Std. Dev.	Min	Max
Log. of gross hourly wage	6873	6.164	0.433	2.815	8.697
Schooling years	6873	13.858	3.240	4	25
Potential labor-market experience	6873	19.521	10.362	0	51
Denmark, 1994-2001	Obs.	Mean	Std. Dev.	Min	Max
Log. of gross hourly wage	2053	4.811	0.521	-0.326	6.368
Schooling years	2053	14.943	4.592	6	29
Potential labor-market experience	2053	17.173	11.486	0	52
Finland, 1996-2001	Obs.	Mean	Std. Dev.	Min	Max
Log. of gross hourly wage	2341	4.256	0.509	-0.405	7.522
Schooling years	2341	15.423	3.355	5	27
Potential labor-market experience	2341	14.800	9.999	0	46

Table 2. Adjustment model

Dependent variable: Logarithm of gross hourly wage	Belgium	Denmark	Finland
	1994-2001	1994-2001	1996-2001
OLS			
Constant	1.223 (0.000)	0.983 (0.000)	1.193 (0.000)
Logarithm of gross hourly wage (-1)	0.757 (0.000)	0.775 (0.000)	0.627 (0.000)
Schooling years	0.016 (0.000)	0.009 (0.000)	0.023 (0.000)
Potential labor-market experience	0.005 (0.001)	0.001 (0.562)	0.007 (0.018)
Potential labor-market experience squared	-0.000 (0.168)	-0.000 (0.787)	-0.000 (0.288)
OLS, controlling for year effects			
Constant	1.252 (0.000)	0.948 (0.000)	1.179 (0.000)
Logarithm of gross hourly wage (-1)	0.754 (0.000)	0.772 (0.000)	0.624 (0.000)
Schooling years	0.016 (0.000)	0.010 (0.000)	0.025 (0.000)
Potential labor-market experience	0.006 (0.000)	0.002 (0.493)	0.008 (0.014)
Potential labor-market experience squared	-0.000 (0.094)	-0.000 (0.684)	-0.000 (0.308)
GMM-SYS			
Constant	2.102 (0.000)	1.740 (0.000)	2.005 (0.000)
Logarithm of gross hourly wage (-1)	0.443 (0.000)	0.543 (0.000)	0.305 (0.016)
Schooling years	0.073 (0.000)	0.017 (0.001)	0.051 (0.000)
Potential labor-market experience	0.022 (0.000)	0.027 (0.003)	0.016 (0.126)
Potential labor-market experience squared	-0.000 (0.116)	-0.000 (0.011)	-0.000 (0.725)
ABAR1 test (p-value)	(0.000)	(0.001)	(0.029)
ABAR2 test (p-value)	(0.065)	(0.041)	(0.510)
Hansen J test (p-value) – all instruments	(0.030)	(0.552)	(0.006)
Hansen J test (p-value) – instruments for eq. in levels	(0.943)	(0.215)	(0.218)
Obs.	4787	1227	1192
GMM-SYS, controlling for year effects			
Constant	2.901 (0.000)	2.145 (0.000)	2.109 (0.000)
Logarithm of gross hourly wage (-1)	0.335 (0.000)	0.420 (0.000)	0.218 (0.085)
Schooling years	0.062 (0.000)	0.031 (0.000)	0.070 (0.000)
Potential labor-market experience	0.032 (0.000)	0.028 (0.006)	0.014 (0.188)
Potential labor-market experience squared	-0.000 (0.000)	-0.000 (0.023)	0.000 (0.922)
ABAR1 test (p-value)	(0.000)	(0.001)	(0.033)
ABAR2 test (p-value)	(0.121)	(0.117)	(0.493)
Hansen J test (p-value) – all instruments	(0.256)	(0.738)	(0.127)
Hansen J test (p-value) – instruments for eq. in levels	(0.877)	(0.379)	(0.171)
Obs.	4787	1227	1192

P-values of estimated coefficients, in parentheses, are based on White-corrected standard errors for OLS and on Windmeijer-corrected standard errors for GMM-SYS.

Table 3. Static returns to schooling in terms of net potential earnings

	(1) OLS	(2) OLS	(3) RE	(4) RE	(5) GMM-SYS	(6) GMM-SYS
Belgium	0.067 (0.000)	0.066 (0.000)	0.055 (0.000)	0.050 (0.000)	0.163 (0.000)	0.110 (0.000)
Denmark	0.043 (0.000)	0.046 (0.000)	0.042 (0.000)	0.044 (0.000)	0.043 (0.000)	0.054 (0.000)
Finland	0.059 (0.000)	0.062 (0.000)	0.048 (0.000)	0.053 (0.000)	0.093 (0.000)	0.102 (0.000)
Control for individual fixed effects	no	no	yes	yes	yes	yes
Control for year fixed effects	no	yes	no	yes	no	yes
Control for endogeneity	no	no	no	no	yes	Yes

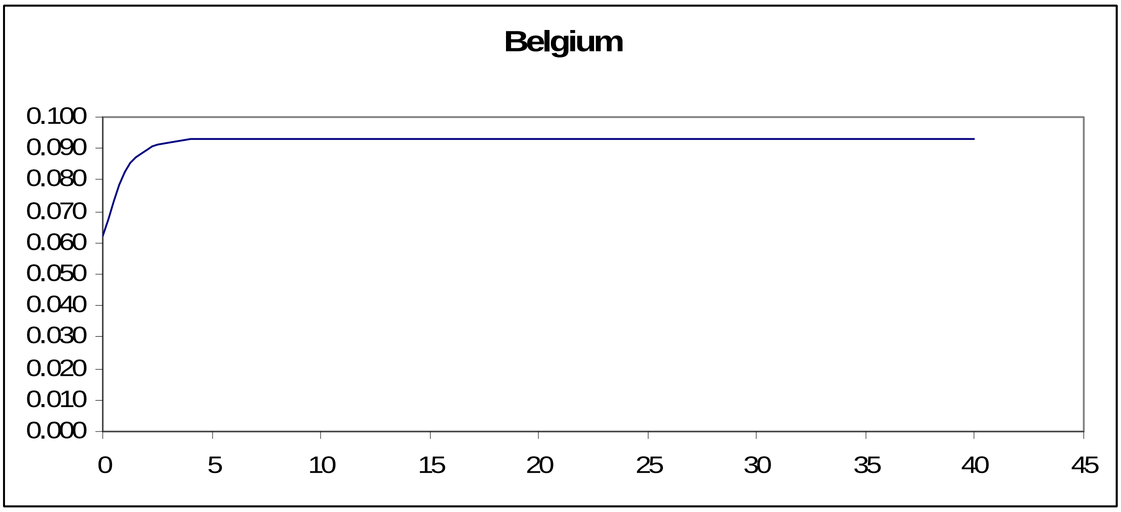
All the regressions control include constant term, experience and experience squared.
P-values of estimated coefficients, in parentheses, are based on White-corrected standard errors for OLS and on Windmeijer-corrected standard errors for GMM-SYS.

Table 4. Adjustment model with additional controls, Belgium 1994-2001

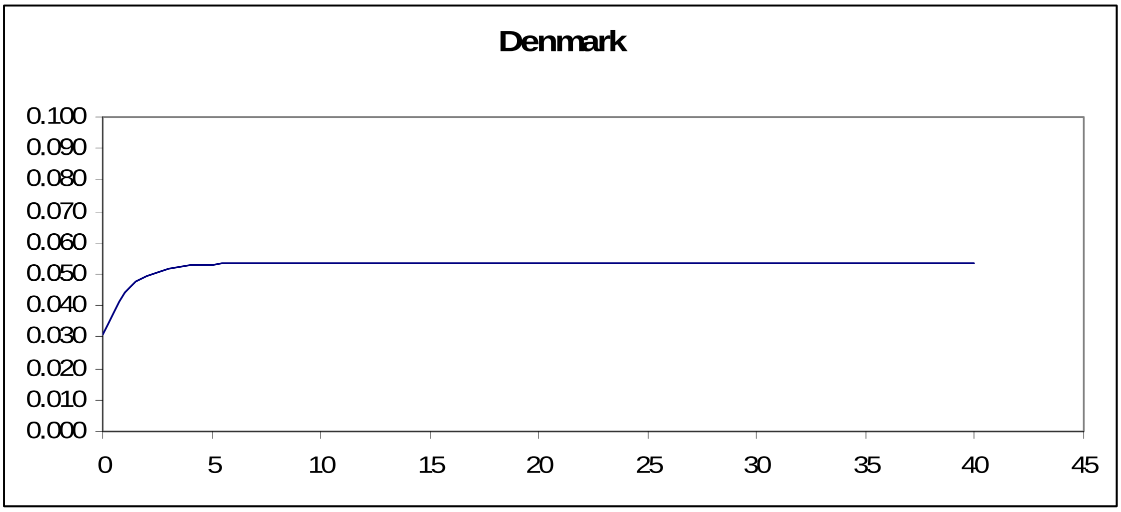
Dependent variable: Log. of gross hourly wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.660	2.879	3.280	3.229	3.222	3.287	3.239	3.422
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log. of gross hourly wage (-1)	0.415	0.369	0.335	0.337	0.338	0.324	0.329	0.303
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Schooling years	0.052	0.046	0.040	0.040	0.040	0.040	0.043	0.041
	(0.000)	(0.009)	(0.018)	(0.020)	(0.020)	(0.022)	(0.015)	(0.027)
Potential experience	0.023	0.032	0.023	0.023	0.023	0.025	0.025	0.023
	(0.005)	(0.000)	(0.031)	(0.028)	(0.031)	(0.027)	(0.030)	(0.053)
Potential experience squared	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.108)	(0.013)	(0.129)	(0.120)	(0.132)	(0.113)	(0.139)	(0.207)
Occupation 1		0.163	-0.066	-0.075	-0.074	-0.032	-0.054	-0.044
		(0.411)	(0.745)	(0.727)	(0.734)	(0.883)	(0.795)	(0.833)
Occupation 2		0.143	0.147	0.142	0.142	0.172	0.149	0.190
		(0.397)	(0.362)	(0.402)	(0.399)	(0.318)	(0.394)	(0.268)
Occupation 3		0.141	0.024	0.019	0.019	0.020	0.013	0.078
		(0.394)	(0.887)	(0.917)	(0.914)	(0.911)	(0.941)	(0.669)
Occupation 4		0.383	0.322	0.317	0.317	0.369	0.361	0.418
		(0.006)	(0.018)	(0.026)	(0.026)	(0.013)	(0.012)	(0.004)
Occupation 5		-0.157	-0.078	-0.082	-0.081	-0.077	-0.084	-0.038
		(0.281)	(0.568)	(0.554)	(0.569)	(0.598)	(0.558)	(0.803)
Occupation 6		-1.579	-2.521	-2.513	-2.503	-2.979	-3.002	-4.663
		(0.555)	(0.405)	(0.406)	(0.404)	(0.358)	(0.354)	(0.262)
Occupation 7		0.109	-0.028	-0.031	-0.030	-0.016	-0.024	-0.089
		(0.468)	(0.839)	(0.822)	(0.835)	(0.912)	(0.866)	(0.553)
Occupation 8		0.0851	-0.051	-0.064	-0.062	-0.045	-0.042	-0.123
		(0.547)	(0.719)	(0.712)	(0.718)	(0.797)	(0.810)	(0.519)
Job status (1 if supervisor)			0.304	0.300	0.299	0.298	0.296	0.203
			(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.041)
Marital status (1 if married)				0.048	0.048	0.035	0.024	-0.044
				(0.803)	(0.803)	(0.855)	(0.902)	(0.820)
Chronic health problem (1 if yes)					0.009	0.008	0.000	-0.002
					(0.963)	(0.967)	(0.997)	(0.990)
Sector of production (1 if agriculture)						0.324	0.319	0.256
						(0.401)	(0.407)	(0.525)
Migration status (1 if immigrant)							-0.042	-0.148
							(0.746)	(0.359)
Sector of activity (1 if private sector)								0.134
								(0.069)
ABAR1 test (p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ABAR2 test (p-value)	(0.235)	(0.437)	(0.702)	(0.717)	(0.717)	(0.730)	(0.702)	(0.740)
Hansen J test (p-value)								
- all instruments	(0.428)	(0.435)	(0.578)	(0.518)	(0.512)	(0.475)	(0.449)	(0.531)
- instruments for eq. in levels	(0.849)	(0.605)	(0.491)	(0.568)	(0.601)	(0.611)	(0.562)	(0.555)
Observations	1581	1581	1581	1581	1581	1581	1581	1581

All the regression models control for year effects. Occupation 9 is the excluded category.
P-values of estimated coefficients, in parentheses, are based on Windmeijer-corrected standard errors.

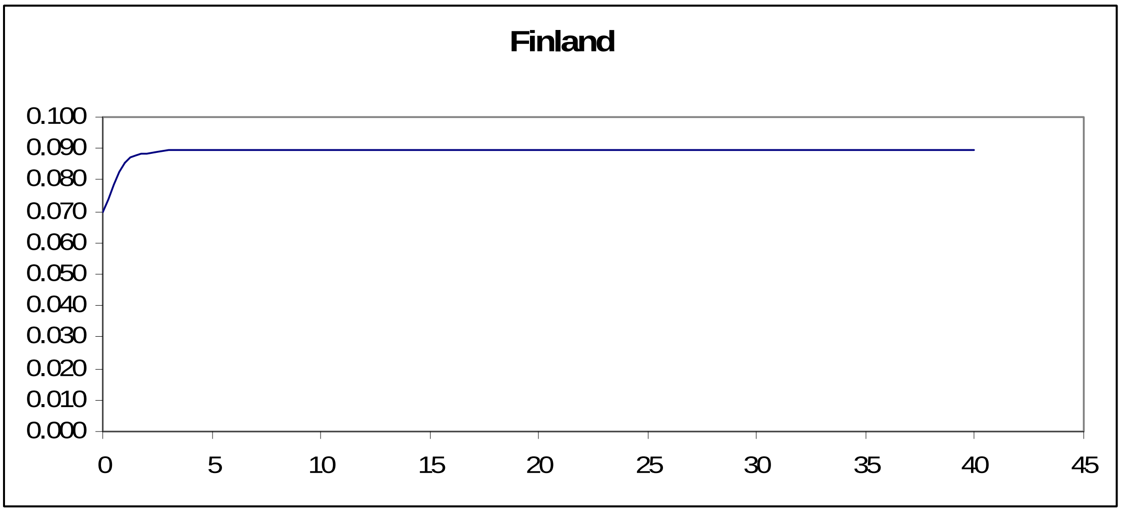
Figure 1. Returns to schooling in terms of observed earnings $\beta(z)$



Belgium: $\beta(0) = 0.062$, $\beta(\infty) = 0.093$, and $\beta = 0.110$



Denmark: $\beta(0) = 0.031$, $\beta(\infty) = 0.053$, and $\beta = 0.054$



Finland: $\beta(0) = 0.070$, $\beta(\infty) = 0.089$, and $\beta = 0.010$

The horizontal axis measures potential labor-market experience z