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It's the Opportunity Cost, stupid! How Self-Employment responds to Financial Incentives of Return, Risk and Skew

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How self-employment responds to financial incentives of return, risk and skew*

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Abstract

There is no robust empirical support for the effect of financial incentives on the decision to work in self-employment rather than as a wage earner. In the literature, this is seen as a puzzle. We offer a focus on the opportunity cost, i.e. the wages given up as an employee. Information on income from self-employment is of inferior quality and this is not just a problem for the outside researcher, it is an imminent problem of the individual considering self-employment. We also argue that it is not only the location of an income distribution that matters and that dispersion and (a)symmetry should not be ignored. We predict that higher mean, lower variance and higher skew in the wage distribution in a particular employment segment reduce the inclination to prefer self-employment above employee status. Using a sample of 56,000 recent graduates from a Dutch college or university, grouped in approximately 120 labor market segments, we find significant support for these propositions. The results survive various robustness checks on specifications and assumptions.

JEL codes: J 24; L 26

Keywords: entrepreneurship, self-employment, wage-employment, income distribution, income risk, income skew, income variance, occupational choice, labor market entry, labor market segments, opportunity cost.

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1. Introduction

Imagine someone just graduating from school and considering whether to work as an employee or in self-employment. Economists perceive that differences in income will be among the factors determining the choice. But obtaining information on potential income from self-employment is a formidable job, much more so than obtaining information on potential pay as an employee. There are far fewer self-employed workers than employees with a given education to act as informants, accounting rules for exactly determining income from independent business are not unequivocal, the range of possible outcomes is much wider and often not even foreseeable, professional abilities and competences, as determinants of potential income, are harder to predict than performance in a controlled employee status and the environment for a self-employed worker is inherently more dynamic. The literature often stresses that a researcher is unable to obtain good, reliable data on self-employment income for econometric analysis. We argue that this is not just a problem for the outside researcher, but an imminent problem that also confronts the subject of her research.

Effects of financial incentives in the choice between employee or self-employment status have been hard to establish, but given the problems noted above this should in fact be no surprise. There is a marked asymmetry in the quality of information on potential income from self-employment and from employee status. Therefore, in our model of the choice of employment status, we will focus on the opportunity cost of self-employment rather than on the benefits. Indeed, we report robust support for the moments of the wage distribution as determinants of the decision to become self-employed. A lower mean wage income in one's labor market segment increases the probability of choosing for self-employment. Higher variance and lower skew in the distribution of wage incomes also increase it. And as in most of the literature, we find no effect of self-employment income.

The weak and mixed results on the effect of financial incentives in the choice for self-employment have been presented as "something of a puzzle since they suggest that entrepreneurs do not respond robustly to pecuniary incentives.... However, there is so much economic evidence that individuals adjust their behavior in response to changes in relative prices that it would be puzzling if the same calculus ceased to apply entirely in the realm of entrepreneurship as an occupational choice.' (Parker, p. 110).[1] Both Astebro (2010) and Parker (2009) stress the information problem as a prominent factor in potential explanations for the puzzle. Parker (2009, p 110) refers to poor data quality and measurement error as common phenomena in observed entrepreneurial earnings levels. In fact, entrepreneurial incomes remain often unreported or, if not, they are systematically underreported, both in tax filings and public surveys. Astebro even refers to lack of interest among the self-employed: 'Entrepreneurs are wary of revealing accurate income data to third parties' (Astebro, 2010, p. 36). Both authors note the difficulties in extracting uniform entrepreneurial income measures from the reported data and make them comparable to wage earnings. Some researchers define the entrepreneur's income as the amount the entrepreneur draws from the firm on an annual basis, whereas other

[1] Hyytinen et al. (2008) call this the 'returns to entrepreneurship puzzle', see also Astebro (2010) or Hamilton (2000). We are aware of the fact that "entrepreneur" and "self-employed" are not identical concepts. We use "entrepreneur" only when we discuss the literature. When we present our own results, we will refer to self-employment.

researchers use the firm's net profit, or alternatively, the sum of the value growth of the firm and 'draw' as a proxy of the entrepreneur's income (Parker, 2009, p. 363).[2] [3] No doubt, this lack of a uniform concept of self-employment income is also a problem for individuals who consider self-employment.

Not only researchers, but also the subjects themselves will have a much sharper picture of the opportunity cost of self-employment than of the income it will bring. It is even conceivable they actually care more about opportunity cost than about financial returns, as non-pecuniary benefits are often found to be among the key arguments for preferring self-employment: autonomy (Benz and Frey, 2008), a tendency towards entrepreneurship caused by genetic factors (Nicolaou, Cherkas, Hunkin and Spector, 2008), cognitive biases arising from overoptimism (Lowe and Ziedonis, 2006; Dushnitsky, 2010) and/or overconfidence (Hayward, Shepherd and Griffin, 2006). A focus on financial opportunity cost rather than on financial returns aligns well with this perspective on potentially self-employed workers.

We do not only consider the opportunity cost in terms of mean incomes, but we acknowledge the possibility that utility differences between the two options will, more in general, also result from entirely different probability distributions of incomes offered. No doubt, the three dominant characteristics of a distribution are location, dispersion and (a)symmetry. Higher variance in earnings of entrepreneurs compared to employees is a stylized fact (Astebro, 2010; Parker, 2009) and requires a risk premium for risk averse individuals (King, 1974; Cramer et al., 2002; Caliendo et al., 2009; Bonin et al., 2007). Recent studies have also provided evidence that the distribution of entrepreneurial earnings has stronger (positive) skew than the wage distribution. Skew may play a role for entrepreneurship choices as 'a few extremely high prices have a disproportionately great attractive force', Marshall (1890, 1930, p. 554). Indeed, economic theory has established that declining absolute risk aversion, an almost inevitable hypothesis, requires a positive appreciation of skew (Astebro et al., 2009; Tsiang, 1972; Hartog, 2011). The relevance of skew in choices under uncertainty has been demonstrated in several applications such as gambling and betting (Garrett and Sobel, 1999; Golec and Tamarkin, 1998) or in the literature of lifetime wealth accumulation, where the appreciation of skew is called prudence (Gollier, 2001, p 238). A positive premium for variance and a negative premium for skew in wages across different types of educations, established for several countries in different settings (Hartog, 2011) indicates that variance and skew are relevant for choice of education cum occupation. Not accounting for the second and third moments of the income distributions may flaw the comparison and thus be an explanatory factor in the lack of consistent support of the role of financial incentives.

We derive propositions from a simple model on the role of financial incentives for the choice between self-employment and wage employment. Our observations are individuals in self-employment or wage

[2] An additional complicating factor is that many business owners do not earn 'business incomes' but pay themselves a wage in their incorporated business. If this is the case, the entrepreneur can hardly be distinguished from a wage employee. Entrepreneurs often incorporate their business when they have personnel and thus run larger (and more successful) firms. The difficulty of distinguishing these entrepreneurs from wage employees may thus lead to a smaller sample of entrepreneurs and underestimates of true entrepreneurial earnings.

[3] Researchers may also deal incorrectly with the entrepreneurs' negative incomes and with top-coding or may erroneously include 'returns to capital' to their (labor) income measures (Parker, 2009, p. 368).

employment who recently graduated from more than 100 different types of tertiary education. We argue, precisely based on the arguments outlined above, that the individuals are poorly informed on incomes from self-employment and we focus on the effects of moments of the distribution of wage income. We predict that a higher mean wage income increases the opportunity costs of self-employment and thus reduces the probability of entrepreneurship. A higher variance pushes up the inclination to self-employment, as one gives up a more risky alternative. A higher skew, the third moment, reduces this inclination as one would give up a better probability to end up in an extended upper tail of the wage distribution. By simultaneously analyzing the effects of the first three moments of the wage distribution we squarely acknowledge one of the caveats discussed above, the incompleteness of a comparison based on only mean (or median) income levels.

By focusing on opportunity cost as expressed in the wage distribution, we avoid the problem of poor measurement of self-employment income. We do so by estimating our model on data covering 118 labor market segments defined from detailed information about major track in field of study of 56,000 graduates. The data apply to new graduates who enter the labor force for the first time and have not yet been tied up in any of the alternatives. As a consequence our sample is homogeneous in terms of (no) labor market experience and education level.

The validity of our approach hinges on three assumptions. The first assumption is made when defining labor market segments as fields of study with well defined curriculums in vocational colleges or universities leading to a specific degree (e.g sociology, physics, fiscal law, food technology, etc). We postulate that the relevant distribution of wages is defined by individuals with a particular type of education. We thus assume intra-group homogeneity in terms of the earnings distributions facing the individuals (Reich et al., 1973) relative to the wage distribution across labor market segments. We assess the validity of this assumption by also considering a random grouping into labor market segments.

Second, we assume that individuals know the distribution of wages within their labor market segment but do not know the education specific distribution of income from self-employment. Thus, we assume that students only observe a general distribution of earnings generated by self-employment that is common for all labor market segments. The assumption is motivated by the verifiable facts that there are very few entrepreneurs within each labor market segment and that their incomes are less observable. In our robustness checks, we use as much information on self-employment income as our data allow. But even if the assumption were violated, this would be econometrically harmless as long as the moments of the distributions of wages and of self-employment incomes are independent.[4] We find no evidence of strong correlations between any of the three moments of the two income distributions; our sensitivity checks are compatible with (modest) underestimation of effects of opportunity cost.

The third assumption is that there are no confounding factors underlying the choice for a particular field of study that affect both its wage distribution and the likelihood of self-employment. We discuss the role

[4] If the financial attractiveness of the entrepreneurship option were positively correlated with the financial attractiveness of the alternative, this would lead to a downward bias of the true effect. On the contrary, if there were a negative correlation between these two distributions, the effect of pecuniary return, risk and skew in wage employment on entrepreneurship choices would be overestimated.

of risk attitude, ability and immanent distribution of productivity by education and we claim that our results survive concerns on these grounds.

The remainder of the paper is organized as follows. Section 2 discusses the theoretical model and the resulting propositions. In Section 3 we discuss the data. In Section 4 we present results of testing the propositions and assumptions. Section 5 concludes.

2. Theoretical model and propositions

A graduate entering working life, after completing an education, has a choice between self-employment and working for a wage as an employee. Both options bring financial returns (*w* as wage earner, *p* as self-employed) and non-pecuniary returns (ψ). Non-pecuniary returns reflect the individual's appreciation of the relevant characteristics of self-employment versus employee work such as autonomy (Hyytinen et al., 2008), the differential scope of activities and tasks (Benz and Frey, 2008), the greater insecurity in other dimensions than income (Hamilton, 2000) and a different social status (Parker and Van Praag, 2010).

We assume that the utility derived from working, either as a self-employed entrepreneur (SE) or as a wage employee (WW), is linearly separable in the utility derived from *w* or *p* and ψ:

$$U_{WW} = U(w) + U(\varphi_{WW}) \tag{1a}$$

$$U_{SE} = U(p) + U(\varphi_{SE}) \tag{1b}$$

Assuming separability implies that the valuation of these non-pecuniary aspects is independent of income. Graduates base their occupational choice on a comparison of expected utility levels in each of the occupations. The likelihood of choosing self-employment can thus be derived from:

$$P(SE) = P[E(U_{SE}) > E(U_{WW})] \tag{2}$$

Substituting (1) in (2) and expressing the differences in expected utility derived from non-pecuniary factors in both occupations within the same segment[5] by a (latent) individual specific variable $\varepsilon = E(U(\varphi_{WW})) - E(U(\varphi_{SE}))$, it follows that

$$P(SE) = P[\varepsilon < E(U(p)) - E(U(w))] \tag{3}$$

[5] Segments are defined by education, see below.

where ε remains unobserved and reflects the individual-specific difference in non-pecuniary returns between self-employment and wage-employment within the given labor market segment. Suppose the wage distribution (*w*) and entrepreneurial income distribution (*p*) are characterized by the following parameters:

$$E[w] = \mu_w; \quad E[(w-\mu_w)^2] = \sigma_w^2; \quad E[(w-\mu_w)^3] = \kappa_w^3 \tag{4}$$

$$E[p] = \mu_p; \quad E[(p-\mu_p)^2] = \sigma_p^2; \quad E[(p-\mu_p)^3] = \kappa_p^3 \tag{5}$$

Using Taylor series approximation, we derive expressions for the expected utility of wage-employment versus self-employment in equations (6) and (7), respectively, where U(μ_w) is expanded around $\bar{y}$ (the expected income level for graduates, i.e., a weighed average of μ_w and μ_p)

$$\begin{aligned} E[U(w)] &= E[U(\mu_w) + U'(\mu_w)(w-\mu_w) + \tfrac{1}{2}U''(\mu_w)(w-\mu_w)^2 + \tfrac{1}{6}U'''(\mu_w)(w-\mu_w)^3 + \ldots] \\ &= U(\bar{y}) + U'(\bar{y})(\mu_w - \bar{y}) + \sum_{i=2}^{\infty} \tfrac{1}{i} U^{(i)}(\bar{y})(\mu_w^i - \bar{y}) + \tfrac{1}{2}U''(\mu_w)\sigma_w^2 + \tfrac{1}{6}U'''(\mu_w)\kappa_w^3 + \ldots \end{aligned} \tag{6}$$

$$\begin{aligned} E[U(p)] &= E[U(\mu_p) + U'(\mu_p)(p-\mu_p) + \tfrac{1}{2}U''(\mu_p)(p-\mu_p)^2 + \tfrac{1}{6}U'''(\mu_w)(w-\mu_w)^3 + \ldots] \\ &= U(\bar{y}) + U'(\bar{y})(\mu_p - \bar{y}) + \sum_{i=2}^{\infty} \tfrac{1}{i} U^{(i)}(\bar{y})(\mu_p^i - \bar{y}) + \tfrac{1}{2}U''(\mu_p)\sigma_p^2 + \tfrac{1}{6}U'''(\mu_p)\kappa_p^3 + \ldots \end{aligned}$$

(7)

Substituting these expressions in (3), we obtain:

$$P(SE) = P[\varepsilon_i < a + U'(\bar{y})(\mu_p - \mu_w) + \tfrac{1}{2}U''(\mu_p)\sigma_p^2 + \tfrac{1}{6}U'''(\mu_p)\kappa_p^3 - \tfrac{1}{2}U''(\mu_w)\sigma_w^2 - \tfrac{1}{6}U'''(\mu_w)\kappa_w^3] \tag{8}$$

where the constant term *a* absorbs all that has been left out. Equation (8) expresses a standard probit (or logit) model for the choice of self-employment status vis-a-vis the alternative of wage employment. The coefficients can be estimated if we observe sufficient numbers of sufficiently distinct observations for the distribution of wages (*w*) and self-employment incomes (*p*).

Employment segments are defined by field of education, as we take individuals' education as completed. This does not rule out potential substitution with graduates from other fields: the effects are simply included in the observed wage distribution. Presumably, individuals consider their perspective over some time horizon.[6] We assume that individuals, when deciding on their employment status, know the parameters of the wage distribution but do not know where in the wage distribution they would end up if

[6] An implicit assumption of our approach is that the distribution of wages among recent graduates adequately characterizes the distribution over that horizon. This may be justified by a high correlation of distribution parameters for different experience lengths and by the fact that the individual may still be unaware of the duration of his commitment.

choosing wage employment. We take our observations from 118 distinct wage distributions (k = 118 labor market segments defined by a degree field).[7]

For the reasons outlined in the introduction, graduates have far less information on self-employment incomes, let alone self-employment incomes specific to their field of education. We will assume they will use the parameters for self-employment income without differentiating by field of education. In an analysis of self-employment by field of education, the self- employment income prospects are then identical for all individuals and will reduce to a constant; thus, attention fully falls on the parameters of the opportunity cost.

There is no need to deny that originally, this assumption arose out of necessity: with often less than 10 self-employed workers per field one cannot reliably characterize a distribution. But upon reflection, it is not as extreme as it may perhaps seem at first sight. We do not compare highly educated professionals to the local grocery store owner or to a self-employed carpenter: all our respondents have completed tertiary education. And it is actually quite conceivable that subjects indeed use much cruder information on self-employment income than on employee income. To them, just as to us, information on self-employment income is limited by data and definition problems and has often low reliability. These problems are aggravated if one desires information by field of education, with very few examples around to assess income from self-employment. Perhaps, subjects even care little about precise information as other aspects of self-employment matter much more to them. In our robustness tests, we check the validity of the assumption to the extent we can: we include self-employment income parameters by field of education for a subsample with sufficient numbers of observed self-employed workers and we also estimate with self-employment income parameters for aggregates of intrinsically related fields of education. Our core conclusions easily survive. We may note that, statistically, the only requirement is independence: if the variation in the distribution of self-employment income is independent of the variation in the distribution of wages, our estimates are unbiased.[8]

Under this assumption we can estimate the parameters b, c and d by means of the following probit-equation, where a absorbs the effect of the common income distribution for entrepreneurs:

$$P(SE) = P[\varepsilon_i < a - b\mu_w + c\sigma_w^2 - d\kappa_w^3] \tag{9}$$

The coefficients b, c and d are defined in the first, second and third derivative of the utility function; we take them here as positive numbers. With utility increasing in the first moment (from a taste for consumption), the second derivative of utility negative (from risk aversion) and the third derivative positive (from skew affection, as implied by declining absolute risk aversion, cf Tsang, 1972), we predict that the probability of self-employment among graduates from a field of education will decrease in the mean of the wage

[7] In the Netherlands, tertiary education is not characterized by a major, but it is a field defined by a specific curriculum right from the beginning, e.g. economics or chemistry.

[8] This holds conditional on ignoring higher moments in our Taylor series expansion of the utility function.

distribution in that field, increase in the variance of wages and decrease in the skew of wages for the graduate's field of education.[9]

3. Data

In this section, we shall first discuss briefly the relevant features of the Dutch educational system. We will then discuss the data sources and descriptive statistics.

3.1 The Dutch system of higher education

In the Netherlands, 52 vocational colleges and 14 universities offer programs in higher education. Both types of post- secondary education offer a broad array of study programs at the Bachelor level. During the time period captured by our data, universities offered only combined four-year programs leading to a Master's degree, whereas the vocational colleges offer more practically oriented bachelor programs of four years.[10] Students starting these programs were typically 18 years old and fresh from high school. The number of students in the academic year 2008/2009 who graduated from vocational colleges with a bachelor degree was 52,000, whereas the number of students that entered the labor market with a Master degree was approximately 28,000.

3.2 Data sources and definitions

Our sample consists of 79,415 recent graduates from tertiary education. It is a random draw of approximately 7,500 recent graduates per annum in the years 1999 to 2008, from a yearly survey to monitor the labor market outcomes of graduates in the 118 largest degree fields, half in higher vocational education and half in university education fields. The special feature of the monitor is the detailed information on study background and early career earnings of many individuals in many degree fields in tertiary education. Individuals fill out extensive questionnaires about their study program and grades, the activities they undertook as a student, individual background and current labor market situation, such as job search activities, occupational status (unemployed, self-employed, wage-employed) and details about their income. They do so, on average, 20 months after graduation, in January. Thus, our sample includes graduates from the academic years 1997/1998 until 2006/2007.

The Dutch research institute SEO has been commissioned by the prominent weekly magazine

[9] We have abstracted from the fact that the derivatives and hence the coefficients will vary with μ_w. Presumably, this is a small, secondary, effect.

[10] The bachelor master (BAMA) structure was introduced in the Dutch system of higher education in 2002-2003. The first graduations within the new structure took place in 2005-2006 (academic bachelor program of 3 years) and 2006-2007. Only the last wave of observations (January, 2008) may theoretically include these university bachelor graduates since the 2008 wave is held among graduates of the academic year 2005-2006. The few students who entered the labor market with an academic bachelor degree in the first possible year, i.e., 2005-2006 are not included in the 2008 sample. Therefore, the distinction between a degree from a vocational college and a university is implied by the distinction between bachelor and masters degrees.

Elsevier to gather and analyze these data. *Elsevier* publishes a leading special issue every year about the labor market prospects of the 118 specific degree fields (80% of all graduates from tertiary education have degrees from these fields).[11] Appendix Tables A1 and A2 list all vocational and academic degree fields respectively (first column) and the number of wage-employed and self-employed observations in each (second column).

Our dependent variable is occupational status. It is based on the answer to the question: "What is your status in the labor market at the moment?" We are interested in particular in the distinction between self-employed entrepreneurship and wage employment. Table 1 shows how the distribution of individuals among the various answering categories (and non-response, small sized labor market segments or age) diminishes our effective sample size from 79,415 to 56,138 graduates. Respondents could select only one, the most applicable category.

The second key variable is the income distribution per labor market segment. To estimate equation (9), we need observations on the three moments μ_w, σ_w^2 and κ_w^3. Calculated moments of the wage distribution per degree field are based on the wages of employed respondents in the field who report their income.[12] Income data for the various years are expressed in real terms (for the year 2008) by correcting for inflation (consumer price index). Hourly wages are calculated as monthly income divided by the reported number of hours worked per month. Hourly wages below 5 euro have been set to missing, given the minimum wage laws that apply. Wages higher than three standard deviations above the average wage level in their degree field have also been set as missing. Deleting outliers is relevant because the moments of the wage distribution are sensitive to extreme values.[13]

Table 1
Definition of the sample

Initial sample size	79,415
Inactive in the labor market	12,335
Temporary workers	3,083
Education degree field unknown	342
Education degree field small (n<50)	343
Graduate age >30	7,175
Effective sample size	56,138

3.3 Descriptive statistics

As shown in Table 2, the average (median) number of individuals in our sample with identical degrees is 476 (465). This defines the average (median) size of the 118 labor market segments. The largest labor market segment includes 1502 individuals (economics, Msc), the smallest only 59 (horticulture and agriculture, Bsc).

[11] The data have been obtained with the permission of Elsevier and SEO Economic Research.

[12] Tables A1 and A2 show the wage moments and the numbers of observations per degree field with a wage income.

[13]Hourly self-employed entrepreneurial incomes are calculated likewise, although 'outliers' are not excluded. For self-employed entrepreneurs, minimum wages do not apply and occasional very high incomes may occur. Therefore, and also because of the low number of observations we start from, we do not delete extreme values in the income distribution of entrepreneurs. All results remain qualitatively the same when we delete these observations from the self-employed income distribution (or, alternatively, when we do not delete extreme observations from the wage income distributions).

Only 3.6 percent of labor market participants are self-employed.[14] It is a common finding that the self-employment rate among recent graduates is very low (Parker, 2009). Table 2 also shows that the fraction of entrepreneurs varies considerably per degree field. The minimum is zero. This applies to 3 out of 118 degree fields: "Food technology" (Bachelor), "Special needs teacher" (Bachelor) and "Language and culture" (Master). The three degree fields with the highest fraction of entrepreneurs are "Visual arts & design" (Bachelor) with a fraction of 35%, "Theater" (Bachelor, 20%) and "Dance" (Bachelor, 19%).[15] These education degrees are all offered in the vocational colleges. The degree fields in universities with the highest fractions of entrepreneurs are "Film, television and theater studies" (13%) and "Industrial design" (12%).

Table 2

Descriptive statistics: Labor market segments, occupational choice and sample sizes

	Individuals (n)	Per degree field (k =118)				
		Average	*Med*	*Std dev*	*Min*	*Max*
# labor market participants	56,138	476	465	274	59	1502
# wage earners, income known	51,080	437	424	259	33	1418
# self-employed, income known	1,538	13	9	18	0	152
% self-employed	3.64	4.3	2.6	5.8	0	37
% wage earners, income known	94.4%					
% self-employed, income known	75.2%					

Only 75 percent of the self-employed report earnings, a clear illustration of our claim in the introduction that 'Entrepreneurs are wary of revealing accurate income data to third parties' (Astebro, p. 36, 2010). The combination of a much lower number of self-employed than wage earners per segment and the lower response rates to questions about earnings among self-employed induces us to use the self-employment income data with great caution only. The average (median) number of self-employed per labor market segment who report their income is only 13 (9). Moreover, only 50 out of the 118 labor market segments include at least ten observed incomes of self-employed. The number of labor market segments with at least 20 observed incomes for self-employed is only 19.

Table 3 shows the descriptive statistics of the wage distributions across individuals (first column) and labor market segments (right hand side columns) in terms of the first three central moments, i.e. μ_w, σ_w^2 and κ_w^3 from equation 9. The table shows that labor market segments are not terribly different in terms of the average wage income, ranging from 8.54 to 13.13 per hour with a standard deviation of 0.837. However, the variance of the wage incomes within a labor market segments as well as the skew vary widely across segments. In particular, the standard deviation of κ_w^3 is very large. The wage variance and skew in the population of wage earners are larger than the average variance and skew within labor market segments.

[14] The percentage of entrepreneurs in the sample of individuals differs from the percentage of entrepreneurs in the sample of labor market segments, due to the fact that labor market segments vary in size leading to a different weighing of individual observations.

[15] The degree field with the highest fraction of entrepreneurs is also the one with the highest number of entrepreneurs, i.e. 240.

The lower half of Table 3 shows the (available) statistics of the distribution of entrepreneurial income, *p*. The usual comparison to the wage distribution applies. Self-employment incomes are somewhat higher on average (11.2 versus 10.2) with a lower median level (9.5 versus 9.8). The variance is more than 12 times larger than the wage variance for employees (77 versus 6). The skew of the *p* -distribution is almost 100 times the skew of *w* (3260 versus 34). Consistent with the picture painted by the upper half of Table 3, the variance and skew of *p*, like for *w*, are particularly large across labor market segments, more so than within.

Table 3
Descriptive statistics of the wage and self-employment income distributions

	n_w = 51,080 wage observations, incomes known	k =118 Labor market segments/degree fields			
Income statistics in €/h	*Mean*	*Mean*	*Std dev*	*Min*	*Max*
μ_w	10.244	10.081	0.837	8.540	13.128
σ_w^2	6.017	5.168	3.801	.886	32.352
κ_w^3	33.683	25.173	57.441	-.0449	450.99
Median of w	9.848	9.975			
Self-employed, incomes known, (n_p = 1,538)		Labor market segments/degree fields (k = 50, includes segments >= 10 observations of p)			
μ_p	11.241	11.471	2.357	7.136	18.404
σ_p^2	77.194	62.744	82.109	9.730	411.670
κ_p^3	3260	2172	5934	-15.066	29144
Median of p	9.490	10.550			

*The statistics for wage income earners, when based on the same selection of 50 labor market segments as the sample for which the self-employment income statistics are shown, are similar to those for *k*=118.

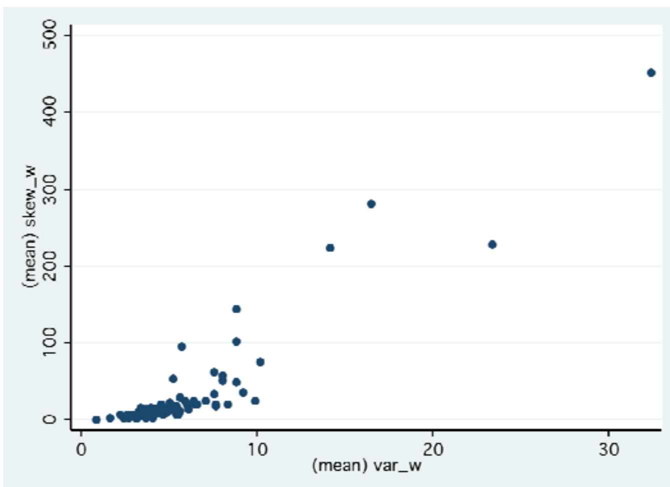
The upper left quadrant of Table 4 depicts the correlation levels between the first three central moments of the wage distribution of each of the labor market segments. These correlation levels are all positive. The correlation between $\boldsymbol{\sigma_w^2}$ and κ_w^3 amounts to 0.92 and points to problems of multicollinearity. At that level we cannot trust estimates of separate effects of variance and skew at face value, especially if the standard errors are large and the coefficient estimates change by much in response to small changes in the model (in terms of adding/excluding either variables or observations). We therefore consider not only the second and third moments of the wage distribution but in an alternative set of specifications replace them by the (standardized) coefficient of variation (σ_w / μ_w) and the commonly used (scale free) measure of skew κ_w^3 / σ_w^3, respectively. The lower left quadrant of Table 4 shows that using these scale free measures of risk and skew reduces the three relevant correlations to the manageable levels of 0.29, -0.04 and 0.56 respectively.

We pursue a second way of alleviating the potential multicollinearity problem by a visual inspection of the 118 data-points in the space defined by σ_w^2 (on the horizontal axis) and κ_w^3 (on the vertical axis), see Figure 1.

Table 4								
Descriptive statistic: Correlations between the moments of the wage distribution in labor market segments								
	k=118 labor market segments				k=114 labor market segments			
	μ_w	σ_w^2	κ_w^3	σ_w/μ_w	μ_w	σ_w^2	κ_w^3	σ_w/μ_w
μ_w	1.000				1.000			
σ_w^2	0.543	1.000			0.433	1.000		
κ_w^3	0.384	0.919	1.000		0.071	0.689	1.000	
σ_w/μ_w	0.294	0.894	0.798	1.000	0.061	0.909	0.702	1.000
κ_w^3/σ_w^3	-0.036	0.401	0.573	0.557	-0.156	0.387	0.857	0.506

Figure 1

Descriptive statistic: the relationship between σ_w^2 and κ_w^3 for k = 118 labor market segments



The figure indicates that excluding the four labor market segments in the upper right part of the graph may decrease the correlation between risk and skew substantially. The four labor market segments that are excluded –from right to left- are 'physiotherapy (Bachelor)', 'music (Bachelor)', 'logopedy' (Bachelor), and 'pedagogy' (Master). This decreases the correlation between σ_w^2 and κ_w^3 successively from 0.92 to 0.85, 0.81, 0.75 to, finally, 0.68 for k =114. The right hand side of Table 4 shows all resulting correlations. In the sequel, we consider four sets of analyses; with scaled versus unscaled measures of risk and skew and with k= 118 versus k=114. This will reduce the impact of multicollinearity problems and show the robustness of the results to changes in the setup of the measures and the sample.

Table 5 shows the descriptive statistics of the control variables that are included in the regression equations, either as a further test of robustness or as a test of assumptions. The factors that are commonly used to explain the variation in self-employment choices in a sample of labor market participants are included (Parker, 2009). These are labor market characteristics (year and region), personal characteristics (gender, age, parental education levels and risk attitude) and human capital variables such as education levels and grades.[16]

Table 5
Descriptive statistics of the control variables

	All individuals (n=56,138)		Wage employees (n_w=54,092)		Self-employed (n_{pp}=2,046)	
	Mean	*St Dev*	*Mean*	*St Dev*	*Mean*	*St Dev*
Labor market characteristics						
Year = 1999 (dummy)	0.110	0.313	0.110	0.313	0.115	0.319
Year = 2000 (dummy)	0.096	0.295	0.095	0.293	0.099	0.299
Year = 2001 (dummy)	0.090	0.286	0.090	0.286	0.083	0.276
Year = 2002 (dummy)	0.086	0.280	0.086	0.280	0.077	0.267
Year = 2003 (dummy)	0.100	0.300	0.102	0.303	0.062	0.241
Year = 2004 (dummy)	0.103	0.304	0.104	0.305	0.080	0.271
Year = 2005 (dummy)	0.118	0.323	0.118	0.323	0.126	0.332
Year = 2006 (dummy)	0.106	0.308	0.106	0.308	0.121	0.326
Year = 2007 (dummy)	0.112	0.315	0.110	0.313	0.139	0.346
Year = 2008 (dummy)	0.079	0.270	0.079	0.270	0.099	0.299
Region South of NL (dummy)	0.205	0.404	0.206	0.404	0.174	0.379
Region North of NL (dummy)	0.076	0.265	0.076	0.265	0.073	0.260
Region West of NL (dummy)	0.529	0.499	0.526	0.499	0.578	0.494
Region East of NL (dummy)	0.190	0.392	0.190	0.392	0.175	0.380
Personal characteristics						
Male (dummy)	0.447	0.497	0.444	0.497	0.514	0.500
Age (years effective range 21-30)	26.025	1.729	26.012	1.724	26.388	1.834
Parents' education level (normalized average)	0.000	1.000	-0.0082	0.978	0.206	1.033
Risk attitude in year 2003 (n=6077)[1]	22.757	20.034	22.471	19.796	29.952	24.238
Human capital characteristics						
Secondary degree with academic orientation (dummy)	0.522	0.500	0.5235	0.499	0.4799	0.500
Secondary education, GPA (scale 1-10)	6.957	0.600	6.957	.6005	6.958	.5819
# languages studied in secondary school	2.864	.825	2.8639	.8237	2.886	.8616
# science subjects studied in secondary school	2.295	1.3494	2.3024	1.3499	2.110	1.3236
Tertiary degree Msc (dummy)	0.513	0.500	0.5171	0.500	0.4154	0.493
Tertiary education, GPA (scale 1-10)	7.177	.529	7.172	.5268	7.275	.583

[1]Risk attitude is measured in terms of the stated reservation price to participate in a lottery where the bet is winning 1000 euro with a probability of 10%. Thus, risk aversion would imply a reservation price below 100. The question is included in the questionnaire of 2003 only, see Section 4.2.

4. Estimation results

In this section we will first test the propositions resulting from the model. We will then test the assumptions underlying the model and perform robustness checks.

[16] The table suggests that the likelihood of being self-employed is higher for males who are older (in a range from 21 to 30), have lower levels of risk aversion, parents with higher education levels and a bachelor degree with high grades.

4.1 *Testing of propositions: The effect of the wage distribution in the labor market segment on the choice for self-employment*

We have estimated four specifications, determined by excluding outlying segments or not, combined with scaling the distribution moments or not. In Table 6, we estimate the choice equation at the aggregate level of field of education. The dependent variable, $P[SE]_k$, is the fraction in segment k that is self-employed 20 months after graduation**.** Control variables are average values per labor market segment. Table 7 shows the results of a probit model at the individual level, with standard errors clustered by labor market segments. The effects shown are marginal effects, i.e. the percentage increase in the probability of self-employment, $P[SE]_i$, when increasing the regressor by one unit (measured for an individual in the sample with average values for all regressors). As controls we use labor market dummies (regions and years) and personal characteristics (gender, age and parental education levels).[17] [18]

Our preferred specification excludes the four outlying segments, uses unscaled moments and is estimated on individual data using the controls specified in the previous section. Excluding the segments mitigates the multicollinearity problem, unscaled moments are closest to the specification we derived in Section 2 and individual data are most suited to control for individual characteristics. As Table 7, panel B, shows, our predictions are fully supported. The first and the third moment of the wage distribution have a significantly negative effect on the inclination to choose self-employment, the second moment has a significant positive effect. As the corresponding results in Table 7, panel A show, the results are not affected by including controls. If we estimate at the aggregate level of the labor market segment (Table 6) we get essentially the same results, whether we include controls or not (except for loss of significance in one case).

Scaling the distribution parameters does not affect the key conclusions: we still get significant confirmation of the predicted signs. The coefficients of the first moment decline by roughly 40%. The coefficients of the other moments increase, as should be expected: if the value of a regressor falls from dividing by a scaling factor, the value of the estimated coefficient will go up. Across all the specifications, the coefficient of the second moment increases roughly by a factor 40 in absolute value and the coefficient of the third moment by a factor 20. Judged by the mean values of the moments in Table 3, one would predict increases by a factor 25 and 15, respectively.[19] Of course, the whole purpose of the rescaling is to get away from multicollinearity and not to rescale by the same constant for all observations. But the calculation suggests that the effect of rescaling is more or less in the ballpark that one might expect and that reducing multicollinearity does not dramatically upset parameter estimates.

The effect of excluding the four extreme labor market segments on estimated parameter values is very small and reduces the significance level in just a few cases, as can be seen from all pairwise comparisons.

[17] Risk attitude is added as a regressor to the equation in a later stage when testing our assumptions. Its inclusion reduces the size of the sample to ten percent only due to the fact that it has been measured in year 2003 only. The set of human capital variables will be added to the equation later as well.

[18] Due to the low number of observations at the aggregate level of labor market segments, we do not include the sets of average labor market characteristics and average personal controls simultaneously into the regression equations.

[19] The mean value of σ_w^2 is 6, the value of σ_w / μ_w at mean values is 2.4/10; thus rescaling at these mean values would predict an increase by a factor 25.

This confirms the conclusion from the scaling exercise: we have no indications that multicollinearity renders our estimates essentially unreliable.

Table 6
The fraction of self-employed and the wage distribution in a labor market segment (OLS at the k-level)

Panel A No controls								
Dependent: $P[SE]_k$	k=118				k=114			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0336***	.0067	-.0182***	.0058	-.0297***	.0064	-.0179***	.0055
σ_w^2	.0231***	.0035	.8154***	.1179	.0182***	.0038	.7012***	.1296
κ_w^3	-.0010***	.0002	-.0213***	.0056	-.0008***	.0003	-.0167***	.0053
Prob > F	0.000		0.000		0.000		0.0000	
R^2	0.3292		0.2976		0.2163		0.2415	
Panel B Labor market characteristics included as controls								
Dependent: $P[SE]_k$	k=118				k=114			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0361***	.0070	-.0206***	.0063	-.0315***	.0067	-.0195***	.0059
σ_w^2	.0224***	.0034	.8159***	.1184	.0178***	.0037	.6785***	.1290
κ_w^3	-.0010***	.0002	-.0191***	.0059	-.0007**	.0003	-.0139**	.0055
Prob > F	0.000		0.000		0.0000		0.0000	
R^2	0.4404		0.4084		0.3681		0.3807	
Panel C Personal characteristics included as controls								
Dependent: $P[SE]_k$	k=118				k=114			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0383***	.0080	-.0219***	.0066	-.0323***	.0077	-.0221***	.0065
σ_w^2	.0171***	.0035	.6280***	.1261	.0126***	.0037	.4968***	.1337
κ_w^3	-.0006**	.0002	-.0115**	.0055	-.0004	.0003	-.0090*	.0052
Prob > F	0.0000		0.0000		0.0000		0.0000	
R^2	0.4655		0.4329		0.3670		0.3703	

The *p*-values are based on robust standard errors. A significant coefficient at the 10% (5%) [1%] level is denoted by * (**) [***]. A constant term is included in all equations.

4.2 *Testing of assumptions and robustness checks*

<u>Definition of labor market segments</u>

As noted in the introduction, the validity of our approach hinges on a sensible definition of labor market segments. Table 3 already indicated that the wage variance within labor market segments is smaller than the variance between segments, as one would expect with sensibly defined labor market segments, see the Introduction. As a further check on the sensibility of the defined labor market segments, we repeated the analyses for 118 'labor market segments' that are formed by random assignment of individuals to segments a hundred times. For these 'segments' we didn't establish any of the joint significant effects of the wage distribution in a segment on the occupational choice of individuals within that segment. The relationship between self-employment and the moments of the wage distribution is not some mechanical relationship that would hold in any arbitrary decomposition of the labor force.

Table 7

The individual probability of being self-employed and the wage distribution in a labor market segment

Panel A Dprobit, clustered by labor market segments, no controls								
Dependent: *dummy Self-emp*	k= 118, n= 56,138				k=114, n =53,819			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0244***	.0074	-.0157***	.0059	-.0223***	.0075	-.0122***	.0042
σ_w^2	.0146***	.0039	.5345***	.1335	.0142***	.0050	.5747***	.1768
κ_w^3	-.0007***	.0002	-.0158***	.0044	-.0006***	.0002	-.0129***	.0040
Prob > χ^2	0.0000		0.0004		0.0120		0.0032	
Pseudo R^2	0.0546		0.0545		0.0380		0.0439	
Panel B Dprobit, clustered by labor market segments, labor market and personal characteristics included								
Dependent: *dummy Self-emp*	k=118				K=114			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0263***	.0067	-.0171***	.005147	-0.0242***	0.0064	-0.0138***	0.0037
σ_w^2	.0136***	.0034	.5274***	.11179	0.0136***	0.0042	0.5590***	0.1527
κ_w^3	-.0006***	.0002	-.0127***	.00376	-0.0005***	0.0002	-0.0104***	0.0036
Prob > χ^2	0.0000		0.000		0.0000		0.0000	
Pseudo R^2	0.0739		0.0754		0.0593		0.0635	

The p-values are based on robust standard errors. A significant coefficient at the 10% (5%) [1%] level is denoted by * (**) [***]. A constant term is included in all equations.

<u>The role and independence of self-employment income distributions in labor market segments</u>

We have taken the approach of measuring the effect of wage income distributions only, instead of also including self-employment income distributions, because the literature has acknowledged that the latter are difficult to observe, for various reasons. These reasons apply in our case too. Only a small fraction of the sample is self-employed (3.6%), and a large fraction of the self-employed does not reveal their income at all. As a consequence, only 50 (19) out of the 118 labor market segments include at least 10 (20) observed incomes of self-employed. Moreover, the incomes show a large variance and this may reflect substantial measurement error. We have argued that individuals do not base their occupational choice on the self-employment income distribution within labor market segments, but on the self-employment income distribution in general.

Table 8 and Table 9 show how our results change upon including the first three central moments of p into the regression equations. The samples are limited to the 50 labor market segments in which there are at least 10 observations of *p* and to 47 when the sample of *k* =114 forms the basis. Table 8 shows the results at the level of labor market segments *k* (comparable to Table 6), whereas Table 9 shows the results at the individual level *n* (comparable to Table 7). The bottom half of both tables shows the benchmark results, i.e., when only considering the labor market segments with at least ten observations of *p* but where the moments of *p* remain excluded.

Table 8

Adding the first three moments of the self-employment income distribution per segment at level k

Panel A The central moments of the self-employment income distribution included where n_p>=10								
Dependent: $P[SE]_k$	*k*= 50				*k*= 47			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0476***	.0144	-.0238*	.01227	-.0408***	.0139	-.0258**	.0113
σ_w^2	.0287***	.0068	.9253***	.2307	.0166*	.0098	.8571***	.2762
κ_w^3	-.0013***	.0004	-.0249	.0175	-.0004	.0010	-.0083	.0168
μ_p	-.0082	.0054	-.0094**	.0041	-.0056	.0052	-.0046	.0040
σ_p^2	3.55e-06	.0005	.0094	.0706	-.0002	.0005	-.0504	.0648
κ_p^3	2.10e-06	6.15e-06	.0161	.0128	3.31e-06	6.61e-06	.0210*	.0121
Prob > *F*	0.0000		0.0000		0.0109		0.0019	
R^2	0.4639		0.4590		0.3269		0.3938	
Panel B The benchmark where n_p>=10								
Dependent: $P[SE]_k$	*k*= 50				*k*= 47			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-0.0567***	0.0127	-0.033**	0.0116	-0.0463***	0.0128	-0.0305***	0.0106
σ_w^2	0.0313***	0.0063	1.0617***	0.2403	0.0193**	0.0092	0.8383***	0.2751
κ_w^3	-0.0014***	0.0004	-0.0317*	0.0175	-0.0006	0.0010	-0.0101	0.0167
Prob > *F*	0.0000		0.0002		0.0022		0.0012	
R^2	0.4270		0.3426		0.2854		0.3059	

The tables show that our essential conclusion on the signs of the moments is not affected by the inclusion of the *p*-moments into the equations but that we loose precision, as one might expect with strong reduction in the number of observations. In addition, the moments of *p* themselves hardly affect the occupational choices of individuals. This lack of results is in line with previous findings and with the model we have proposed.

The results shown in Tables 8 and 9 include only those labor market segments with sufficient numbers of entrepreneurs, i.e., n_p>=10. This may lead to a biased sample excluding labor market segments with few entrepreneurs. In Table 10, we check our results for the full sample with self-employment income measures calculated for 13 segments. The segments are aggregates, for self-employment income only, of fields of education that are intrinsically related (e.g. fields in engineering, in teaching, in arts) and add up to sufficient number of self-employed to calculate moments of the income distribution (see the second column of tables A1 and A2). Thus, the underlying assumption is now that individuals assess self-employment income from a set of related fields, instead of lumping all fields together (for instance, business economics, creative therapy, electrical engineering, etc).

Table 9
Adding the first three moments of the entrepreneurial income distribution per segment at level n

Panel A Dprobit, clustered by labor market segments, moments of p added to panel B of Table 7, where n_p>=10								
Dep: *dummyEntr*	k= 50, n = 29,019				k=47, n = 27,398			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0318***	.0096	-.0168**	.0072	-0.0269***	0.0096	-0.0126**	0.0063
σ^2_w	.0168***	.0044	.5476***	.1466	0.0128*	0.0078	0.7053***	0.1923
κ^3_w	-.0007***	.0002	-.0111	.0098	-0.0001	0.0006	-0.0067	0.0083
μ_p	-.0066*	.0038	-.0071**	.0023	-0.0051	0.0036	-0.0004*	0.0022
σ^2_w	-.00004	.0003	-.0112	.0484	-0.0001	0.0003	-0.0547	0.0388
κ^3_w	2.08e-06	3.08e-06	.0145*	.0087	1.97E-06	3.25E-06	0.0213	0.0074
Prob > χ^2	0.0000		0.0000		0.0013		0.0000	
Pseudo R^2	0.0670		0.0733		0.0527		0.0657	
Panel B The benchmark, Dprobit, clustered by labor market segments where n_p>=10								
Dep: *dummyEntr*	k= 50, n = 29,019				k=47, n = 27,398			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0421***	0.0114	-.0283***	0.0101	-.0348***	0.0112	.0209***	0.0069
σ^2_w	.0205***	0.0053	.7433***	0.2276	.0158**	0.0080	.7569***	0.2700
κ^3_w	-.0009***	0.0003	-.0228*	0.013	-.0003*	0.0006	-.0087	0.0101
Prob > χ^2	0.0000		0.001		0.0023		0.0006	
Pseudo R^2	0.0612		0.0556		0.0474		0.0506	

When we include the first three central moments of the entrepreneurial income distribution from the 13 segments, we get basically the same results as before. The moments of the wage distribution maintain their predicted signs when we include self-employment income moments, the magnitudes of the coefficients barely change and the self-employment income moments themselves have no significant effect. Only the first moment of the wage distribution looses significance, in case of scaled moments. Once again we find significant effects of opportunity cost and no effects of the self-employment income distribution.[20]

[20] We also noted that our estimates are still unbiased if the distribution of self-employment income within a segment is independent of the distribution of wages. In all other cases, our estimates may be biased. The bias would be downwards in the case of a positive correlation and upwards in the case of a negative correlation. Table 11 shows our estimates, necessarily based on a modest number of observations. The correlations are positive, but quite small. Comparing the results in Tables 6 and 7 with those in 8, 9 and 10 indicates that including the *p*-moments in large majority leads to higher estimated coefficients of the moments of the wage distribution moments. This is in line with underestimation when we omit variables that correlate positively. When we compare the point estimates, in Table 8 and Table 9, for estimation excluding and including self-employment income, their ratio's are mostly around 1.2 to 1.3, which would be compatible with omitted variable bias at equal coefficients and the correlations as measured in Table 11. We conclude that the results we have presented for the full sample, if biased, are mostly likely an underestimate of the true effect of opportunity costs.

Table 10
Adding the moments of the *p*-distribution with an alternative definition of labor market segments

Dprobit, clustered by alternative labor market segments, moments of *p* added to panel B of Table 7								
Dep: *dummyEntr*	*k*= 118, 13 clusters, *n* = 56,138				*k*=114, 13 clusters, *n* = 53,819			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.01934**	.0096	-.0092	.0062	-.0176*	.0092	-.0085	0.0063
σ_w^2	.0126***	.0037	.4607***	.1088	.0127***	.0045	.5403***	0.1666
κ_w^3	-.0005***	.0002	-.0120***	.0043	-.00050***	.0002	-.0116***	0.0040
μ_{p_alt}	-.0046	.0067	-.0063	.0051	-.0039	.0074	-.0030	.0062
$\sigma_{p\_alt}^2$	-.00001	.0011	.0283	.0495	-.0000	.0011	.0132	.0521
$\kappa_{p\_alt}^3$	-4.98e-07	.0001	-.0004	.0049	6.02e-07	.0000	-.0013	.0043
Prob > χ^2	0.0000		0.0000		0.0170		0.0000	
Pseudo R^2	0.0566		0.0612		0.0400		0.0456	

Table 11
Correlations between the moments of the *w*- and *p*-distributions in labor market segments*

	k=118 labor market segments (50)	*k*=114 labor market segments (47)
μ	0.396	0.382
σ^2	0.197	0.205
κ^3	0.232	0.113
σ/μ	0.213	0.026
κ^3/σ^3	0.018	-0.120

*The correlations that involve an element of the distribution of entrepreneurial incomes have been calculated for the sample of 50 (47) labor market segments (out of the original 118 or 114) in which there are at least 10 entrepreneurial incomes observed.

4.3 Potential sources of bias

Biased moments

In our statistical analysis we use moments of the wage distribution as observed in the data. The distribution is realized after choices have been made and an individual may have private information on the distribution that will apply in his/her particular case. Correction for selectivity bias may be essential if one wants to retrieve the true risk that an individual is facing but the key question here is to what extent this is relevant for the individual's decision making. Econometric corrections for selectivity bias are often quite sensitive to specification and generally not very robust (eg. Chen, 2008; Mazza, Van Ophem and Hartog, 2010) but direct assessments of individuals' information on future incomes point in a single direction: there is no evidence that individuals systematically correct observations for private information (see for example Betts, 1996;

Dominitz and Manski, 1996; Brunello, Lucifora and Winter-Ebmer, 2004; Webbink and Hartog, 2004; Wolter and Weber, 2004; Schweri, Hartog and Wolter, 2011).

Omitted variables

Omitted variables, if correlated with a regressor, will lead to a biased estimate of the effect of that regressor. Variables that directly come to mind are risk attitude and human capital or ability. Both are known to affect the choice for entrepreneurship, are likely to affect the choice for a degree field and are also likely to affect (preferred) expected levels and variances of the wage distribution.

A comparison of Panel A with Panel B in Table 7 may be considered a first test of the possible effects of the omission of risk attitude. It shows that including controls for, among others, gender and age hardly affect the estimates of the coefficients of the first three moments of the wage distribution. Males are known to be less reluctant to take risks and risk aversion increases when people get older (Hartog et al., 2002). The estimates stand this first test.

A second test exploits the fact that our dataset includes an indicator of (stated) risk preference. Respondents were asked to value participation in a hypothetical lottery paying out €1000 with a 10 percent chance. Unfortunately, this indicator is available for only one out of the 10 waves of graduates in our sample (see Table 5 and its footnote). The average willingness to pay for participation in this hypothetical lottery reported by 6077 graduates was €22.8 (median €15), see Table 5. Thus, on average, the respondents in our sample are risk averse. The reported maximum was €99. The reservation price for participating in such a hypothetical lottery has been shown to be a valid (inverse) indicator of risk aversion and behavior under risk (see Cramer et al., 2002; Dohmen et al., 2011; Hartog et al., 2002). Table 5 shows that the average reservation price in the sample of entrepreneurs is significantly higher than in the sample of employees (€29.95 versus €22.47) in line with earlier applications (Cramer et al., 2002).

We replicate the analysis of Table 7 for this single wave of graduates and then include the stated risk preference variable as an additional regressor in the equation, see Panel A of Table 7 and Table 12.[21] The results show a clear positive correlation between self-employment and the lottery reservation price. But what's more important, the estimated coefficients for the wage moments are not affected by the inclusion of a (strongly significant) risk preference variable; the magnitudes and standard errors only marginally different from the ones in Table 7. We conclude that our results are not likely to be driven by omitting a measure of risk attitude.[22]

[21] The replicated results for this wave compare well to the results presented in Table 7. Significance levels drop slightly due to the smaller sample, but conclusions remain unaltered. These results are not shown in Table 12.

[22] Actually, our model indicates that risk attitude should not be included as a separate regressor: risk attitude is reflected in the regression coefficients for variance and skew. Thus, the key issue is not an omitted variable problem but coefficient heterogeneity. In the single wave we have data for, we interacted variance and risk attitude. Results were in the right direction (smaller effects for the less risk averse) but statistically weak.

Table 12
The effect of controlling for a measure of risk attitude at the individual level

A risk attitude measure added to Panel B of Table 7								
Dependent: *dummy Entr*	*k*=118, *n* = 6,077				*k*=114, *n* = 5,835			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0296***	.0092	-.0187***	.0075	-0.0283***	0.0093	-0.0159***	0.0056
σ_w^2	.0168***	.0044	.6018***	.1594	0.0168***	0.0059	0.6314***	0.2216
κ_w^3	-.0008***	.0002	-.0183***	.0057	-0.0007***	0.0003	-0.0147***	0.0053
Lottery reservation price	.0006***	.0001	.0006***	.0001	0.0006***	0.0001	0.0006***	0.0001
Prob > χ^2	0.0000		0.000		0.0000		0.0000	
Pseudo R^2	0.1087		0.1034		0.0842		0.0880	

The *p*-values are based on robust standard errors. A significant coefficient at the 10% (5%) [1%] level is denoted by * (**) [***]. A constant term is included in all equations.

Another stylized fact from the empirical entrepreneurship literature indicates that ability or, more in general human capital, affects the choice for entrepreneurship (Parker, 2009). Human capital might also induce people to choose certain degree fields and thereby affect the income distribution. Thus, human capital is the second obvious candidate to possibly confound our results. Table 13 shows that this is not the case. The analysis shown in Table 7 Panel B is repeated with inclusion of a set of human capital factors.[23] The estimated coefficients of the three measures characterizing the wage distribution show the same pattern as before.

Table 13
The effect of controlling for measures of human capital at the individual level

Human capital controls added to panel B of Table 7								
Dependent: *dummy Entr*	*k*= 118, *n* = 56,138				*k*=114, *n* =53,819			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0259***	.0071	-.0158***	.0053	-0.0241***	0.0067	-0.0130***	0.0044
σ_w^2	.0129***	.0032	.4983***	.1031	0.0130***	0.0040	0.5290***	0.1454
κ_w^3	-.0005***	.0002	-.0122***	.0035	-0.0004**	0.0002	-0.0102***	0.0036
Pseudo R^2	0.0771		0.0792		0.0619		0.066	

The *p*-values are based on robust standard errors. A significant coefficient at the 10% (5%) [1%] level is denoted by * (**) [***]. A constant term is included in all equations. The human capital controls included here are listed in Table 5 (type of degree, grades, courses).

Field of education as a source of bias

Our data use income distribution moments grouped by type of education (academic discipline, field of education). Hence, we observe wage data for individuals who have chosen a particular field of education and

[23] The most obvious measures of human capital (education level and experience), are already controlled for in our sample of graduates from tertiary education at the start of their career.

we relate self-employment status to wage observations belonging to these preselected fields. What may go wrong here?

Consider taste for risk. Other things equal, a risk lover will choose an education track generating incomes with high variance more often. Risk lovers will also choose self-employment more often. Then self-employment will correlate positively with income variance across educations. We find indeed a positive correlation between self-employment and wage variance. However, the argument requires furthermore that the variance in the wage and self-employment income distributions correlate positively, for which we find only weak evidence in our data, see Table 11. Another observation required for the validity of this argument, to the extent that the labor market compensates for risk taking (Hartog, 2011), is that variance will be correlated positively with the mean income in a segment. This would generate a positive correlation between self-employment and mean income, contrary to what we find. As risk lovers would be attracted to high skew educations, we would also find positive correlation between skew and self-employment, again contrary to what we find. Thus, this potential spurious link runs counter to two of our three key findings.

Consider an omitted relevant ability that stimulates self-employment (e.g. the ability for fast and robust decision making). If this ability also stimulates to choose an education field with higher productivity as a wage earner, we would see a positive correlation between mean wage and self-employment; we find the opposite. The higher ability may reduce wage variance, as abler workers make fewer errors and have better foresight of pitfalls and dangers of failure; this would again predict the opposite of what we find, a negative correlation between self-employment and variance.

Omitted moments

In the introduction we noted that previous studies may have found no effect of income on occupational choice because they only include one (or two) moments of the relevant income distribution. We test this presumption for the specifications of Panel B of Table 7, see Table 14.

Table 14
Including fewer moments of the wage distribution at the individual level

Excluding κ_w^3 from the equation of panel B, Table 7								
Dependent: *dummy Entr*	K= 118, n = 56,138				k=114, n =53,819			
	Unscaled moments		Scaled moments		Unscaled moments		Scaled moments	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-.0204***	.0075	-.0133***	.0053	-0.0202***	0.0063	-0.0113***	0.0037
σ_w^2	.0046***	.0015	.3898***	.1025	0.0091***	0.0034	0.4339***	0.1545
Pseudo R^2	0.0526		0.0630		0.0525		0.0542	

Excluding σ_w^2 and κ_w^3 from the equation of panel B, Table 7				
Dependent: *dummy Entr*	K= 118, n = 56,138		k=114, n =53,819	
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*
μ_w	-0.0032	.0067	-0.0116**	.0055
Pseudo R^2	0.0167		0.0234	

The p-values are based on robust standard errors. A significant coefficient at the 10% (5%) [1%] level is denoted by * (**) [***]. A constant term is included in all equations. The human capital controls included here are listed in Table 5.

The first moment has no effect on status choice if we omit the second and the third moment, just as in the earlier literature. As the top panel shows, substantial change in the estimated coefficient of the first moment only emerges if both the second and the third moment are omitted.

5. Conclusion

We set out to provide an understanding of the remarkable lack of support in the self-employment literature for the effect of financial returns on the decision to select self-employment above wage employment. Various explanations have been put forth for this puzzling lack of support. It is hard to believe that preferences for income entirely cease to play a role for the labor market choice between salaried and self-employment.

One explanation is that income data for the self-employed are poor and difficult to compare to wage earnings. Another explanation is that, besides the mean, variance and skew of the earnings distributions are also different and may drive the choice between these options. We try to address these empirical issues with a sample of recent graduates from tertiary education in the Netherlands. This sample is homogeneous with respect to age, education level and labor market experience and can be divided, based on degree fields, into labor market segments with their own wage distributions.

We find robust support for the effect of opportunity cost (moments of the wage distribution) and no significant effect of the financial returns to self-employment. Lower mean, higher variance and lower skew of the wage distribution for an individual's type of education increase the probability of self-employment. Robustness checks suggest that the conclusion is quite solid and that our estimates are more likely to give an underestimate than an overestimate. Lack of support for the moments of the self-employment income distribution is compatible with measurement error blurring estimated coefficients. It is also compatible with a blurred vision of the subjects themselves. The significant effects of opportunity cost of self-employment do indicate however, that the choice for self-employment is guided by financial incentives. Empirical research seeking to distinguish econometric problems of estimation under measurement errors and ignorance cum indifference among subjects would be a challenging next step.

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Table A1. Descriptive statistics of fields of study (Bachelor)

Labor market segment	Grouped segm	N obs	Self employed	wage variance	wage skewness	mean log(wage)	mean wage €)	N obs wage	Mean Entr. income	N obs Entr. income
Business Economics/Business Sciences	Economics	653	0.012	0.0262	0.0029	2.221	10.23	625	11.61	7
Commerce	Economics	586	0.031	0.0301	0.0050	2.215	9.60	554	11.37	15
Business Informatics	Economics	671	0.031	0.0278	0.0032	2.250	10.14	642	11.86	18
Communication	Economics	597	0.050	0.0314	0.0032	2.218	9.66	557	10.24	26
Accountancy	Economics	558	0.005	0.0315	0.0026	2.224	10.23	525	6.81	1
International Business and Languages	Economics	433	0.007	0.0275	0.0043	2.192	9.34	418	9.79	2
Tourism & Leisure	Economics	475	0.013	0.0338	0.0049	2.110	9.32	455	8.92	4
Hotel Management	Economics	531	0.026	0.0295	0.0036	2.190	9.59	509	9.50	13
Small Business and Retail Management	Economics	335	0.093	0.0356	0.0045	2.224	10.32	289	9.21	23
Management, Economics & Law	Economics	525	0.015	0.0280	0.0020	2.212	9.99	503	10.56	4
Logistics & Economics	Economics	649	0.014	0.0277	0.0035	2.217	10.17	620	8.81	7
Facility Services	Economics	612	0.023	0.0279	0.0034	2.191	9.63	596	14.19	13
Journalism	Journalism	587	0.177	0.0346	0.0010	2.248	10.24	508	11.15	85
Business Management	Economics	163	0.049	0.0209	0.0012	2.233	9.60	153	14.21	5
Fiscal Economics	Economics	269	0.019	0.0356	0.0025	2.258	10.27	260	7.42	4
European professions	Economics	177	0.028	0.0349	0.0042	2.209	9.63	164	8.88	4
Leisure Management	Economics	213	0.042	0.0352	0.0055	2.143	9.14	196	8.44	8
International Business & Management	Economics	73	0.055	0.0369	0.0021	2.223	9.79	66	4.48	2
Real Estate	Economics	121	0.033	0.0382	0.0041	2.191	9.18	119	3.36	1
Marketing management	Economics	69	0.058	0.0293	0.0033	2.205	9.44	64	10.71	3
Personnel & Labour	Social sciences	575	0.023	0.0284	0.0027	2.232	9.92	550	16.10	12
Socio-Cultural Studies	Social sciences	499	0.048	0.0342	0.0025	2.211	9.60	457	8.91	18
Social Work & Services	Social sciences	624	0.011	0.0218	0.0006	2.278	10.22	599	7.49	6
Social Pedagogy	Social sciences	908	0.013	0.0263	0.0021	2.217	9.78	858	8.88	11
Socio-Legal Services	Social sciences	414	0.010	0.0234	0.0027	2.255	10.10	397	8.39	4
Information Management	Social sciences	385	0.016	0.0311	0.0037	2.205	9.65	366	8.30	3
Creative Therapy	Social sciences	162	0.056	0.0369	0.0029	2.251	9.98	147	9.48	7
Medical Laboratory Technician	(Para) medical	569	0.005	0.0232	0.0042	2.157	9.04	547	8.10	3
Nursing	(Para) medical	882	0.010	0.0200	0.0018	2.241	10.07	847	9.76	8
Physiotherapy	(Para) medical	724	0.057	0.0284	-0.0003	2.358	14.34	642	16.33	30
Speech Therapy	(Para) medical	568	0.067	0.0315	0.0033	2.239	11.42	489	18.40	32
Nutrition & Dietetics	(Para) medical	568	0.019	0.0295	0.0036	2.237	10.11	529	11.16	9

Table A1 (Continued) Descriptive statistics of fields of study (Bachelor)

Ergotherapy	(Para) medical	709	0.082	0.0258	0.0017	2.283	10.79	623	13.18	43
Medical Imaging & Radiotherapy	(Para) medical	259	0.004	0.0121	0.0012	2.212	9.19	252	8.23	1
Oral Hygiene	(Para) medical	105	0.057	0.0154	0.0004	2.339	11.79	94	26.40	3
Environmenal Management/Technology	Agriculture	438	0.018	0.0287	0.0032	2.236	9.79	414	12.96	6
Agri-Business	Agriculture	365	0.033	0.0255	0.0031	2.237	9.64	334	11.51	11
Animal Husbandry	Agriculture	433	0.095	0.0480	0.0082	2.151	9.46	380	7.14	21
Food Technology	Agriculture	98	0.000	0.0284	0.0034	2.245	9.80	96		0
Horticulture & agriculture	Agriculture	59	0.186	0.0392	-0.0023	2.161	8.86	48	10.49	5
Primary School Teacher	Teaching	896	0.004	0.0190	0.0016	2.285	10.78	812	8.20	3
Physical Education Teacher, Grade 1	Teaching	472	0.023	0.0364	0.0010	2.314	11.41	432	11.96	10
Dutch Teacher	Teaching	320	0.031	0.0320	0.0043	2.283	10.70	302	10.42	7
Economics Teacher (general & business)	Teaching	370	0.019	0.0271	0.0024	2.259	10.66	351	8.37	6
Special Needs Teacher	Teaching	392	0.000	0.0183	0.0013	2.299	10.33	356		0
Social Studies Teacher	Teaching	93	0.022	0.0311	0.0064	2.200	9.24	91	13.11	2
Education	Teaching	276	0.011	0.0263	0.0012	2.256	10.53	256	29.50	3
Science Teacher	Teaching	452	0.007	0.0275	0.0017	2.316	10.92	434	6.37	2
Geography/History Teacher	Teaching	497	0.026	0.0419	0.0036	2.280	10.98	471	10.13	10
Arts & Crafts Teacher	Teaching	86	0.128	0.0540	0.0094	2.186	9.60	69	9.20	10
English/French/German Teacher	Teaching	603	0.013	0.0378	0.0030	2.294	11.58	558	8.59	6
Visual Arts & Design	Teaching	678	0.354	0.0453	0.0027	2.148	9.81	426	7.66	152
Music	Arts	329	0.368	0.0492	-0.0001	2.288	12.42	179	11.71	68
Theater	Arts	98	0.204	0.0314	0.0027	2.130	9.28	72	11.76	12
Dance	Arts	60	0.200	0.1231	0.0050	1.976	9.13	39	9.50	9
Chemcial Technician	Engineering	240	0.008	0.0306	0.0047	2.180	9.05	226	7.50	2
Structural Engineering	Engineering	506	0.020	0.0251	0.0041	2.206	9.35	474	8.98	9
Electrical Engineering	Engineering	453	0.026	0.0258	0.0039	2.247	9.75	430	8.36	8
Civil Engineering	Engineering	430	0.007	0.0271	0.0048	2.216	9.84	410	7.27	2
Chemical Engineering	Engineering	651	0.011	0.0236	0.0031	2.248	9.99	625	9.38	6
Applied Informatics	Engineering	862	0.057	0.0272	0.0031	2.250	10.11	788	10.55	38
Mechanical Engineering	Engineering	442	0.020	0.0306	0.0044	2.225	9.76	418	10.70	9
Naval Officer	Engineering	98	0.010	0.0756	0.0105	2.097	9.11	87	8.45	1
Physics Engineering	Engineering	99	0.010	0.0194	0.0019	2.243	9.59	91	16.80	1
Fashion Management and Technology	Engineering	160	0.081	0.0322	0.0049	2.160	10.17	145	9.35	9
Car Technology	Engineering	112	0.018	0.0242	0.0038	2.243	10.70	107	1.82	2

Table A2. Descriptive statistics of fields of study (Master)

	Grouped segm	N obs	self employed	wage variance	wage skewness	mean log(wage)	mean wage €)	N obs wage	Mean Entr. income	N obs Entr. income
Dutch	Humanities/Languages	549	0.0729	0.0267	0.0019	2.294	10.67	508	11.20	30
English	Humanities/Languages	441	0.0680	0.0362	0.0021	2.263	10.77	399	11.84	24
Other languages	Humanities/Languages	356	0.0534	0.0342	0.0018	2.252	10.81	328	9.08	15
Philosophy/Theology	Humanities/Languages	189	0.0899	0.0387	0.0000	2.299	10.52	162	10.73	12
History	Humanities/Languages	571	0.0490	0.0338	0.0007	2.277	10.59	527	11.11	23
Language & Culture (general)	Humanities/Languages	395	0.0582	0.0315	0.0021	2.255	10.09	374	9.79	19
Art History & Archaeology	Humanities/Languages	265	0.1019	0.0362	0.0035	2.221	9.44	235	8.67	19
Corporate Communications	Humanities/Languages	334	0.0120	0.0233	0.0015	2.255	10.01	323	15.02	4
European Studies	Humanities/Languages	68	0.0294	0.0225	0.0040	2.243	10.12	67	5.56	2
Film, Television & Theatre	Humanities/Languages	146	0.1301	0.0459	0.0041	2.235	10.59	123	11.12	14
Alpha Information science	Humanities/Languages	305	0.0492	0.0255	0.0013	2.286	10.46	286	9.21	9
Chemistry	Techn/Engineering	516	0.0039	0.0367	0.0043	2.199	9.64	502	7.92	2
Computer Science	Techn/Engineering	319	0.0439	0.0306	0.0022	2.301	10.42	298	14.51	10
Biology	Techn/Engineering	779	0.0282	0.0361	0.0015	2.193	9.62	748	11.12	16
Pharmacy	Techn/Engineering	503	0.0298	0.0244	-0.0012	2.427	12.58	465	14.88	13
Pure Mathematics/Physics	Techn/Engineering	533	0.0131	0.0366	0.0027	2.224	9.98	519	9.05	6
Agricultural Science	Techn/Engineering	67	0.0299	0.0214	0.0021	2.337	10.86	63	9.00	1
Chemi/Techn Agri-sciences	Techn/Engineering	357	0.0280	0.0271	0.0019	2.277	10.19	332	8.73	7
Bioprocessing & Food Tech	Techn/Engineering	692	0.0159	0.0333	0.0016	2.259	10.23	660	9.21	9
Architecture	Techn/Engineering	820	0.0512	0.0213	0.0022	2.296	10.74	771	12.41	32
Mechanical Engineering	Techn/Engineering	747	0.0134	0.0217	0.0010	2.352	11.32	702	11.27	9
Electrical Engineering	Techn/Engineering	458	0.0240	0.0219	0.0008	2.345	11.30	428	17.08	8
Chemical Engineering	Techn/Engineering	555	0.0126	0.0291	0.0014	2.330	10.96	540	20.59	4
Civil Engineering	Techn/Engineering	720	0.0181	0.0180	0.0016	2.329	10.83	695	14.80	9
Technology & Management	Techn/Engineering	747	0.0281	0.0201	0.0005	2.385	11.59	696	9.03	19
Industrial Design	Techn/Engineering	416	0.1226	0.0240	0.0016	2.299	10.32	365	11.04	38
Aerospace Engineering	Techn/Engineering	146	0.0411	0.0218	0.0012	2.359	10.79	138	12.23	4
Applied Computer Science	Techn/Engineering	364	0.0632	0.0193	0.0012	2.328	10.73	331	9.85	19
Applied Math/Physics	Techn/Engineering	674	0.0089	0.0312	0.0013	2.287	10.40	647	13.06	5
Economics	Economics&law	1502	0.0220	0.0250	0.0007	2.349	11.32	1435	14.12	29
Business Science	Economics&law	808	0.0186	0.0241	0.0007	2.352	11.39	775	11.71	11
Econometrics	Economics&law	509	0.0138	0.0260	-0.0006	2.360	11.75	492	11.90	6

Table A2 (Continued) Descriptive statistics of fields of study (Master)

Fiscal Economics	Economics&law	218	0.0138	0.0161	0.0001	2.420	11.72	208	9.82	1
Business Administration	Economics&law	835	0.0335	0.0224	0.0001	2.355	11.52	783	10.81	26
Dutch Law	Economics&law	1078	0.0176	0.0210	0.0010	2.341	11.29	1028	10.11	14
Notarial Law	Economics&law	467	0.0064	0.0273	0.0012	2.339	10.97	449	4.97	1
Fiscal Law	Economics&law	509	0.0118	0.0175	0.0000	2.414	12.38	494	20.89	4
International Law	Economics&law	71	0.0000	0.0275	-0.0005	2.332	10.71	69		0
Healthcare	Health	782	0.0128	0.0300	0.0002	2.316	10.90	740	13.26	8
Medicine	Health	998	0.0070	0.0237	-0.0003	2.416	11.92	975	27.02	6
Biomedical Sciences	Health	610	0.0082	0.0274	0.0013	2.238	9.76	590	11.83	5
Veterinary Science	Health	278	0.0612	0.0232	0.0000	2.369	11.19	253	9.76	12
Sociology	Social sciences	491	0.0305	0.0294	-0.0001	2.304	10.50	470	11.97	9
Psychology	Social sciences	1093	0.0357	0.0358	0.0001	2.305	10.92	1037	17.52	34
Politics	Social sciences	463	0.0454	0.0265	-0.0004	2.341	11.21	440	10.78	18
Education Science	Social sciences	698	0.0143	0.0295	0.0004	2.336	11.73	661	13.45	8
(Applied) Education	Social sciences	380	0.0342	0.0232	0.0010	2.336	11.17	354	12.41	12
Cultural Anthropology	Social sciences	367	0.0436	0.0340	0.0018	2.249	10.64	347	12.48	15
Communication	Social sciences	705	0.0369	0.0260	0.0018	2.300	10.63	663	12.45	20
Socio-Cultural Science	Social sciences	779	0.0257	0.0259	0.0013	2.315	10.69	750	9.93	17
Public Administration	Social sciences	1080	0.0194	0.0223	0.0008	2.361	11.30	1032	12.13	19
Human Geography & Plann	Social sciences	1069	0.0178	0.0241	0.0008	2.309	10.47	1026	12.04	16