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TWEEKERKENSTRAAT 2
B-9000 GENT
Tel. : 32 - (0)9 – 264.34.61
Fax. : 32 - (0)9 – 264.35.92

WORKING PAPER

A distance function approach to school-leavers' efficiency in the school-to-work transition.

Bart Defloor
Luc Van Ootegem
Elsy Verhofstadt

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Bart Defloor, Luc Van Ootegem(§), Elsy Verhofstadt[1]

University College Ghent and SHERPPA Ghent University

(§ K.U.Leuven, Research Institute for Work and Society)

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Abstract

Two conventional approaches to study the school-to-work transition are the duration period to the first job and the satisfaction in (or for some specific characteristics of) the first job. This paper compares these two approaches with an analysis of the efficiency of school-leavers' first job achievement. The transformation of resources, when leaving school, into achieved first job characteristics is analysed using a multi-input multi-output stochastic distance function approach. This allows to assess the efficiency of this conversion process. Inter-individual differences in transformation efficiency are important, especially when policy makers want to focus on reasons for resource-inefficiency that are beyond the control of the individual.

The empirical analysis is based on the 1978 birth cohort of the Flemish SONAR data. The variation in efficiency is explained in terms of individual-specific conversion factors that influence job efficiency: the social (family) background, the motivation to work, the number of search channels used and the sector of employment. The most important positive factor is education (a higher number of successful school years). The results are compared with the average duration to the first job and average job satisfaction. The efficiency analysis provides additional information. Most attention is attracted to the role of the social background, more specifically having a non-Belgian background, for the school-to-work transition.

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1. Introduction

Employment policy faces the challenge of implementing strategies that stimulate young people to enter the labour market and find a -preferably high quality- job as soon as possible after graduating. The existing literature on the school-to-work transition focuses mainly on the (duration of the time) period between leaving school and finding a job (for an overview see Ryan, 2001). The duration of unemployment also takes a prominent position in European policy (see the different 'Employment in Europe' reports of the European Commission). This leaves aside issues of what kind of job is acquired, the main policy concern is preventing youth unemployment. Researchers analysing this issue rely on static approaches using standard labour market performance data about youth (un)employment or they use a more dynamic approach using duration analysis (see Vanoverberghe et al., 2008; Manfredi and Quintini, 2009). The duration of the unemployment spell is then related to socio-economic and individual characteristics. The main question in this part of the literature is what influences the job finding process. The quality of the job is usually not under consideration.

In the literature on the measurement and analysis of job quality, many indicators are proposed to analyse job quality (Kalleberg and Vaisey, 2005; Clark, 2005; Leschke and Watt, 2008). Part of the literature links job quality characteristics with job satisfaction (Diaz-Serrano and Cabral Vieira, 2005; D'Addio et al., 2007; SVR, 2007) and often quality and satisfaction are used synonymously. The formal identity between job quality and job satisfaction is the consequence of a revealed preference idea that also underpins the distance function methodology that we use in this paper. This implies that it is assumed that the observed combination of job characteristics is also the preferred combination of characteristics. As such, (an examination of the concept) job quality is not the issue of this research (more on this in Schokkaert et al., 2009). We will use (only) one specific operationalisation of job quality, based on Green (2006) who has identified five key job characteristics. The distance function analysis aims at explaining the technical (in)efficiency in attaining those job characteristics. A natural consequence of the distance approach is that the efficiency results are not neutral with respect to individual preferences since this method completely respects those preferences and consequently the specific individual combination of the job characteristics.

The point of departure of this paper is that, before finding a first job (e.g. when being at school), youngsters build resources for the labour market. When leaving school, the aim is to transform these resources into a job with the best possible job characteristics for that specific person. We assume that school-leavers aim at a high quality job, which is then a job with characteristics that are on (or as close as possible to) their efficiency frontier. A distance function concept, which reflects the efficiency of the process in which school-leavers transform resources into job characteristics, will underpin our evaluation of the first job performance. The impact of conversion factors on (in)efficiency may provide interesting information for policy choices. We estimate and model the distance and conversion efficiency for 2400 Flemish school-leavers based on five job characteristics, three resources and several conversion factors.

A production function methodology is usually applied to model efficiency in industries[2]. Applications to individual transformation functions are rather scarce. An example is Li and Mumford (2009) who apply the methodology to educational outputs for children. They argue that the limited number of empirical applications for individuals might reflect the scarcity of relevant multidimensional cross-sectional data. In the next section, we dwell on the multiple-input multiple-output production function approach and the distance function theory (and the relation with job quality). The third section clarifies the empirical specification and section four presents an application to Flemish school-leavers' efficiency in finding a first job. Section five concludes.

2. Theoretical framework: the multi-output production and distance function

Assume that there are N (working) individuals (indexed $i=1,\ldots,N$). Each individual has K resources at his disposal and achieves M job characteristics. The vector of (public and private, market and non-market) resources individual i has access to is $x_i \in \mathbb{R}_+^K$. There is also an individual fixed effect, $v_i \in \mathbb{R}$, that determines, together with x_i, which combinations of job characteristics the individual can obtain. This amounts to the correspondence $B_i = Q(x_i, v_i) : \mathbb{R}_+^K \times \mathbb{R} \to B_i$. Out of B_i, the individual obtains one combination of job characteristics $b_i \in B_i \subset \mathbb{R}_+^M$.

Each individual has an S-dimensional vector of individual specific conversion factors $z_i \in \mathbb{R}_+^S$ that influence this process. These conversion factors are non-monetary constraints upon the individual. The individual's conversion function converts resources into job characteristics:

$$b_i = f\left(Q(x_i, v_i), z_i\right) : \mathbb{R}_+^M \times \mathbb{R}_+^S \to \mathbb{R}_+^M \tag{1}$$

We want to measure the efficiency of individuals in transforming their resources into job characteristics and want to investigate how this process is influenced by the conversion factors.

[2] Examples are railways (Bosco, 1996; Coelli and Perelman, 2000), hospitals (Löthgren, 2000; Ferrari, 2006), cooperatives (Galdeano-Gómez, 2008) and banking (Koutsomanoli-Filippaki et al., 2009).

In most of the existing literature on efficiency measurement, the entities under consideration are firms in a specific industry which produce one output using a number of inputs. This type of problem lends itself easily to econometric analysis, since there is only one dependent variable. Things become more complicated when there are more outputs, like in (1), because there is more than one dependent variable (i.e. more than one job characteristic). The problem can be solved by creating a single index aggregating the outputs (see Coelli and Perelman, 2000; Löthgren, 2000) or by relying on the micro-economic concept of the distance function, which allows for a multi-input multi-output approach. We will analyse the issue at hand using the latter approach because creating a single index a priori entails important value judgements.

The output distance function is an alternative representation of the production function, containing the same information. Define individual *i*'s output set B_i as the set of all possible output vectors b_i that are obtainable using an input vector x_i (Coelli and Perelman, 1999; Ray, 2004 and Coelli et al., 2005):

$$B_i = \left\{ b_i \in R_+^M : x_i \text{ can yield } b_i \right\}$$

The output distance function is defined on the output set as:

$$d_i(x_i, b_i) = \min_\delta \left\{ \delta : \left(b_i / \delta \right) \in B_i \right\}$$

The output distance function ($d_i(x_i, b_i) \in [0,1]$) gives the minimum amount by which an output vector can be deflated and still remain achievable with the given input vector.[3] It measures the ratio of the actual achieved bundle relative to the maximal achievable bundle, using the same input vector x_i. If b_i is on the boundary of the set, $d_i(x_i, b_i) = 1$ and the individual is fully efficient in converting his resources into job characteristics. If b_i is below the boundary, $d_i(x_i, b_i) < 1$. The output distance function is homogeneous in outputs, meaning that if outputs are increased with a certain proportion (keeping inputs fixed), the distance increases with the same proportion. This function can be used to represent interactions in the given multi-output multi-input context (see Färe et al., 1993 and Coelli and Perelman, 1999 and 2000).

Figure 1 below clarifies things. Two opportunity sets (*AA'* and *BB'*) are shown for two job characteristics (b_1 and b_2). These sets show what combination of job characteristics an individual can achieve given his resources. When an individual's resources are extended, the frontier shifts

[3] The properties of the output distance function follow from assumptions on the output set, these are given in Färe and Primont (1990). In short, the output set satisfies closedness, boundedness, convexity and disposability. The distance function $d_i(x_i, b_i)$ is continuous, non-decreasing and convex in b, it is homogeneous of degree one in outputs and quasi-concave and decreasing in x.

outwards (e.g. from AA' to *BB'*). We consider an individual with frontier *AA'*. The individual can be anywhere on or below this frontier. An individual is said to be fully efficient when he reaches point *D* (or *F*). In general individuals will be below the frontier, e.g. in point *C* (or *E*). The distance function approach assumes that D (or F) maximizes utility and that the individual minimizes the distance to this point. The distance measures how close the individual is to the frontier and is a measure of efficiency. For an individual at *C* (or E) with frontier *AA'*, the distance is the ratio *0C/0D* (or *0E/0F*). The distance equals 1 if the individual is fully efficient, i.e. when he is on the frontier as in point *D* (or F).

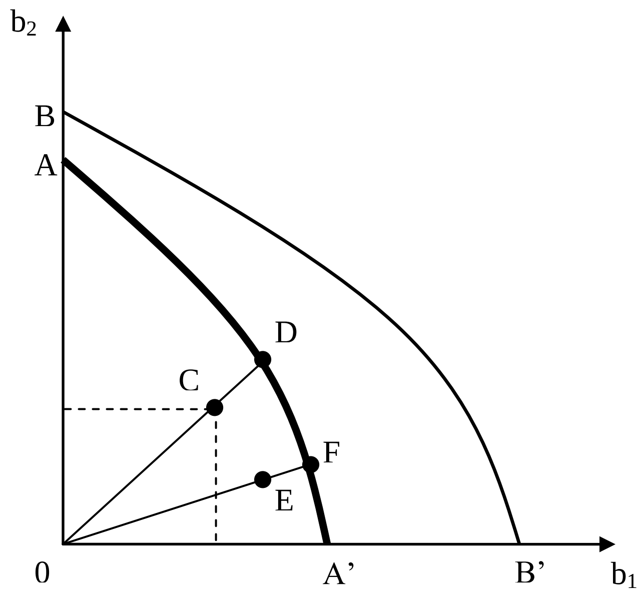


Figure 1. Opportunity sets and distance functions

Given the resources a school-leaver has at his disposal, the (in)efficiency of the observed job characteristics can depend on two things in general. First, an individual's conversion factors enable or disable a person to transform resources into job characteristics more or less efficiently. Secondly, as mentioned in the introduction, the efficiency and distance function approach are not neutral with respect to an individual's choices and preferences. Both factors will be empirically illustrated when studying Flemish school-leavers efficiency in section four. Here, we will develop the underlying arguments and their theoretical and policy relevance.

School-leavers enter the labour market with a certain vector of individual resources, e.g. more or less education or more or less information about job openings etc. With these resources in hand and given external factors, such as e.g. the regional labour market or an economic situation of bust or boom, they aim to find a good job. For the moment, we assume that a good job is one as in point D. There can be different reasons why an individual is more or less efficient. These reasons have to do with conversion efficiency. Two individuals with the same resources may find a job with different quality. Some of these conversion factors are under the control of the individual, such as his personal motivation. But there can also be issues that are beyond the individual's control, such as his gender or race. From the point of view of policy (and so ethics), there is a major difference between these two kind of reasons. Of course, it is also policy relevant that an individual needs sufficient resources in the first place. But as some individuals might be helped with an extension of their resources, others could be helped by making them more efficient in the transformation of resources into job quality. In the next section, we will elaborate on the combination of resource and conversion effects (see figure 3).

Let's now turn to the (second) issue of efficiency and preferences. If an individual is in point C but has a higher preference for job characteristic 1, he can decide to choose for another point, e.g. a point like E in figure 1. For the same resources, a good job is now one with a combination of job characteristics as in point F. This shows that the efficiency numbers based on the distance function approach are not neutral with respect to an individual‘s choices and preferences. It could be that some combination of job characteristics can be achieved more easily, as e.g. E is more efficient than C in figure 1[4].

The last point is the consequence of the revealed preference aspect of the distance function approach and it is crucial for the question what constitutes a good job and how job quality is defined and measured here. Observation of a point like C (or E) implies that we assume that the individual prefers the combination of job characteristics as in D (or F). This implies that the relative weights attached to each job characteristic are individual specific and based on the preferences of each individual and thus on the observation of each individual's actual situation. The quality of a job and the determination of the weight for each job characteristic are then based on the observed outcome that is assumed to reveal preferences[5]. In the general literature on job quality however, there is no such agreement on the design of a weighting scheme (Davoine and Erhel, 2006). There are basically two extreme options. The researcher can come up with his own weighting scheme or he can let the respondents themselves provide information about the weighting. Job characteristics that are valued more will then get a larger weight. This is what is implicitly behind this efficiency or distance function concept when we want to link it up with the concept of (and the existing literature on) job quality.

[4] This observation is independent of the assumption of homothetic preferences, this assumption holds for CD as well as EF (as well as any other 'expansion path').

[5] Technically, in addition to homothetic preferences, the slope of the indifference curve (the marginal rate of substitution between job characteristics) is assumed to be equal to the slope of the frontier where the 'expansion path' crosses the frontier.

3. Empirical specification of the distance function

In order to calculate an individual's achievement relative to the frontier, we need information on the form of the distance function. There are several ways to do this, such as data envelopment analysis, parametric linear programming, corrected ordinary least squares and stochastic frontier analysis (see Coelli and Perelman (1999) for a description and comparison of these different methods). Data envelopment analysis has, for our purpose, some disadvantages. With DEA it is not possible to differentiate the frontier, second it is not possible to disentangle inefficiency and noise and it is sensitive to outliers (this also applies to the deterministic approaches such as linear programming and corrected OLS). We use stochastic frontier analysis, which is a statistical technique that allows splitting up inefficiency and noise components in the conversion process. This model has been simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977).

The distance function contains the same information as the underlying possibilities frontier, the distance function is a complete representation of technology (Färe and Primont, 1990). A functional form has to be specified for the distance function. Also distributions for the noise and the inefficiency components of the error term have to be chosen (Coelli and Perelman, 1999). We choose a flexible functional form in order to minimize a priori restrictions on the relationships between the variables. One such a specification is the translog form as used by i.a. Morrison-Paul et al. (2000). We will use this specification because it is flexible, easy to calculate and because it permits the imposition of homogeneity.

The translog distance function for the case of M outputs and K inputs is specified as follows:

$$\ln d_i = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln b_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln b_{mi} \ln b_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K}\sum_{l=1}^{M} \gamma_{kl} \ln x_{ki} \ln b_{li}$$
$$i = 1,\ldots,N$$

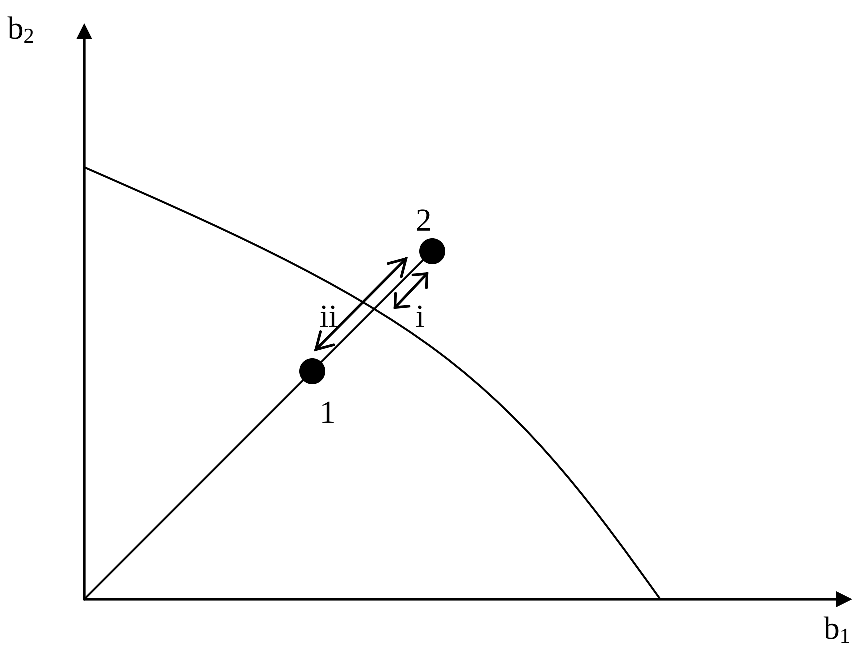
The distance d_i measures how much an individual achieves relative to the frontier, it is a measure of efficiency that equals 1 when the individual is on the frontier and it is below 1 when individuals are below the frontier[6]. In appendix 1 this expression is rewritten in order to facilitate econometric estimation:

[6] This implies that $\ln d_i < 0$. So $-\ln d_i$ is a measure of inefficiency. When the individual is perfectly efficient, $\ln d_i = 0$ (there is no inefficiency).

$$
\begin{aligned}
&-\ln b_{Mi} = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{b_{mi}}{b_{Mi}} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln \frac{b_{mi}}{b_{Mi}} \ln \frac{b_{ni}}{b_{Mi}} + \sum_{k=1}^{K} \beta_k \ln x_{ki} + \\
&\frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K} \sum_{l=1}^{M-1} \gamma_{kl} \ln x_{ki} \ln \frac{b_{li}}{b_{Mi}} + v_i + u_i \\
&i = 1, \ldots, N
\end{aligned}
$$

This is the traditional form in which a stochastic frontier model is estimated. The frontier is stochastic with random disturbance v_i (Aigner et al., 1977). Observe that the error structure consists of two parts: v_i, representing statistical noise, the individual fixed effect ($v_i \sim iidN\left(0, \sigma_v^2\right)$) and u_i, representing inefficiency (see Kumbhakar et al., 1991; Huang and Liu, 1994 or Morrison-Paul et al., 2000). The v_i's are assumed to be independently distributed from the u_i's (Coelli et al., 2005). Since $\ln d_i \leq 0$ and hence $u_i \geq 0$, there is an asymmetrical error structure. The economic logic behind this is that the job finding process is subject to two distinguishable random disturbances with different characteristics. The symmetrical error term v_i has to do with luck, measurement errors and omitted variables in the model. The asymmetrical error term u_i has to do with inefficiency.

Inefficiency is measured as the distance between the (individual specific) stochastic frontier and the individual's achievement. This is illustrated in figure 2.



<u>Figure 2. Measurement of inefficiency in the distance function approach</u>

The individual has a deterministic frontier represented by the concave line. He achieves a job characteristics vector 1. Vector 2 represents the stochastic frontier, which is what the individual could have achieved maximally. The individual is lucky, his stochastic frontier lies above the deterministic frontier[7]. The individual's achievement falls short of the stochastic frontier, it is even below the deterministic frontier. Arrow *i* measures the individual's luck. It shows how far the stochastic frontier is from the deterministic frontier, represented by the term v_i. Arrow *ii* measures the amount by which the individual's achievement falls short of what he could have achieved maximally. This is the amount of inefficiency represented by the term u_i.

As argued in Kumbhakar et al. (1991), Huang and Liu (1994) and Battese and Coelli (1995) the u_i's are assumed to be a function of a number of individual conversion factors z_i that influence the transformation process of resources in job characteristics. We model the error structure following Battese and Coelli (1995). The one-sided error term u_i is assumed to be generated by truncation (at zero) of a normal distribution with mean $\overline{u_i}$ and variance σ_u^2, $u_i \sim N\left(\overline{u_i}, \sigma_u^2\right)$. The technical inefficiency is specified as follows:

$$u_i = \delta_0 + \sum_{s=1}^{S} z_{is}\delta_s + w_i .$$

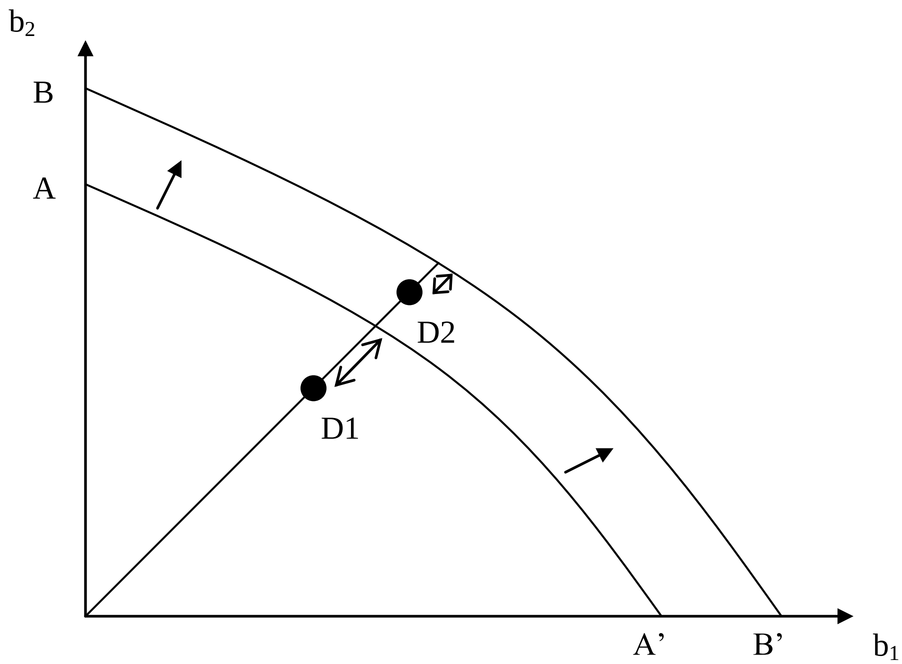
The z_{is}'s are individual *i*'s conversion factors, δ_0 and the δ_s's are parameters explaining inefficiency and w_i is defined by the truncation of the normal distribution with zero mean and variance σ_u^2. The point of truncation is $-\delta_0 - \sum_{s=1}^{S} z_{is}\delta_s$, so $w_i \geq -\delta_0 - \sum_{s=1}^{S} z_{is}\delta_s$. This is needed to ensure that $u_i \geq 0$.

We will use educational attainment, one of the input (resource) variables in the stochastic frontier model, also as a conversion factor (*z*-variable) as suggested by Kumbhakar et al. (1991) and Battese and Coelli (1995)[8]. The consequence of this is shown in figure 3. Take an individual with opportunity set AA' who is situated at point D1. The opportunity set is a function of the x-variables. If the person's education increases, the opportunity set moves outwards from frontier AA' to BB'. At the same time the amount of education also influences efficiency. When this effect is positive this means that more educated individuals are also more efficient in

[7] For an unlucky individual, vector 2 would be below the deterministic frontier.

[8] We also attempted to estimate a non-neutral stochastic frontier, as proposed by Huang and Liu (1994). In this model, there are interaction effects between x-variables and z-variables in the conditional mean model. These attempts were not satisfactory since none of the interaction terms had a significant coefficient. The other resources (information about employment possibilities and the regional unemployment rate) did not yield significant results as conversion factors in the (in)efficiency estimation.

transforming resources into job characteristics. After the increase in education, the individual will move closer to the boundary of the (new) opportunity set, to a point like D2.



<u>Figure 3. Resources and conversion efficiency</u>

4. Empirical application: Flemish school-leavers' efficiency

The multiple-input multiple-output distance function approach will underpin our evaluation of the first job after leaving school. It is assumed that school-leavers, having certain resources (e.g. educational attainment) when entering the labour market, try to get a high quality job with characteristics (e.g. wage or level of autonomy) that are as close as possible to their efficiency frontier. In our basic model (see expression (1)), the vector of an individual's job characteristics depends on his resources and on a vector of individual conversion factors. For this application to school-leavers' job finding efficiency, we consider resources as labour market related circumstances that are given when the school-leaver enters the labour market. Some of these resources were at least partially within the control of the individual (e.g. educational level or information attained), others are external to the individual (e.g. economic or labour market situation). Conversion factors explain why school-leavers with comparable resources attain jobs with different quality. On the one hand there are factors for which the individual can be considered responsible (e.g. personality, motivation, choices made), on the other hand some variables are beyond the control of the individual but can cause for discrimination (e.g. gender, nationality, social background). Conceptually, and in a broader setting, we could also consider these to be resources. But since a translog model does not allow for categorical variables to be used as resources, we can consider them only as conversion factors. First we present the specific data on school-leavers' first job that are used. Then we discuss the estimation technique and the conversion (in-)efficiency results. We end with comparing the results with approaches that are more commonly used, also in policy circles, and that look at search duration when the school-to-work transition is analysed or job satisfaction as job quality measure.

4.1. The data on school-leavers and their first job

We use a survey database for Flanders (SONAR) that has been specifically created to study the transition from education to the labour market. This focus implies that it contains a mass of labour market information for school-leavers in their first work experience. We use the data of the birth cohort 1978. The sample was randomly selected. Trained interviewers performed the oral interviews at the interviewees' home address. The analysis is thus based on self-reported information of the respondents. We study the quality of the first job, defined as the first paid employment after leaving the educational system. It is a job with tenure of at least one month and for at least one hour a day and one day per week.

In the analysis at hand, we will use three kinds of resources that should help finding a (good) job: education, information about employment possibilities and the regional unemployment situation. Educational attainment is measured by the number of successful school years after the age of twelve. We construct a variable indicating whether the individual received information about employment possibilities already during his education. This variable is a factor score based on several items: information about how to apply for a job, information about the official employment agency and about temporary employment agencies, information about local companies and vacancies and about job centres and information about self-employment. The third resource, the regional unemployment rate at the moment of leaving school, is an example of a resource that is fully beyond the control (and also independent of the reporting) of the school-leaver. We use the inverse of the unemployment rate (we expect a negative correlation between the unemployment rate and the quality of the first job) such that for all resource variables the hypothesis is that more resources lead to better jobs.

There are numerous job characteristics that might be used to describe a job (and its quality). We selected and constructed five job characteristics that are rather generally valued aspects of work, in line with the five key job characteristics as identified by Green (2006): skill utilisation, work effort, personal discretion, wages and risk. The first job characteristic is (full time equivalent) net income. Wage is a main determinant of labour supply and thus a key aspect of job quality. However, there are several studies that indicate that intrinsic aspects of the job itself are more important than pay (e.g. Clark, 2005). Our data contain a self-assessment of the worker on several characteristics of the job. The respondents were asked to evaluate 19 items on a 4-point scale, ranging from completely agree, rather agree, rather disagree to completely disagree. Using factor analysis we reduced this set to four variables that reflect the other key features as defined by Green (2006): physically demanding work as indicator of risk, work requiring effort and perseverance, skill utilisation and autonomy in the job as an indicator for personal discretion. In the model, we include the inverse of physically demanding work. Then all job characteristics are positive indicators of a better job.

Some of the conversion factors are in line with the more 'traditional' control variables as gender (a dummy for women), having children (dummy) and the number of successful school years after being twelve years old[9]. The inclusion of more specific conversion factors is possible from the dataset. These are otherwise often concealed but are specifically relevant when studying (the efficiency of) school-to-work transition. The workers' family background is quantified using the nationality of the grandmother (indicating a migration background) and the educational level of the mother. A dummy variable for club membership (any kind of club: youth movement, sports club, political movement) can be considered as an indicator of social capital. Also, we have the respondents' answers to questions related to their idea about who they think is responsible for their position in life. A factor score for 'locus of control internal' indicates whether respondents believe that they themselves are responsible for their achievements in life. A factor score for 'locus of control external' specifies the position that this responsibility belongs to some higher power or to other people. Furthermore, we have information (factor scores) about the degree to which the motivation to work results from the content of the job or from material aspects related to the job. The dummy variable 'student work' reveals whether the person has been working in the past during the school holidays. Another set of variables is related to job search behaviour. We have data on the number of search channels or organisations that are used and on the duration of the search period (ie the number of months between leaving education and starting in the first job). The last set of variables is about the sector in which the career starts[10]. We distinguish between four sectors: the agrarian sector, the industrial sector and the commercial

[9] See the discussion in section 3 about the inclusion of resource variables as conversion factors.
[10] We consider the sector of employment as conversion factor and not as a resource. The sector is not given at the moment one leaves school and offers services to the labour market. The choice of a certain sector can influence the efficiency of otherwise comparable school-leavers.

and non-commercial services sector. Appendix 2 offers an overview of the association between the different conversion factors.

4.2. Results of the multiple-output production and distance function approach

The results of the estimation procedure, obtained from maximum likelihood estimation performed in STATA, are shown in table 1 below. The upper part of the table shows the results of the stochastic frontier model. The bottom part shows the results of the efficiency regression. In the estimation $\sigma_s^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2 / \sigma_s^2$.

Table 1: Stochastic frontier model and (in-)efficiency results

	Coef.	**Std. Err.**	**z**	**P>|z|**
physically demanding work (α_{b2})	0,525	0,129	4,08	0,000
work requiring effort and perseverance (α_{b3})	0,604	0,111	5,44	0,000
skill utilisation (α_{b4})	0,954	0,161	5,91	0,000
autonomy (α_{b5})	0,068	0,179	0,38	0,703
number of succesful school years (β_{x1})	-0,387	0,224	-1,73	0,083
received information during education (β_{x2})	-0,809	0,250	-3,23	0,001
unemployment rate when leaving school (β_{x3})	-0,059	0,155	-0,38	0,701
α_{b22}	0,195	0,013	15,04	0,000
α_{b23}	-0,093	0,012	-8,10	0,000
α_{b24}	-0,041	0,014	-2,88	0,004
α_{b25}	-0,025	0,017	-1,51	0,132
α_{b33}	0,249	0,017	14,88	0,000
α_{b34}	-0,083	0,013	-6,46	0,000
α_{b35}	0,005	0,016	0,32	0,750
α_{b44}	0,328	0,026	12,54	0,000
α_{b45}	-0,084	0,023	-3,71	0,000
α_{b55}	0,084	0,039	2,12	0,034
β_{x11}	-0,042	0,068	-0,61	0,541
β_{x12}	-0,011	0,031	-0,36	0,715
β_{x13}	0,023	0,022	1,04	0,298
β_{x22}	0,049	0,083	0,59	0,555
β_{x23}	-0,014	0,030	-0,47	0,637
β_{x33}	-0,026	0,015	-1,76	0,078
γ_{b2x1}	0,010	0,017	0,56	0,574
γ_{b2x2}	-0,040	0,022	-1,82	0,068
γ_{b2x3}	-0,018	0,013	-1,40	0,162
γ_{b3x1}	0,049	0,016	3,16	0,002
γ_{b3x2}	-0,037	0,020	-1,89	0,058

γ_{b3x3}	0,007	0,015	0,50	0,620
γ_{b4x1}	-0,042	0,024	-1,77	0,077
γ_{b4x2}	-0,025	0,029	-0,88	0,379
γ_{b4x3}	0,001	0,019	0,04	0,971
γ_{b5x1}	-0,013	0,028	-0,46	0,644
γ_{b5x2}	-0,031	0,033	-0,95	0,340
γ_{b5x3}	0,001	0,023	0,05	0,960
α_0	3,029	0,654	4,63	0,000
(In)Efficiency Regression				
number of succesful school years (δ_1)	-0,403	0,085	-4,74	0,000
gender: women (δ_2)	-0,015	0,011	-1,37	0,169
having children (δ_3)	0,016	0,030	0,52	0,604
mother low educational level (δ_4)	-0,033	0,010	-3,43	0,001
grandmother not Belgian nationality (δ_5)	0,030	0,014	2,09	0,036
club membership (δ_6)	0,003	0,009	0,36	0,721
locus of control internal (δ_7)	0,002	0,005	0,41	0,682
locus of control external (δ_8)	-0,002	0,004	-0,42	0,677
motivation to work: content of the job (δ_9)	0,015	0,005	3,16	0,002
motivation to work: material aspects (δ_{10})	-0,017	0,005	-3,71	0,000
student work (δ_{11})	-0,003	0,011	-0,30	0,764
number of search channels (δ_{12})	-0,008	0,002	-4,34	0,000
duration of search period (δ_{13})	0,000	0,000	0,76	0,445
industrial sector (δ_{14})	0,079	0,041	1,91	0,056
sector of commercial services (δ_{15})	0,154	0,042	3,70	0,000
sector of non commercial services (δ_{16})	0,155	0,042	3,67	0,000
δ_0	0,764	0,162	4,72	0,000
σ_s^2	0,018	0,001		
γ	0,139	0,056		
σ_u^2	0,003	0,001		
σ_v^2	0,016	0,001		

Number of observations: 2400 Wald chi^2: 6094,00
Log likelihood: 1492,05 Prob>chi^2: 0,000

The results of the stochastic frontier model are well behaved. The coefficients of the job characteristics are positive, those of the resources are negative. Having better job characteristics (keeping resources fixed) brings an individual closer to the boundary, hence efficiency is higher. Having more resources (keeping outputs fixed) moves the boundary further away, so the individual will be less efficient. Also most of the second order coefficients for the outputs, the α_{bii} variables, are positive, which points to a concave transformation function.

The null hypothesis of no inefficiency (γ=0) is rejected. The estimated value of γ indicates that 13,9% of the variation around the estimated frontier is due to differences in technical efficiencies. This rather low figure might be caused by the fact that individuals have to be lucky to find a good first job, or by the fact that individuals are badly informed about the job characteristics in their first job. In the latter reasoning, individuals are only interested in finding a job, not so much in the quality or characteristics of this first job.

Efficiency numbers range between 39% and 99% with an average of 92%, so there is considerable variation in the efficiency. More or less 90% of the individuals in the sample have an estimated efficiency level of over 80%, indicating that efficiency is rather high (see figure 4). In the process of finding a first job most individuals manage to achieve a high efficiency, while the group of underachievers is very small.

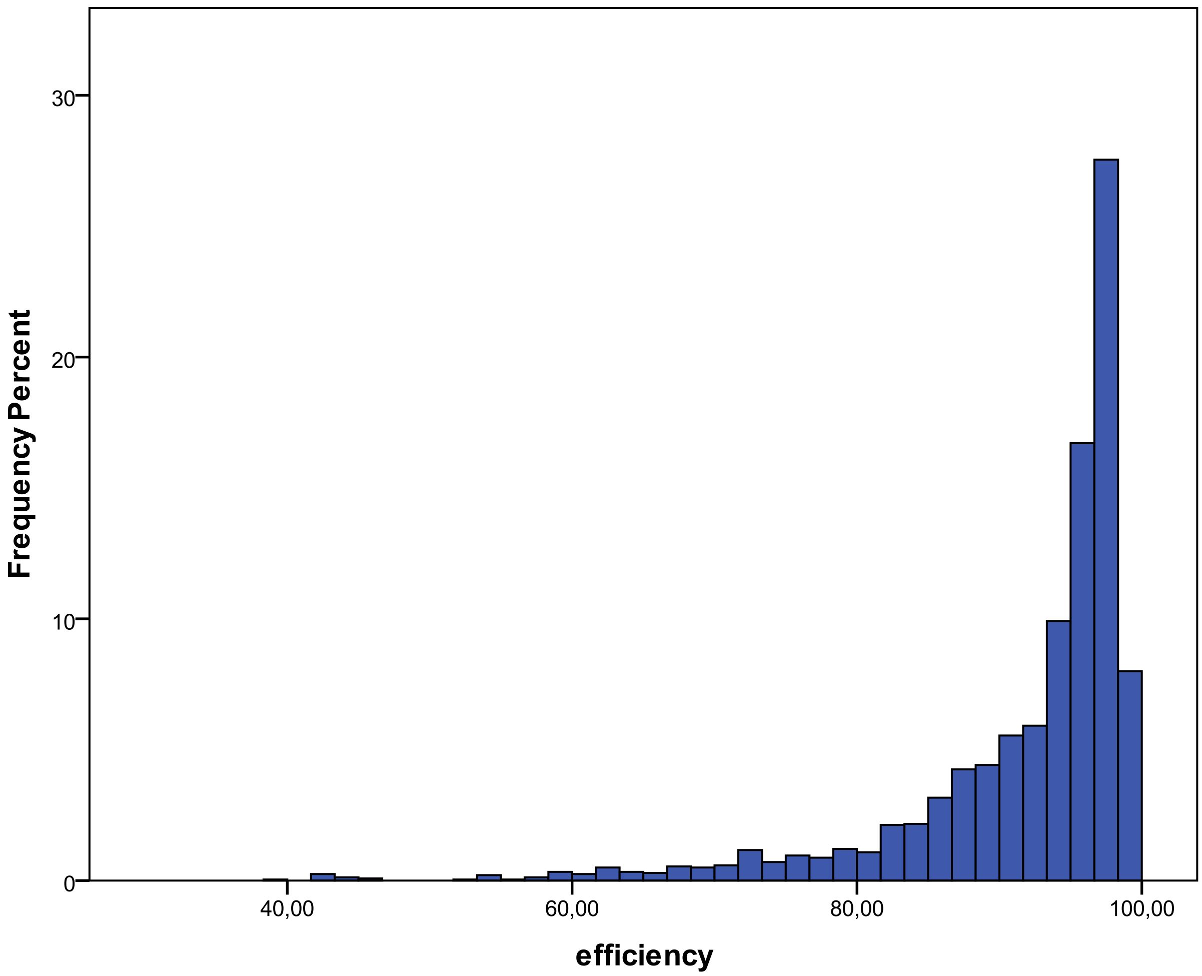


Figure 4. Distribution of the technical efficiency

The second part of table 1 shows the influence of the conversion factors in explaining the (in)efficiency that goes along with certain characteristics. Note that we estimate inefficiency which means that a conversion factor with a positive sign increases inefficiency (and thus decreases efficiency). Factors increasing efficiency are those with a negative sign. Looking (at a 5% significance level) at the coefficients of the socio-economic and social background indicators, we see that jobs with more efficiency are acquired by those people that have more (years of) schooling, a grandmother with the Belgian nationality and a mother that is lower educated. Of the more traditional socio-economic indicators, only educational attainment is significant, this is not the case for gender or for having children. When considering the more specific conversion characteristics, the striking result emerges that a more material motivation, and a motivation that has less to do with the content, increases conversion efficiency. From the point of view of search behaviour, a more intensive search process (using more search channels) is rewarded with better job characteristics. The duration of the search period has no significant influence. The variables that measure 'locus of control' (signalling whether respondents believe that they themselves or rather others are responsible for their achievements in life) have no significant effect. Having worked during school holidays and club membership do not influence conversion efficiency either. More efficiency can be found when people start their career in the agrarian sector (the dummy that is left out of the model) compared to the commercial or non-commercial services.

Some of these general observations need some more discussion. We will elaborate on the findings concerning the influence on efficiency of education, of social background and of labour motivation. A higher educational attainment (approximated by having a higher number of successful years of schooling) significantly and strongly increases efficiency (the negative sign in the inefficiency estimation) as well as it increases the frontier as such (the negative coefficient in the frontier estimation). Taken together, this means that higher schooling enables school-leavers to be more efficient in acquiring a job with reported characteristics that reflect higher opportunities (see figure 3 in the previous section).

The influence of the social background parameters seems paradoxical at first sight. Having a non-Belgian grandmother has a negative impact on efficiency. On the other hand, having a mother with a lower educational degree is positive for conversion efficiency. The former effect might be explained by discrimination. When employers discriminate against ethnical minorities, those will be less efficient in transforming resources into job characteristics. To interpret the finding that young workers whose mother has a lower educational degree are more efficient, it is fruitful to keep in mind that the information about the job characteristics is self-reported. Respondents with a kind of social background that coincides with having a lower educated mother might have experienced different characteristics in the job of their parents compared to those respondents that have a more highly educated mother. Such experiences influence expectations and thus preferences, especially about the first job characteristics, and the frame of reference that is used to make an assessment of the first job characteristics. This explains the higher reported appreciation for the own job characteristics.

Also the influence of the labour motivation variables is remarkable: those who are (more) motivated by the content of their job are less efficient while individuals who are (more) motivated by the material aspects of a job are more efficient in transforming resources into job characteristics. Differences in attitude towards work thus influence the opportunities to get a job close to the best achievable job resulting from ones resources. As was illustrated in figure 1, an individual with a higher preference for job characteristic 1 (eg wage here representing a more material motivation) and a lower valuation for job characteristic 2 (eg autonomy here pointing at the content of the job) can choose a job that corresponds more with job characteristics as in point E (or F on the frontier). The findings on job motivation then confirm that (ceteris paribus) preference differences influence efficiency. The choice for a job with a combination of characteristics that is more in favour of a material motivation (like in point E instead of point C in this example) can facilitate efficiency. Also, people that are more motivated by the content of a job might be more critical with respect to the intrinsic job characteristics and evaluate these as being worse, consequently we will evaluate them as being less efficient.

In general and from the perspective of policy, the resources or conversion factors that influence efficiency can be split up based on the level of personal control that is involved The social (family) background is clearly beyond the control of the young workers. Most of the other influences are partly or even fully controllable by the people themselves (motivation to work, search channels, sector of employment). Schooling, both a very important resource and a conversion factor, is an issue of shared responsibility of the individual and society: a higher number of successful years of schooling moves the individual closer (are more efficient) to a frontier that also reflects more opportunities (see also figure 3). In the next section, we elaborate on the role of education and social background for the efficiency of the school-to-work transition and investigate the consequences for social policy.

4.3. Comparing efficiency with search duration (and job satisfaction): implications for policy

In table 2, we compare the (in)efficiency estimations from our stochastic frontier estimation and two more conventional lines of research of the school-to-work transition: the duration of the inactivity or search period and the reported job satisfaction. For several sub-groups we compute the average duration before finding the first job (in months), the average efficiency (d_i ranging from zero to one for increasing efficiency) and the average job satisfaction (on a scale from 'very unsatisfied' (1) to 'very satisfied' (5)). In policy circles, search duration and job satisfaction data are (for the greater part) the typical data used in political debate and to guide decisions.

Except for the effect of gender, all data on efficiency and search duration point in the same direction. Education and social background parameters strongly influence the efficiency and the length of the (first) job searching process. More education manifestly facilitates the school-to-work transition. Education is found to be a decisive factor for a quick transition from school to work in several studies (Rees, 1986; Ryan, 2001; Bradley and Taylor, 1991; Bratberg and Nilsen, 2000; Nielsen et al., 2003; Vanoverberghe et al., 2008). Education is a decisive factor for reaching job efficiency as well. This is not reflected in a significantly lower satisfaction for lower educated workers. The latter of these results is in line with the finding that higher education does not significantly increase job satisfaction because it coincides with increased expectations (Verhofstadt et al., 2007). For the two indicators of family background (nationality of the grandmother and educational level of the mother) table 2 shows that respondents with a less favourable background suffer twice: search duration is longer and they are less efficient in the transformation of resources into job characteristics. Job satisfaction is also lower, although the difference is not large (and for the case of nationality not significant). The effect of ethnicity on the employment probability of young people is in line with the literature (Rees, 1986; Ryan, 2001; Vanoverberghe et al., 2008) and is mostly explained by discrimination. Social background variables are clearly beyond the control of the young workers and so these groups should be the subject of specific and targeted policy.

The data on search duration and efficiency clearly follow a similar pattern. This makes that policy recommendations can be refined based on our results and conclusions. Refinements are necessary in both directions. On the one hand, table 2 presents descriptive statistics only. Obviously this can be misleading. The example of the role of gender will be used to clarify this point. On the other hand, it is an eye-catching observation that the effect on efficiency of having a lower educated mother is positive (table one) while the group of respondents that has a lower educated mother is less efficient and has to search longer (table 2).

Table 2: Search duration, efficiency and job satisfaction for specific groups' first job

Average	search duration (months)	efficiency (from 0 to 1)	satisfaction (from 1 to 5)
Succesful school years: max 5	**10,33**	**0,74**	3,73
Succesful school years: min 10	**3,53**	**0,98**	3,86
Men	**4,75**	**0,91**	3,76
Women	**5,79**	**0,93**	3,80
Education mother: primary or lower secondary	**6,19**	**0,91**	**3,71**
Education mother: higher secondary or tertiary	**4,79**	**0,93**	**3,81**
Nationality grandmother: Belgian	**4,88**	**0,92**	3,79
Nationality grandmother: not Belgian	**9,79**	**0,85**	3,66
Motivation to work from content: low	5,48	0,90	**3,51**
Motivation to work from content: high	5,08	0,91	**3,93**
Motivation to work from material aspects: low	**4,54**	**0,93**	3,75
Motivation to work from material aspects: high	**6,47**	**0,88**	3,76

Bold: significant differences (at 0.05%) between the groups for the one indicator.

Women on average seem to need a significantly longer search period than men, but their calculated efficiency is higher (table 2). In fact, gender is the only variable for which the duration approach and the efficiency analysis lead to (significantly) opposite conclusions. But such kind of bi-variate information does not take into account the role of many other possible influences (besides gender) such as education, job motivation … that have *an effect* on the school-to-work transition at the same time. Taking into account the effect of all these considerations simultaneously (in a multivariate analysis, table 1) results in the conclusion that there is no real (or net) effect of gender on efficiency. This makes that gender differences can be covered by other policy choices.

The reported lower efficiency (table 2) of the group of respondents that have a lower educated mother can be refined with a similar reasoning. This results from the correlations of the educational level of the mother with other variables (eg. the educational level of the respondent himself) that are not considered here. When taking into account these other influences, and also due to effects of self-reporting and expectations, the resulting net-effect (table 1) of this particular aspect of the family background is even reversed[11]. But this cannot be an excuse for policy for not trying to consider the effects of the social background on the school-to-work transition.

In summary, the implications for school-to-work transition policy are clear. More education strongly increases efficiency in general. But, also after controlling for the efficiency effects of longer education, discrimination remains a problem. Preventing the negative impact of ethnical background on the school-to-work transition will require other policy options that should address also the demand side of the labor market.

5. Conclusions

In this paper, we address the issue why some Flemish school-leavers are more or less efficient in transforming resources into functionings in their first job. Stochastic frontier analysis is used to calculate conversion efficiency for every individual. This makes it possible to differentiate between random 'noise' on the one hand and 'efficiency'-effects on the other hand.

In the empirical analysis, the efficiency differences are explained making use of a number of conversion factors. The most important socio-economic variable that increases efficiency is (the number of years of) schooling. Also, a more intensive search process (using more search channels) yields more efficiency. Job motivation plays a role in that a more material motivation, and a motivation that has less to do with the content of the work, increases conversion efficiency. The social background is important: more efficiency is acquired by those people that have a grandmother with the Belgian nationality and a mother that is lower educated.

The interpretations and policy implications of these results are made by comparing with two criteria that are more commonly used for the study of the school-to-work transition: the length of the search duration period and the satisfaction in the first job. It is clear (and not surprising) that (more) education increases efficiency in the school-to-work transition. We concentrate more particularly on the interplay between the role of education and of the social background for the efficiency of the school-to-work transition. From the efficiency-analysis, while people with a non-Belgian background (grand-mother) are less efficient, it seems that respondents with a lower

[11] Such reversal is also the case for respondents that are more motivated by material aspects. They are less efficient than those having less material motivation (table 2), although the net-effect of a more material motivation on efficiency is positive (table 1) because the latter corrects for the correlation between the educational level and a more material ambition.

educated mother are ‘better off’. Both groups are however worse off when looking at average search duration or average efficiency. This dichotomous result allows for conclusions to be drawn at the specific level of accompanying policy prescriptions as well as on the more general level of the theoretical implications of using a multiple input-output framework and distance function approach (and the accompanying efficiency concept) to evaluate job quality.

On the level of policy conclusions, the classical general recommendations (that education smoothens the school-to-work transition) remains, but with a serious modification towards some specific social background influences. For young people with a non-Belgian background, more education as such will not solve ethnical discrimination problems they face. Other and more structural policy measures should be taken here such that also the labour market demand side can be convinced.

However, the social background influence also shows that more efficiency also results from the hopes and ambitions (preferences and the adaptation of expectations) of certain groups specifically. More provocatively, it might be stated that adaptation to ethnical discrimination seems to be much “harder” than adaptation of expectations because of having a lower educated mother. From the theoretical point of view of using a multiple input-output and distance function approach to evaluate job quality, the results illustrate that the approach respects preference differences (or preference formation).

Further research and other applications should try to gain insight in the nature and causes of these effects. A first possibility could be to compare the methodology when non-self reported data-information can be used. Other applications of the distance function approach, also for more general quality of life issues that are inherently multi-dimensional, could be revealing.

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Appendix 1: Empirical specification

We start from the specification of the translog distance function for the case of *M* outputs and *K* inputs as follows:

$$\ln d_i = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln b_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln b_{mi} \ln b_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K}\sum_{l=1}^{M} \gamma_{kl} \ln x_{ki} \ln b_{li}.$$
$$i = 1,\ldots,N$$

Certain regularity conditions must hold for this function. The restrictions required for homogeneity of degree 1 in outputs are:

$$s.t., \forall h,k,l$$
$$\sum_{m=1}^{M} \alpha_m = 1$$
$$\sum_{n=1}^{M} \alpha_{mn} = \sum_{l=1}^{M} \gamma_{kl} = 0;$$

and those required for symmetry are:

$$\alpha_{kl} = \alpha_{lk}$$
$$\beta_{kl} = \beta_{lk}.$$

A problem for the estimation is that the dependent variable $\ln d_i$ is unobserved. In order to solve this, we impose homogeneity, a property of the distance function. Homogeneity implies that:

$d\left(x,\omega b\right) = \omega d\left(x,b\right)$, for any $\omega > 0$.

Following Coelli and Perelman (1999), one of the outputs, b_M, is chosen to set $\omega = \frac{1}{b_M}$. Then we get [12]

[12] The job characteristic b_M is chosen arbitrarily. The results are not sensitive to selecting other outputs as normalisation.

$$\ln \frac{d_i}{b_{Mi}} = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{b_{mi}}{b_{Mi}} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln \frac{b_{mi}}{b_{Mi}} \ln \frac{b_{ni}}{b_{Mi}} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K} \sum_{l=1}^{M-1} \gamma_{kl} \ln x_{ki} \ln \frac{b_{li}}{b_{Mi}}.$$
$$i = 1, \ldots, N$$

This equation is still not in a form that can be econometrically estimated because the left hand side is unobserved. It is transformed in the following way:

$$\ln \frac{1}{b_{Mi}} = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{b_{mi}}{b_{Mi}} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln \frac{b_{mi}}{b_{Mi}} \ln \frac{b_{ni}}{b_{Mi}} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K} \sum_{l=1}^{M-1} \gamma_{kl} \ln x_{ki} \ln \frac{b_{li}}{b_{Mi}} - \ln d_i.$$
$$i = 1, \ldots, N$$

In a typical econometric setting, adding an error term allows the function to be fitted through the data. We add the noise term v_i and with $u_i = -\ln d_i$ we get:

$$-\ln b_{Mi} = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{b_{mi}}{b_{Mi}} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln \frac{b_{mi}}{b_{Mi}} \ln \frac{b_{ni}}{b_{Mi}} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K} \sum_{l=1}^{M-1} \gamma_{kl} \ln x_{ki} \ln \frac{b_{li}}{b_{Mi}} + v_i + u_i$$
$$i = 1, \ldots, N$$

which is the equation we estimate.

Appendix 2: Association between the different conversion factors

number of succesful school years (δ_1)
gender: women (δ_2)
having children (δ_3)
mother low educational level (δ_4)
grandmother not Belgian nationality (δ_5)
club membership (δ_6)
locus of control internal (δ_7)
locus of control external (δ_8)
motivation to work: content of the job (δ_9)
motivation to work: material aspects (δ_{10})
student work (δ_{11})
number of search channels (δ_{12})
duration of search period (δ_{13})
industrial sector (δ_{14})
sector of commercial services (δ_{15})
sector of non commercial services (δ_{16})

Correlation among interval variables

	δ_7	δ_8	δ_9	δ_{10}	δ_{12}	δ_{13}
δ_1	-0,116***	-0,098***	0,186***	-0,367***	0,124***	-0,264***
δ_7		0,000	0,088***	0,117***	-0,035*	-0,020
δ_8			0,019	0,135***	0,042**	0,028
δ_9				0,000	-0,016	-0,013
δ_{10}					-0,009	0,074***
δ_{12}						0,072***

*: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$

Cramer's V among categorical variables

	δ_3	δ_4	δ_5	δ_6	δ_{11}	δ_{14}	δ_{15}	δ_{16}
δ_2	0,067***	0,003	0,018	0,171***	0,070***	0,325***	0,033	0,309***
δ_3		0,059***	0,102***	0,062***	0,065***	0,002	0,032	0,018
δ_4			0,165***	0,127***	0,149***	0,106***	0,039*	0,072***
δ_5				0,064***	0,122***	0,060***	0,001	0,058***
δ_6					0,126***	0,021	0,038*	0,018
δ_{11}						0,086***	0,037*	0,088***
δ_{14}							0,506***	0,375***
δ_{15}								0,524***

*: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$