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Entrepreneurs' Human Capital and Heterogeneous Labor Demand of Newly Established Firms

Kathrin Müller *

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Abstract

This paper investigates the effect of founders' human capital on the qualification structure of employees in newly established firms. Different corner solution outcome models are compared regarding their goodness of fit and adequacy. Based on survey data of about 3,000 new-born German firms, I find that the specific and generic human capital of a firm's founders largely determine the share of high-skilled workers and the share of low-skilled workers in young firms. Furthermore, this study provides evidence for a skill-biased technological change and a capital-skill complementarity in young firms.

Keywords heterogeneous labor demand, human capital, start-ups

JEL Classification: J23, J24, L26

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1 Introduction

Addressing the role of start-ups for the creation of sustainable employment is one of the major aims in entrepreneurship research. Based on the results of Birch (1981), who found that young firms were largely responsible for job creation in the U.S. during the 70s, aggregate employment effects are in the interest of most studies. While measuring gross employment creation (number of jobs created by start-ups each year) is relatively easy and done for most developed countries periodically, detailed macroeconomic analyses are difficult because they have to account for the fact that more than half of the start-ups do not survive the first 8-10 years (Boeri and Cramer, 1992) and for crowding out of jobs in matured firms.

Microeconometric analysis disentangles the determinants of firms' start-up size and young firms' employment growth. Several factors have been shown to be related to a firm's start-up size and employment growth in the first years of its existence. These are firm-specific factors such as the legal form of a firm as well as funding and innovation activities and industry characteristics such as economies of scale. Moreover, the generic and specific human capital of new firms' founders have also been shown to be positively related to a firm's early labor demand. As a main novelty, this study is not interested in the quantity, but the quality of jobs created in young entrepreneurial firms. Therefore, the structure of jobs in young firms is investigated. The study aims to identify the determinants of labor demand for different levels of employees' education. Since studies on the firm level have shown that the human capital of the founders is an important predictor for young firms' labor demand when labor is treated as homogeneous, this study focuses on the importance of entrepreneurs' human capital on heterogeneous labor demand.

Heterogeneous labor demand has been investigated mainly for matured firms. In this context, estimating own wage and cross-wage elasticities and testing the hypothesis of a skill-biased technological change have been the major issues. Investigating the impact of entrepreneurs' human capital on heterogeneous labor demand of newly established firms will thus contribute not only to the understanding of young firms' part in creating sustainable employment but also to the literature of heterogeneous labor demand of firms in general.

There are several reasons why entrepreneurs' human capital shall be related to the qualification structure of young firm's employees. Founders' human capital will largely determine the business idea and the type of products and services a firm offers. Typically, high-educated founders will sell more sophisticated products and services. As a consequence, production and sale of this kind of products also require a higher level of human capital of the firm's employees.

Moreover, a higher level of founders' human capital relaxes financial constraints of a new-born firm. Founders with a high level of human capital usually have higher private wealth, and they often receive external financing more easily. Funding is especially important when a firm plans to hire high-skilled personnel because hiring high-skilled workers will be relatively more expensive than hiring medium-skilled or low-skilled workers. Severe financial constraints might therefore hinder young firms to employ high-skilled workers while it might still be possible to hire workers with a lower skill level. Additionally, low-skilled workers might be less reluctant to accept less favorable labor agreements, e.g. fixed-term work contracts or marginal employment.

Furthermore, young firms may face substantial restrictions on the supply of high-qualified labor. Usually, high-skilled workers have better labor market opportunities. Competing with established firms for high-qualified labor, young firms might lose since workers often prefer to work in well-established firms which are typically larger and pay higher wages (Brixy et al., 2007; Van Praag and Versloot, 2007). Furthermore, employment stability is expected to be higher in well-established firms (Schnabel et al., 2008). On the other hand, workers may accept lower salaries if they expect non-financial working conditions, e.g. via flat hierarchies, to be better in young companies. Supply-side restrictions for young firms may be less severe the higher the human capital of the founders. The professional experience and the educational degree of the founders may serve as a signal for good prospects of the firm. Evidently, founders' human capital and survival prospects are related (Brüderl et al., 1992; Bates, 1990).

In order to investigate the importance of founders' human capital for heterogeneous labor demand of young firms empirically, I apply different kinds of corner solution outcome models. Comparing Tobit models to various kinds of hurdle models, hurdle models turn out to fit the data best.

The analysis in this paper covers a wide range of industries. Both manufacturing and services are included. Industries can be distinguished by their technology orientation and knowledge intensity. One can assume that especially in knowledge- and research-intensive industries, such as high-tech manufacturing or knowledge-intensive services, even young firms ask for more skills.

Entrepreneurs' human capital is found to be a major determinant of the qualification structure of the workforce in young firms. Furthermore, the estimation results are in line with the hypothesis of a skill-biased technical change and the hypothesis of capital-skill complementarity.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on heterogeneous labor demand in established firms. After that, I explain the theoretical framework for investigating heterogeneous labor demand. The methods, the data and the results of the empirical analysis are described in Section 4. Finally, I conclude.

2 Literature review

Until today heterogeneous labor demand has been investigated almost exclusively for matured firms above a certain minimum size (often for firms above 5 or 10 employees). When studying employment in newly founded firms, entrepreneurship research has mainly investigated aggregate employment effects (Acs and Müller, 2008; Fritsch, 2006; Boeri and Cramer, 1992) or, at the firm level, employment growth (Calvo, 2006; Davidsson et al., 2002; Almus and Nerlinger, 1999), remuneration levels (Brixy et al., 2007; Brown and Medoff, 2003) and fringe benefits (Bernstein, 2002), employment turnover and stability (Schnabel et al., 2008; Brixy et al., 2005; Burgess et al., 2000; Lane et al., 1996a,b), codetermination (Addison et al., 2003), or start-up size (Gottschalk et al., 2009; Colombo et al., 2004; Mata and Machado, 1996). Studies analyzing the structure of the workforce in newly established firms are rare and solely descriptive (Gottschalk et al., 2008; Weißhuhn and Wichmann, 2000).

Though studies for young firms are missing, there exists a bulk of literature which deals with heterogeneous labor demand for matured firms.

These studies are mainly motivated by shifts in the skill structure in developed economies over the last three decades and rising unemployment among the less skilled workforce. Empirical studies mainly test one or more of the three most prominent explanations for the rise of the share of high-skilled employees in an economy: 1) a skill-biased technical change, 2) increasing internationalization, 3) organizational change within a firm¹. The hypothesis of a skill-biased technological change, i.e. technological progress will lead to larger share of high-qualified workers, is tested within a heterogeneous labor demand framework using different indicators and units of observation. Most common indicators are input and output indicators of innovative activities. These are R&D expenditures (Adams, 1999) and product or process innovations (Hujer et al., 2002). Furthermore, specific ICT indicators, such as the intensities of computer or internet usage (Maurin and Thesmar, 2004; Falk, 2001), or measures of innovative capital or investments (Doms et al., 1997) are used in order to assess the hypothesis of a skill-biased technological change. Studies investigating the hypothesis of a skill-biased technological change are either conducted with longitudinal industry-level data (Berman et al., 1998; Falk and Koebel, 2004; O'Mahony et al., 2008) or cross-sectional and longitudinal firm-level data (Kaiser, 2001; Aguirregabiria and Alonso-Borrego, 2001). The hypothesis of a skill-biased technological change is investigated and confirmed for most developed countries regardless of the indicator used. Jacobebbinghaus and Zwick (2002) show that technological change does not only reduce the relative demand for low-skilled workers, but also reduces the demand for medium-skilled workers. A very informative literature review on the effect of technology on skill structure is provided by Chennells and van Reenen (2002).

Because Greenan and Guellec (1998) descriptively show that organizational change in terms of workers' autonomy and increased communication between workers is positively related to skill upgrading, more recent studies do not only focus on the technological change but also on the organizational changes within the firm. These studies find evidence that organizational change has a positive impact on skill upgrading within a firm (Piva and Vivarelli, 2004; Caroli and van Reenen, 2001; Falk, 2002), especially when combined with a high level of ICT (Bresnahan et al., 2002).

¹A study of Piva and Vivarelli (2004) contains an excellent summary of the empirical literature on these topics both on the industry level and on the firm level.

Most studies dealing with globalization and the structure of the workforce are conducted on the sectoral level. Evidence is less clear since results differ depending on the indicator used to measure internationalization. Feenstra and Hanson (1996) measure international outsourcing by the share of intermediate goods imported out of total goods imported and find a positive influence on the demand for skilled workers, while Slaughter (2000), who measures internationalization by foreign affiliate employment, finds no evidence of foreign direct investment on increased or decreased demand for skilled workers in parent companies. On the contrary, some of the results of a study by Silva (2008) are not consistent with the traditional trade theory in a Heckscher-Ohlin framework, i.e. international trade should lead to an increase in the relative demand for skilled workers in developed countries. Similarly, Elia et al. (2009) find that foreign activities have, on the one hand, a negative impact on the demand for low-skilled workers, but, on the other hand, foreign activities have a negative impact on the demand for high-skilled workers if they take place in high income countries. Evidence on the firm-level is more in favor of the traditional trade theory. Head and Ries (2002) find evidence for a positive relationship between foreign direct investments and skilled employment if offshoring takes place in low-income countries. Also Bandick and Hansson (2009) find a positive relationship between increased foreign presence within the same industry on skill upgrading in Sweden. Furthermore, if a firm becomes foreign-owned, relative demand for skilled labor increases if the firm was non-multinational before, but decreases if the firm was a Swedish multinational entity before the foreign acquisition has taken place.

3 Modeling heterogeneous labor demand

Factor demand for labor of different skill levels can be derived with the help of the duality of a firm's profit maximization problem. Taking the level of desired output (Y) as given, a firm's optimization behavior finds its expression by minimizing the costs. Because of its flexibility, a convenient choice for the cost function in the literature (Chennells and van Reenen, 2002; Caroli and van Reenen, 2001; Betts, 1997) is the translog cost function of Christensen et al. (1973). This function is a second-order approximation to an arbitrary

functional form of the cost function. Analyzing heterogeneous labor demand of newly established firms, I consider a short-run cost function (see Brown and Christensen, 1981) with high-skilled labor L_H , medium-skilled labor L_M and low-skilled labor L_L being variable factors of production. The stock of physical capital K^P and the stock of knowledge capital G , which captures technological change, are treated as quasi-fixed factors of production which do not have to be at their long-run optimal values. I extend the framework of analyzing heterogeneous labor demand as proposed by Bond and Van Reenen (2007) by using the generic and specific human capital of the firm's founders (K^H) as an additional quasi-fixed factor of production. Since founders' human capital largely determines the business idea and the type of products and services a firm offers, relaxes financial constraints and supply side restrictions, human capital is expected to have a positive influence on the skill structure within firms.

The augmented quasi-fixed translog cost function is given by

$$\begin{aligned}
\ln(C) = & a_0 + \sum_i a_i \ln(w_i) + \frac{1}{2} \sum_i \sum_j a_{ij} \ln(w_i) \ln(w_j) \\
& + a_{K_1 Y} \ln(K^P) \ln(Y) + a_{K_2 Y} \ln(K^H) \ln(Y) + a_{GY} \ln(G) \ln(Y) \\
& + a_{K_1 K_2} \ln(K^P) \ln(K^H) + a_{GK_1} \ln(G) \ln(K^P) + a_{GK_2} \ln(G) \ln(K^H) \\
& + a_Y \ln(Y) + \frac{1}{2} a_{YY} (\ln(Y))^2 + \sum_i a_{iY} \ln(w_i) \ln(Y) \\
& + a_{K_1} \ln(K^P) + \frac{1}{2} a_{K_1 K_1} (\ln(K^P))^2 + \sum_i a_{iK_1} \ln(w_i) \ln(K^P) \\
& + a_{K_2} \ln(K^H) + \frac{1}{2} a_{K_2 K_2} (\ln(K^H))^2 + \sum_i a_{iK_2} \ln(w_i) \ln(K^H) \\
& + a_G \ln(G) + \frac{1}{2} a_{GG} (\ln(G))^2 + \sum_i a_{iG} \ln(w_i) \ln(G)
\end{aligned}$$

with $a_{ij} = a_{ji}$ for all i, j and $i, j = H, M, L$. Prices of the variable inputs (skill differentiated wage levels) are denoted by w_i . Applying Shephard's (1953) Lemma, i.e. differentiating the quasi-fixed translog cost function with respect to the logarithm of the i th input price ($\frac{\partial \ln(C)}{\partial \ln(w_i)} = \frac{w_i}{C} \frac{\partial C}{\partial w_i} = \frac{w_i L_i}{C} = S_i$), yields the factor share equations:

$$\begin{aligned}
S_H &= a_H + a_{HH} \ln(w_H) + a_{HM} \ln(w_M) + a_{HL} \ln(w_L) + a_{HY} \ln(Y) \\
&\quad + a_{HK_1} \ln(K^P) + a_{HK_2} \ln(K^H) + a_{HG} \ln(G) \\
S_M &= a_M + a_{MH} \ln(w_H) + a_{MM} \ln(w_M) + a_{ML} \ln(w_L) + a_{MY} \ln(Y) \\
&\quad + a_{MK_1} \ln(K^P) + a_{MK_2} \ln(K^H) + a_{MG} \ln(G) \\
S_L &= a_L + a_{LH} \ln(w_H) + a_{LM} \ln(w_M) + a_{LL} \ln(w_L) + a_{LY} \ln(Y) \\
&\quad + a_{LK_1} \ln(K^P) + a_{LK_2} \ln(K^H) + a_{LG} \ln(G)
\end{aligned}$$

By the the cost function property of linear homogeneity in input prices for each fixed level of output and quasi-fixed production factors (see Diewert, 2008) some restrictions can be placed on the parameters. Homogeneity implies that $\sum_i a_{ij} = 0$ for all j variable factors, $\sum_i a_{iY} = 0$, $\sum_i a_{iK_1} = 0$, $\sum_i a_{iK_2} = 0$, $\sum_i a_{iG} = 0$ and $\sum_i a_i = 1$. Furthermore, symmetry ($a_{ij} = a_{ji}$) is assumed. Because shares sum up to unity one equation is redundant and the system of equations can be simplified to

$$\begin{aligned}
S_H &= a_H + a_{HH} \ln\left(\frac{w_H}{w_M}\right) + a_{HL} \ln\left(\frac{w_L}{w_M}\right) + a_{HY} \ln(Y) \\
&\quad + a_{HK_1} \ln(K^P) + a_{HK_2} \ln(K^H) + a_{HG} \ln(G) \tag{1}
\end{aligned}$$

$$\begin{aligned}
S_L &= a_L + a_{LH} \ln\left(\frac{w_H}{w_M}\right) + a_{LL} \ln\left(\frac{w_L}{w_M}\right) + a_{LY} \ln(Y) \\
&\quad + a_{LK_1} \ln(K^P) + a_{LK_2} \ln(K^H) + a_{LG} \ln(G). \tag{2}
\end{aligned}$$

Both the unknown parameters of equation (1) and equation (2) can be econometrically estimated by appending errors to the equations. The coefficient on the physical capital variable is expected to be positive in equation 1 or to be negative in equation 2 in order to be consistent with capital-skill complementarity. Likewise, both the coefficient on the human capital variable and the coefficient on the stock of knowledge capital are expected to be positive for high-skilled employees or negative for low-skilled employees.

4 Empirical analysis

4.1 The econometric models

4.1.1 Models of corner solution outcomes - Tobit and alternatives

As in many applications investigating demand, we are faced with corner solution outcomes when analyzing heterogeneous labor demand. This gives rise to excess zero observations in the data and therefore a positive probability mass at zero. Applying ordinary least squares including zero observations would result in biased outcomes (Amemiya, 1984). The econometric literature has proposed several econometric models using latent variables in order to deal with censored or corner solution outcomes. The standard Tobit model originally introduced by Tobin (1958) is used most commonly. This type of model is also called Type 1 Tobit according to Amemiya's (1984) classification of censored regression models and is given by:

$$\begin{aligned} y_i^* &= \mathbf{x}'_i \boldsymbol{\beta} + u_i, & i = 1, 2, \dots, n, \\ y_i &= \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0, \end{cases} \end{aligned}$$

with $u_i \sim \mathcal{N}(0, \sigma^2)$. The latent, unobserved dependent variable is denoted by y_i^* , while y_i and \mathbf{x}_i are observed. Maximum likelihood estimation of the standard Tobit model maximizes the log-likelihood function

$$\text{Log}L = \sum_0 \ln \left[1 - \Phi \left(\frac{\mathbf{x}'_i \boldsymbol{\beta}}{\sigma} \right) \right] + \sum_+ \ln \left[\frac{1}{\sigma} \phi \left(\frac{y_i - \mathbf{x}'_i \boldsymbol{\beta}}{\sigma} \right) \right],$$

where $\Phi()$ denotes the cumulative density function of the standard normal distribution and $\phi()$ denotes the standard normal density function. Although widely used in empirical analyses, the standard Tobit model might be too restrictive since it strongly relies on the normality assumption and restricts the model into a single mechanism determining both the probability to demand a certain type of labor and the amount of this type of labor demanded. Technically, this means that $P(y > 0 | \mathbf{x})$ and $E(y | \mathbf{x}, y > 0)$ are restricted to the same set of regressors \mathbf{x} and that $\frac{\partial P(y > 0 | \mathbf{x})}{\partial x_j}$ and $\frac{\partial E(y | \mathbf{x}, y > 0)}{\partial x_j}$ have the same sign.

A small modification of the standard Tobit model proposed by Deaton and Irish (1984) results in the P-Tobit model which allows for two types of zeros. The proportion of firms which potentially employ high-skilled (low-skilled) labor is p , while $1-p$ firms will never employ high-skilled (low-skilled) labor. The amount of high-skilled (low-skilled) labor demanded by potential employers of this type of labor is thereupon determined by the Tobit model. The log-likelihood for the P-Tobit model becomes:

$$\text{Log}L = \sum_0 \ln \left[1 - p\Phi \left(\frac{\mathbf{x}'_i\boldsymbol{\beta}}{\sigma} \right) \right] + \sum_+ \ln \left[p\frac{1}{\sigma}\phi \left(\frac{y_i - \mathbf{x}'_i\boldsymbol{\beta}}{\sigma} \right) \right].$$

Further flexibility is added in more general two-part models introduced by Cragg (1971), the hurdle model and the double-hurdle model. Cragg (1971) presents a framework of models in which the size of y is allowed to be determined by different factors from those determining the probability of y being zero.

Hurdle models have become very popular since they are easy to implement in most statistical software packages and offer flexibility for a wide range of applications. In a first step, a firm has to make the decision either to employ a certain type of labor or not. This choice is indicated by a binary variable d . In the second step, a firm has to decide about the positive amount of high-skilled (low-skilled) labor. The first decision might be represented by a probit model while the second decision follows an appropriate model of positive outcome regression models (e.g. truncated regression, log-linear regression). The conditional density is then given by

$$f(y_i|\mathbf{x}_i) = \begin{cases} \Phi(-\mathbf{z}'_i\boldsymbol{\gamma}) & \text{if } y_i = 0 \\ \Phi(\mathbf{z}'_i\boldsymbol{\gamma}) \cdot f(y_i|\mathbf{x}_i, d_i = 1) & \text{if } y_i > 0. \end{cases}$$

A huge flexibility arises for the modeling of the positive outcomes. Either a standard regression model can be used or, if one wants to guarantee non-negativity of $E(y|\mathbf{x})$, truncated normal regression or log-linear regression can be applied.

If truncated normal regression is chosen in the second stage, the log-likelihood of the model becomes

$$\text{Log}L = \sum_0 \ln \left[\Phi \left(-z'_i \gamma \right) \right] + \sum_+ \ln \left[\Phi \left(z'_i \gamma \right) \cdot \frac{1}{\sigma} \frac{\phi \left(\frac{y_i - \mathbf{x}'_i \beta}{\sigma} \right)}{\Phi \left(\frac{\mathbf{x}'_i \beta}{\sigma} \right)} \right].$$

Since the log-likelihood is separable, the parameters of the model can be estimated in two ways. One possibility is to apply a two-step procedure by first estimating a probit on the binary outcome of employing at least one high-skilled (low-skilled) worker and thereafter applying a truncated-normal regression on the positive outcomes. The second possibility is to maximize the log-likelihood function in one step (see McDowell (2003) for equivalency of these approaches). Since it is necessary to get access to individual likelihoods when conducting commonly used specification tests of non-nested models (e.g. the Vuong (1989) test), parameters of all econometric models are estimated by one-step maximum likelihood estimation even if a two-step procedure would have been possible to apply.

Cragg's (1971) double-hurdle model is a further generalization of the Tobit model. Like in the P-Tobit model, two hurdles have to be overcome in the double-hurdle model in order to observe a positive outcome. The firm has to desire a positive amount of high-skilled (low-skilled) labor and favorable circumstances have to arise for positive outcomes to be observed. The model becomes

$$\begin{aligned} d_i^* &= z'_i \gamma + \epsilon_i, & \epsilon_i &\sim \mathcal{N}(0, 1), & i &= 1, 2, \dots, n, \\ y_i^* &= \mathbf{x}'_i \beta + u_i, & u_i &\sim \mathcal{N}(0, \sigma^2), & i &= 1, 2, \dots, n, \\ y_i &= \begin{cases} y_i^* & \text{if } y_i^* > 0 \text{ and } d_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \text{ or } d_i^* \leq 0, \end{cases} \end{aligned}$$

where u_i and ϵ_i are independently distributed. The log-likelihood function for the double-hurdle model becomes

$$\begin{aligned} \text{Log}L &= \sum_0 \ln \left[\Phi \left(-z'_i \gamma \right) + \Phi \left(z'_i \gamma \right) \Phi \left(-\frac{\mathbf{x}'_i \beta}{\sigma} \right) \right] \\ &\quad + \sum_+ \ln \left[\Phi \left(z'_i \gamma \right) \frac{1}{\sigma} \phi \left(\frac{y_i - \mathbf{x}'_i \beta}{\sigma} \right) \right]. \end{aligned}$$

In contrast to the hurdle model presented above, the likelihood of the

double-hurdle model is not separable.

Because the maximum likelihood estimations may be inconsistent if the common assumption of homoscedasticity is violated, heteroscedastic models are estimated by replacing σ with σ_i (Greene, 2003). Multiplicative heteroscedasticity is specified by $\sigma_i = \sigma \cdot \exp(\mathbf{w}'_i \boldsymbol{\alpha})$. For all models the null hypothesis of homoscedasticity ($\boldsymbol{\alpha} = 0$) is tested using Wald tests.

4.1.2 Specification tests

In order to select the model which best rationalizes heterogeneous labor demand in newly established firms, a sequential strategy is chosen. First, one needs to decide if a logarithmic transformation of the dependent variable might be necessary. Logarithmic transformations are often made in order to meet the assumption of the data following a normal distribution. Therefore, a richer model is fitted which includes the logarithmic transformed model as a special case. The Box-Cox transformation given by

$$y_i^T = \begin{cases} \frac{y_i^\lambda - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \ln(y_i) & \text{if } \lambda = 0 \end{cases}$$

is a useful tool for choosing the right model. An estimate of the parameter λ close to zero indicates that the model should be estimated with the dependent variable logarithmic transformed. If $\lambda = 1$, i.e. $y^T = y - 1$, no transformation is necessary. A further advantage of the Box-Cox transformation is that it relaxes the normality assumption on the conditional distribution of the dependent variable. Box-Cox versions of the hurdle model and the double-hurdle model are estimated using maximum likelihood estimation. The log-likelihood function of the Box-Cox hurdle model is given by

$$\text{Log}L = \sum_0 \ln [\Phi(-\mathbf{z}'_i \boldsymbol{\gamma})] + \sum_+ \ln \left[\Phi(\mathbf{z}'_i \boldsymbol{\gamma}) y_i^{\lambda-1} \frac{1}{\sigma} \phi \left(\frac{y_i^T - \mathbf{x}'_i \boldsymbol{\beta}}{\sigma} \right) \right]$$

and the log-likelihood function of the Box-Cox double-hurdle is

$$\begin{aligned} \text{Log}L &= \sum_0 \ln \left[1 - \Phi \left(\mathbf{z}'_i \boldsymbol{\gamma} \right) \Phi \left(\frac{\frac{1}{\lambda} + \mathbf{x}'_i \boldsymbol{\beta}}{\sigma_i} \right) \right] \\ &+ \sum_+ \ln \left[\Phi \left(\mathbf{z}'_i \boldsymbol{\gamma} \right) y_i^{\lambda-1} \frac{1}{\sigma_i} \phi \left(\frac{y_i^T - \mathbf{x}'_i \boldsymbol{\beta}}{\sigma_i} \right) \right]. \end{aligned}$$

Details on the Box-Cox double-hurdle model, which was first presented by Jones and Yen (2000), and its implementation in Stata can be found in the Appendix.

In a second step, the various censored regression models presented in section 4.1 are compared. Nested models can be compared using (adjusted) likelihood-ratio tests. The (unadjusted) likelihood-ratio used to test the P-Tobit model against the Tobit model is given by

$$LR = 2 \cdot [\ln L(\theta_1) - \ln L(\theta_2)], \quad LR \sim \chi^2_{(1)}.$$

Vuong (1989) proposed to use an adjusted likelihood-ratio statistic. The adjusted likelihood-ratio statistic is given by

$$\widetilde{LR} = 2 \cdot [\ln L(\theta_1) - \ln L(\theta_2)] - (p - q), \quad \widetilde{LR} \sim \chi^2_{(p-q)},$$

where p is the number of parameters in model 1 and q is the number of parameters of model 2. This statistic is used to test the double-hurdle model against the Tobit (and P-Tobit) model and to compare the hurdle model with the Tobit model.

A specification test for non-nested models proposed by Vuong (1989) is used to compare the hurdle model with the P-Tobit and to compare the double-hurdle model with the hurdle model. The Vuong statistic is given by

$$V = \frac{\sqrt{N} \bar{m}}{s_m}, \quad V \stackrel{a}{\sim} \mathcal{N}(0, 1)$$

with \bar{m} and s_m being the mean and standard deviation of m_i , defined as $m_i = \ln \left[\frac{f_1(y_i | \mathbf{x}_i)}{f_2(y_i | \mathbf{x}_i)} \right]$. The term $f_j(y_i | \mathbf{x}_i)$, for $j = 1, 2$, denotes the predicted probability that the random variable Y equals y_i . This statistic is used to test the null hypothesis that $E(m) = 0$. V is asymptotic normal distributed

and bidirectional, i.e. the test favors model 1 if $V > 2$ and favors model 2 if $V < -2$. If $|V| < 2$ neither of the models is favored (Greene, 2003).

Additionally, non-nested models can be compared using a non-parametric sign test proposed by Clarke (2003), which tests the null hypothesis $H_0 : \theta = 0$, where θ is the median log-likelihood ratio. The test statistic is the number of positive differences of the individual log-likelihoods ($C = \sum_i I_i \{f_1(y_i|\mathbf{x}_i) - f_2(y_i|\mathbf{x}_i) > 0\}$) and is distributed binominal $\mathcal{B}(C, p = 0.5)$. The intuition behind the test is, that if model 1 is preferred to model 2, more than half the log-likelihood ratios should be greater than zero. The Clarke test can be shown to be asymptotically more efficient than the Vuong test if the distribution of the individual log-likelihoods is leptokurtic, i.e. exhibits thicker tails and higher peaks (e.g. double exponential), while the Vuong test is asymptotically more efficient than the Clarke test if the distribution of the individual log-likelihood ratios is mesokurtic (e.g. normal) or platykurtic (e.g. uniform) (Clarke, 2007).

Table 1: Specification tests - overview

Model	Test type	Restriction
Linear model vs. log transformation	Box-Cox	$\lambda = 1$ (linear) $\lambda = 0$ (log transformed)
P-Tobit vs. Tobit	LR	$p = 1$
Double-hurdle vs. Tobit	adj. LR	$\gamma_0 = \infty \wedge \gamma_1 = 0, \dots, \gamma_k = 0$
Double-hurdle vs. P-Tobit	adj. LR	$\gamma_1 = 0, \dots, \gamma_k = 0$
Hurdle vs. Tobit	adj. LR	$\frac{\beta}{\sigma} = \gamma$
Hurdle vs. P-Tobit	Vuong, Clarke	
Double-hurdle vs. hurdle	Vuong, Clarke	
Hurdle vs. double-hurdle	Vuong, Clarke	

Table 1 summarizes the approach for model selection and gives an overview of the specification tests and the restrictions to be tested.

4.2 The data and variables

Cross-sectional firm-level data of the first wave of the KfW/ZEW Start-Up Panel is used for investigating young firm's heterogeneous labor demand. The KfW/ZEW Start-Up Panel is a yearly survey of newly established firms and was launched in 2008. This project is a cooperation between the Centre of European Economic Research (ZEW), the KfW bank group, a state-owned

German bank with tasks on behalf of the state, and the business information and debt collecting organization Creditreform, Germany's largest credit rating agency.

The data source for the first wave is a stratified² random draw of all firms founded as legally independent companies between 2005 and 2007. The survey was conducted by means of computer-assisted telephone interviews in 2008. More than 5,000 start-ups founded between 2005 and 2007 have been surveyed about the sociodemographical characteristics of the founders (the number of team members, educational background, professional experience, etc.), the employment and financing structure and other firm characteristics, for example innovation activities. Only firms with at least one employee in 2007, which is true for around 60 percent of all newly established firms in the sample, are included in the regressions. After dropping observations with missing data for the variables investigated, I end up with 2,988 observations.

Sectoral data about labor costs in 2007 for different skill groups are retrieved from the German Federal Statistical Office. Average sectoral wage for high-skilled, medium-skilled and low-skilled workers are merged with firm-level data of the KfW/ZEW Start-Up Panel according to a firm's 3-digit NACE code.

Even if they employ at least one person besides the founders, newly established firms are relatively small. The mean number of employees, excluding the founders, is 5.5 persons. The median number of employees is 3. If founders are included, on average 6.9 persons work in a young firm in the sample. The median number of employees including the founders is 4.

A summarizing description of all variables included in the econometric analysis is provided in Table 2. The variables are chosen according to the theoretical and conceptual considerations derived in Section 1 and 3. Descriptive statistics are provided in Table 3.

Since I have no information about firm-level labor costs, I use employment shares instead of factor cost shares as dependent variables. This approach is common in the empirical literature investigating heterogeneous labor demand although it is less appropriate theoretically. But using employment shares

²The sample is stratified by sector, year of foundation and KfW funding. Stratification criteria result in oversampling of firms operating in high-tech manufacturing and high-tech services as well as overrepresentation of firms which have received funds from KfW.

instead of cost shares has the advantage to be able to decompose the effect of certain regressors (e.g. technology, human capital) into a relative wage component and a relative employment component (see Chennells and van Reenen, 2002). The average share of high-skilled employees in young firms of the sample is about 12.5 percent. Low-skilled employees account on average for 28.2 percent of all employees. Hence, the majority of jobs created in young firms requires a medium skill-level.

As expected, the data exhibits a high number of zero values. About 81 percent of all firms in the sample do not employ any high-skilled employees, which amounts to 2,430 observations. Excess zeros are also present in case of the number of low-skilled employees. In total, 1,821 firms (61 percent) do not employ any low-skilled employees.

Price sensitivity is captured by including the logarithm of relative wages at the sectoral level (NACE 3-digit).

The output, which should be included in the regressions according to the theoretical model, is difficult to measure in young firms. Newly established firms often do not realize sales in the first year(s). Therefore, a measure which relies on turnover figures might not be the right measure for output in case of young firms. Furthermore, often firms are reluctant to provide data about sales or profit either because they do not like to reveal sensitive data or because they do not remember the exact number. For this reason, I proxy output by the total number of employees (including the founders) which should reflect the expectations about the future value added created by the firm.

The capital stock is calculated via summing up all investments made since foundation and assuming an annual depreciation rate of 6 percent. Yearly data on capital investment is missing for a number of firms. In order not to lose a lot of observations because of capital stock missings, observations with capital stock missings are included in the analysis. A particular value is assigned to these observations and they are marked using a dummy variable ($miss \log(K)$)³.

Concerning human capital, I distinguish between professional experience as a measure of specific human capital and the educational degree of the

³This method is called *dummy variable adjustment* or *missing indicator method* and is frequently used in econometric analysis (Allison, 2001). A value of $\log(0.5)$ was assigned to these observations.

founders as a measure of generic human capital. Professional experience is measured in two dimensions: industry experience and entrepreneurial experience (previous self-employment). Industry experience is measured by the years of industry experience of the founder. If the start-up was established by a team of founders the years of industry experience are retrieved for the founder with the longest industry experience. Entrepreneurial experience is further divided into successful entrepreneurial experience (the previous business still exists) and entrepreneurial experience which was not successful (the previous business has either become insolvent or has been voluntarily closed).

With respect to professional education, I distinguish between five educational degrees. In case of team foundations the highest educational degree within the team of founders is chosen. If the founder did not complete any kind of professional training after school, he is assigned the lowest level of education (*without*). A common type of professional education in Germany is company-based vocational training (*vocational training*). The German apprenticeship system is a dual system. Apprentices are trained both in a vocational school and the firm and receive a certificate after completing their training. Having completed vocational training serves as reference category in the regressions. After completing vocational training further education is provided by professional schools. In those schools craftsmen or technicians get further training. A certificate issued after passing master craftsman exams is required in some professions in order to establish a business or to train apprentices (*master craftsman*). Higher education at universities is captured by two dummy variables. *University degree* denotes that the highest educational degree of the founder is a university degree which is comparable to a bachelor's or master's degree. *PhD* denotes that the founder has additionally completed postgraduate or postdoctoral studies afterwards.

Table 2: Descriptive statistics of the variables included in the estimations

Variable	Description
Dependent variables	
S_H	Share of high-skilled employees
S_L	Share of medium-skilled employees
Independent variables	
$Log(\frac{H}{M})$	Logarithm of $\left(\frac{\text{labor costs high-skilled}}{\text{labor costs medium-skilled}}\right)$
$Log(\frac{L}{M})$	Logarithm of $\left(\frac{\text{labor costs low-skilled}}{\text{labor costs medium-skilled}}\right)$
$Log(L_{2007})$	Logarithm of the number of employees (with founders)
$Log(K)$	Logarithm of firm's capital stock
Miss $log(K)$	Missing capital stock
<i>Human Capital - professional experience</i>	
Log(industry exp.)	Logarithm of years of experience in the same industry
Entr. exp. (n. s.)	Entrepreneurial experience (not successful). The founder's previous business has become insolvent or has been liquidated.
Entr. exp. (s.)	Entrepreneurial experience (successful). The entrepreneur's previous business still exists.
<i>Human Capital - highest educational degree</i>	
Without	No professional education
Vocational training	Completed vocational training
Master craftsman	Completed professional school, e.g. master craftsman's diploma
University degree	Completed higher education, university or university of applied science
Ph.D.	Completed postgraduate/postdoctoral education
R&D	Firm is conducting R&D continuously.
Team	Firm was founded by a team of founders.
Het. educ. degr.	Founders have different educational degrees.
<i>Year of foundation</i>	
Founded 2006	Firm started operations in 2005.
Founded 2006	Firm started operations in 2006.
Founded 2007	Firm started operations in 2007.
<i>Industry</i>	
High-tech manuf.	Industry: High-tech manufacturing
Software	Industry: Software
Techn.-int. serv.	Industry: Technology-intensive services
Knowl.-int serv.	Industry: Knowledge-intensive services
Low-tech manuf.	Industry: Low-tech manufacturing
Busin.-related serv.	Industry: Business-related services
Cons.-related serv.	Industry: Consumer-related services
Construction	Industry: Construction
Retail and wholesale	Industry: Retail and wholesale

Table 3: Descriptive statistics of the variables included in the estimations

Variable	Mean	Std. dev.
Dependent variables		
S_H	0.125	0.296
S_L	0.282	0.403
Independent variables		
$Log(\frac{H}{M})$	0.569	0.117
$Log(\frac{L}{M})$	-0.326	0.160
$Log(L_{2007})$	1.548	0.745
$Log(K)$	10.586	3.173
Miss $log(K)$	0.132	0.338
<i>Human Capital - professional experience</i>		
Log(industry exp.)	2.329	1.700
Entr. exp. (n. s.)	0.123	0.329
Entr. exp. (s.)	0.253	0.435
<i>Human Capital - highest educational degree</i>		
Without	0.028	0.166
Vocational training	0.315	0.464
Master craftsman	0.261	0.439
University degree	0.360	0.480
Ph.D.	0.036	0.187
R&D	0.171	0.377
Team	0.310	0.463
Het. educ. degr.	0.093	0.291
<i>Year of foundation</i>		
Founded 2005	0.352	0.478
Founded 2006	0.353	0.478
Founded 2007	0.295	0.456
<i>Industry</i>		
High-tech manuf.	0.131	0.338
Software	0.155	0.362
Techn.-int. serv.	0.070	0.255
Knowl.-int serv.	0.062	0.240
Low-tech manuf.	0.130	0.336
Busin.-related serv.	0.060	0.237
Cons.-related serv.	0.132	0.339
Construction	0.116	0.320
Retail and wholesale	0.145	0.352

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

As a proxy for the stock of knowledge capital a dummy variable is used which indicates if the start-up is conducting research and development (R&D) continuously. If a firm claims to conduct R&D continuously, one can expect that the firm has accumulated a larger stock of knowledge capital than firms which do not conduct any R&D activities or only conduct R&D infrequently. The hypothesis of a skill-biased technological change is tested for newly established firms by means of including this dummy variable.

Furthermore, a set of control variables is included in the regressions which are also expected to affect the structure of the workforce in young firms. In order to capture differences in heterogeneous labor demand between foundations of a single person and team foundations, I include a dummy variable which indicates if the start-up was established by a team of founders (*team*). Because of financial pooling, teams should be less financially restricted. Furthermore, ability pooling is expected to take place in case of team foundations. Founders skills are expected to show up more breadth. According to the theory of Lazear (2004) a more general skill-profile is expected to result in higher profits. But higher expected profits should likewise also affect a firm's heterogeneous labor demand. Heterogeneity of the founders is explicitly captured by a dummy variable which indicates if there are several educational degrees within the team of founders (*het. educ. degr.*). Furthermore, I control for the year of foundation and the industry. For the hurdle and double-hurdle models the same set of regressors is chosen for each stage, i.e. $\mathbf{x}_i = \mathbf{z}_i$.

Firm size, industry and the year of foundation are chosen as variables potentially determining the heteroscedasticity. Wald tests on joint significance of these variables are performed in order to test the null hypothesis of homoscedasticity.

4.3 Estimation results

First, the model specification is examined. Heteroscedastic estimation of all models are conducted and joint significance of the variables explaining the heteroscedasticity is tested. Results of the Wald tests are presented in Table 4. It turns out that homoscedasticity can be rejected for both the share of high-skilled employees and the share of low-skilled employees in all models

under examinations. Therefore, I stay with heteroscedastic estimation.

Table 4: Wald test on joint significance of variables included in \mathbf{w}_i

Model	high-skilled		low-skilled	
	Test value $\chi^2(11)$	p-value	Test value $\chi^2(11)$	p-value
Tobit	100.94	[0.000]	277.25	[0.000]
P-Tobit	368.01	[0.000]	52.80	[0.000]
Hurdle (Trunc. normal)	68.04	[0.000]	203.32	[0.000]
Hurdle (Log-linear)	410.85	[0.000]	133.94	[0.000]
Box-Cox hurdle	111.69	[0.000]	42.85	[0.000]
Double-hurdle	58.09	[0.000]	86.35	[0.000]
Box-Cox double-hurdle	49.99	[0.000]	91.59	[0.000]

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

In order to assess the need of logarithmic transformation of the dependent variable, Box-Cox regressions have been made. Estimates of the parameter λ are presented in Table 5. Furthermore, Wald tests of the null hypothesis $\lambda = 0$ (logarithmic transformation) and $\lambda = 1$ (linear model) have been conducted. The null hypothesis of $\lambda = 0$ can be rejected for both the hurdle model and the double-hurdle model. Accordingly, the null hypothesis of $\lambda = 1$ cannot be rejected in case of low-skilled workers in the hurdle model and in case of high-skilled workers in the double-hurdle model. However, $\lambda = 1$ can be rejected on the 10 percent significance level in case of high-skilled workers in the hurdle model and even on the 5 percent significance level in case of low-skilled workers in the double-hurdle model. All in all, there seems to be no need of logarithmic transformation. Therefore, a truncated normal regression as second stage is preferred to a log-linear regression as second stage in the hurdle model. Similarly, the dependent variables have not been transformed in the double-hurdle model. Full results of the Box-Cox hurdle model and the Box-Cox double-hurdle model can be found in Tables 14 and 15 and Table 17 in the Appendix.

Table 6 displays the results of the specification tests. Likelihood-ratio tests indicate that the P-Tobit is preferred to the Tobit model and that the double-hurdle model is preferred to both the Tobit and the P-Tobit model. Furthermore, the hurdle model is preferred to the Tobit model. The tests for non-nested models (Vuong and Clarke tests) show that the hurdle model with truncated-normal regression as second stage is also preferred to the P-Tobit model. However, there is no clear sign whether to prefer either the double-

Table 5: Results of the Box-Cox models - estimates of λ and Wald tests

Model	high-skilled		low-skilled	
	Test-value ($\chi^2(1)$)	P-value	Test-value ($\chi^2(1)$)	P-value
Box-Cox Hurdle	$\hat{\lambda} = 0.629$		$\hat{\lambda} = 0.893$	
H0: $\lambda = 0$	8.13	[0.004]	16.99	[0.000]
H0: $\lambda = 1$	2.82	[0.093]	0.24	[0.621]
Box-Cox Double-Hurdle	$\hat{\lambda} = 1.201$		$\hat{\lambda} = 1.433$	
H0: $\lambda = 0$	18.92	[0.000]	68.50	[0.000]
H0: $\lambda = 1$	0.53	[0.467]	6.25	[0.012]

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

hurdle or the hurdle-model. In case of the share of high-skilled employees the double-hurdle model seems to be preferred while in case of low-skilled employees the hurdle model performs better. Therefore, both the estimation results of the hurdle model with truncated normal regression as second stage and the results of the double-hurdle model are presented below. Estimation results for the Tobit, the P-Tobit, the hurdle models with logarithmic and Box-Cox transformation and for the Box-Cox double-hurdle can be found in the Appendix.

Table 6: Specification tests - results

Model	Test type	high-skilled		low-skilled	
		Test value	P-value	Test value	P-value
P-Tobit vs. Tobit	LR	32.3	[0.000]	690.0	[0.000]
Double-hurdle vs. Tobit	adj. LR	500.1	[0.000]	1101.6	[0.000]
Double-hurdle vs. P-Tobit	adj. LR	468.8	[0.000]	412.5	[0.000]
Hurdle vs. Tobit	adj. LR	482.7	[0.000]	1176.8	[0.000]
Hurdle vs. P-Tobit	Vuong	13.1	[0.000]	12.0	[0.000]
	Clarke	2106	[0.000]	1938	[0.000]
Double-hurdle vs. hurdle	Vuong	1.6	[0.060]	-4.4	[1.000]
	Clarke	1638	[0.000]	1444	[0.968]
Hurdle vs. double-hurdle	Vuong	-1.6	[0.940]	4.4	[0.000]
	Clarke	1350	[1.000]	1544	[0.035]

Notes: [0.000] indicates that the first model is preferred, e.g. P-Tobit is preferred to Tobit.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Let us now have a look on the estimation results of the hurdle and double-hurdle models. The estimated coefficients can be found in Table 7 for the hurdle model and in Table 8 for the double-hurdle models.

In case of separable hurdle models the probability is estimated to employ at least one high-skilled (low-skilled) employee using probit regressions in the first hurdle. The second hurdle estimates the share of high-skilled (low-skilled) employees given that the firm employs at least one high-skilled (low-skilled) employee using a truncated normal regression. Interpretation of the coefficients on their own is limited. However, at least the direction of the effect in the Probit part can be seen immediately from the corresponding coefficient's sign. Furthermore, for variables which are included in both the second stage equation and the heteroscedastic equation, the marginal effects on the conditional mean may not be directly related to the corresponding coefficient in the second stage (Yen and Su, 1995). Interpretation of the coefficients of the double-hurdle model is even more difficult since the model is not separable and both the first and the second hurdle determine the probability of a positive outcome of the dependent variable. Marginal effects have to be calculated.

Table 7: Two-step hurdle model of heterogeneous labor demand

	Share of high-skilled employees			Share of low-skilled employees				
	Probit		Trunc. Reg.	Probit		Trunc. Reg.		
	coeff.	se	coeff.	se	coeff.	se		
$\text{Log}(\frac{H}{N})$	-0.785*	(0.427)	0.195	(0.196)	0.762	(0.501)	0.000	(0.073)
$\text{Log}(\frac{M}{N})$	-0.578*	(0.347)	-0.127	(0.139)	0.542*	(0.318)	0.043	(0.052)
$\text{Log}(L_{2007})$	0.358***	(0.068)	-0.335***	(0.090)	0.373***	(0.041)	-0.413***	(0.051)
$\text{Log}(K)$	0.022*	(0.012)	-0.005	(0.004)	-0.022**	(0.010)	-0.002	(0.002)
Miss $\text{log}(K)$	0.180	(0.176)	-0.051	(0.048)	-0.347***	(0.113)	-0.027	(0.022)
<i>Human Capital - professional experience</i>								
Log(industry exp.)	0.059**	(0.025)	-0.008	(0.015)	-0.057***	(0.015)	-0.005	(0.004)
Entr. exp. (n. s.)	0.120*	(0.063)	0.005	(0.025)	0.040	(0.063)	-0.031	(0.027)
Entr. exp. (s.)	0.151***	(0.056)	0.007	(0.027)	-0.098	(0.063)	-0.007	(0.018)
<i>Human Capital - highest educational degree⁽¹⁾</i>								
Without	-0.438*	(0.226)	0.073	(0.185)	0.477***	(0.151)	0.046**	(0.021)
Master craftsman	-0.246**	(0.113)	0.045	(0.056)	-0.285***	(0.079)	-0.037*	(0.020)
University degree	0.646***	(0.102)	0.097	(0.062)	-0.392***	(0.071)	-0.051***	(0.016)
Ph.D.	1.002***	(0.147)	0.167**	(0.066)	-0.562***	(0.142)	-0.125***	(0.047)
R&D	0.543***	(0.079)	0.059**	(0.023)	-0.155**	(0.062)	-0.002	(0.021)
Team	0.092	(0.092)	0.141***	(0.054)	-0.269***	(0.066)	0.095***	(0.027)
Het. educ. degr.	-0.239*	(0.127)	-0.100**	(0.045)	0.136	(0.087)	0.081**	(0.037)
<i>Year of foundation⁽²⁾</i>								
Founded 2006	-0.006	(0.073)	-0.000	(0.026)	-0.028	(0.052)	0.027	(0.018)
Founded 2007	-0.054	(0.082)	-0.026	(0.033)	-0.134**	(0.057)	0.003	(0.018)
<i>Industry⁽³⁾</i>								
Techn.-int. serv.	0.728***	(0.106)	0.077	(0.078)	-0.288**	(0.134)	-0.039**	(0.020)
Software	0.716***	(0.135)	0.127	(0.092)	-0.118	(0.160)	-0.077***	(0.024)
Knowl.-int. serv.	0.881***	(0.125)	0.041	(0.092)	-0.546**	(0.217)	-0.009	(0.024)
Low-tech manuf.	0.158	(0.110)	-0.070	(0.079)	-0.144	(0.136)	0.005	(0.032)
Busin.-rel. serv.	0.341**	(0.162)	0.090	(0.082)	0.137	(0.169)	-0.011	(0.036)
Cons.-rel. serv.	-0.255*	(0.152)	0.006	(0.103)	0.170	(0.181)	0.039*	(0.021)
Construction	0.063	(0.172)	0.004	(0.072)	-0.282*	(0.146)	-0.081***	(0.018)
Constant	-2.460***	(0.291)	0.922***	(0.254)	-0.227	(0.337)	1.366***	(0.075)
σ_{ϵ}								
Wald test on joint sign. of var. in \mathbf{w}_i ($\chi^2(11)$)	68.04*** [0.000]							
$\text{Log}(\sigma)$	-2.163*** (0.372)							
ll	-1037							
Observations	2988							
	-1732							
	2988							
	203.32*** [0.000]							
	-2.486*** (0.118)							

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.
Source: KIW/ZEW Start-Up Panel 2008, author's calculations.

Table 8: Double-hurdle model of heterogeneous labor demand

	Share of high-skilled employees		Share of low-skilled employees	
	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
	coeff.	se	coeff.	se
$\text{Log}(\frac{H}{N})$	-0.710	(0.459)	0.175	(0.182)
$\text{Log}(\frac{L}{N})$	-0.425	(0.367)	-0.211	(0.128)
$\text{Log}(L_{2007})$	0.612***	(0.062)	-0.293***	(0.048)
$\text{Log}(K)$	0.020*	(0.012)	-0.004	(0.004)
Miss $\text{log}(K)$	0.156	(0.179)	-0.052	(0.052)
<i>Human Capital - professional experience</i>				
Log(industry exp.)	0.068***	(0.026)	-0.007	(0.013)
Entr. exp. (n. s.)	0.132**	(0.066)	-0.003	(0.026)
Entr. exp. (s.)	0.144**	(0.058)	0.016	(0.025)
<i>Human Capital - highest educational degree⁽¹⁾</i>				
Without	-0.516**	(0.241)	0.084	(0.169)
Master craftsman	-0.278**	(0.113)	0.037	(0.052)
University degree	0.642***	(0.112)	0.110*	(0.057)
Ph.D.	1.051***	(0.159)	0.171***	(0.058)
R&D	0.518***	(0.078)	0.069***	(0.024)
Team	-0.003	(0.090)	0.119***	(0.036)
Het. educ. degr.	-0.246*	(0.131)	-0.092**	(0.040)
<i>Year of foundation⁽²⁾</i>				
Founded 2006	-0.012	(0.075)	0.003	(0.026)
Founded 2007	-0.022	(0.089)	-0.041	(0.029)
<i>Industry⁽³⁾</i>				
HT manuf.	0.501***	(0.138)	0.085	(0.093)
Techn.-int. serv.	0.770***	(0.121)	0.099	(0.086)
Software	0.777***	(0.145)	0.136	(0.093)
Knowl.-int. serv.	0.883***	(0.143)	0.064	(0.102)
Low-tech manuf.	0.208*	(0.115)	-0.049	(0.090)
Busin.-rel. serv.	0.484**	(0.196)	0.078	(0.091)
Cons.-rel. serv.	-0.243	(0.160)	-0.035	(0.114)
Construction	0.043	(0.185)	0.031	(0.086)
Constant	-2.778***	(0.266)	0.819***	(0.200)
σ_i				
Wald test on joint sign. of var. in \mathbf{w}_i ($\chi^2(11)$)		58.09***	[0.000]	
Log(σ)		-1.906***	(0.251)	
II		-1028		
Observations		2988		
			86.35***	[0.000]
			-2.392***	(0.137)
			-1769	
			2988	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.
Source: KIW/ZEW Start-Up Panel 2008, author's calculations.

When interpreting the results, one can distinguish three possible effects: the effect of a variable on the probability to employ at least one person of the respective skill-group ($\frac{\partial P(y>0)}{\partial x_j}$), the conditional effect of a variable on the share of workers in a certain skill-group given the firm employs at least one person in this skill-group ($\frac{\partial E(y|y>0)}{\partial x_j}$) and the unconditional effect of a variable on the share of workers in a certain skill-group ($\frac{\partial E(y)}{\partial x_j}$). Since I chose the same set of regressors in each stage ($\mathbf{x}_i = \mathbf{z}_i$), the probability of a non-zero outcome in the hurdle model is given by

$$P^H(y_i > 0|\mathbf{x}_i) = \Phi(\mathbf{x}'_i\boldsymbol{\gamma}).$$

Likewise, the probability for positive outcomes in the double-hurdle model is given by

$$P^{DH}(y_i > 0|\mathbf{x}_i) = \Phi(\mathbf{x}'_i\boldsymbol{\gamma}) \cdot \Phi(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i).$$

In both the hurdle and the double-hurdle model the conditional mean of y_i is given by

$$E^H(y_i|y_i > 0, \mathbf{x}_i) = E^{DH}(y_i|y_i > 0, \mathbf{x}_i) = \mathbf{x}'_i\boldsymbol{\beta} + \sigma_i \cdot \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i),$$

where $\lambda(c)$ denotes the inverse Mills ratio $\lambda(c) = \phi(c)/\Phi(c)$.

Accordingly, the unconditional mean of y_i of the hurdle model is

$$E^H(y_i|\mathbf{x}_i) = \Phi(\mathbf{x}'_i\boldsymbol{\gamma}) \left[\mathbf{x}'_i\boldsymbol{\beta} + \sigma_i \cdot \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \right],$$

while it is

$$E^{DH}(y_i|\mathbf{x}_i) = \Phi(\mathbf{x}'_i\boldsymbol{\gamma}) \cdot \Phi(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \left[\mathbf{x}'_i\boldsymbol{\beta} + \sigma_i \cdot \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \right]$$

in case of the double-hurdle model.

For continuous variables, marginal effects are obtained by differentiating expected outcomes. The marginal effect on the probability to employ a

person of the respective skill-group is calculated as follows

$$\frac{\partial P^H(y_i > 0|\mathbf{x}_i)}{\partial x_{ij}} = \phi(\mathbf{x}'_i\boldsymbol{\gamma})\gamma_j.$$

The conditional effect of a continuous variable on the share of workers in a certain skill-group given the firm employs at least one person in this skill-group amounts to

$$\begin{aligned} \frac{\partial E^H(y_i|y_i > 0, \mathbf{x}_i)}{\partial x_{ij}} &= \beta_j + \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\frac{\partial\sigma_i}{\partial x_{ij}} - \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \left[\beta_j - (\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\frac{\partial\sigma_i}{\partial x_{ij}} \right] \\ &\quad \cdot \left[(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) + \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \right]. \end{aligned}$$

As in McDonald and Moffitt (1980) the unconditional marginal effect can be decomposed in two parts already derived above:

$$\begin{aligned} \frac{\partial E^H(y_i|\mathbf{x}_i)}{\partial x_{ij}} &= \frac{\partial P^H(y_i > 0|\mathbf{x}_i)}{\partial x_{ij}} \cdot E_H(y_i|y_i > 0, \mathbf{x}_i) \\ &\quad + P^H(y_i > 0|\mathbf{x}_i) \cdot \frac{\partial E_H(y_i|y_i > 0, \mathbf{x}_i)}{\partial x_{ij}} \end{aligned}$$

Similarly, marginal effects in the double-hurdle models are obtained:

$$\begin{aligned} \frac{\partial P^{DH}(y_i > 0|\mathbf{x}_i)}{\partial x_{ij}} &= \phi(\mathbf{x}'_i\boldsymbol{\gamma})\Phi(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\gamma_j \\ &\quad + \phi(\mathbf{x}'_i\boldsymbol{\gamma})\Phi(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\sigma_i^{-1} \cdot \left[\beta_j - (\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\frac{\partial\sigma_i}{\partial x_{ij}} \right] \\ \frac{\partial E^{DH}(y_i|y_i > 0, \mathbf{x}_i)}{\partial x_{ij}} &= \beta_j + \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\frac{\partial\sigma_i}{\partial x_{ij}} \\ &\quad - \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \left[\beta_j - (\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i)\frac{\partial\sigma_i}{\partial x_{ij}} \right] \cdot \left[(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) + \lambda(\mathbf{x}'_i\boldsymbol{\beta}/\sigma_i) \right] \\ \frac{\partial E^{DH}(y_i|\mathbf{x}_i)}{\partial x_{ij}} &= \frac{\partial P^{DH}(y_i > 0|\mathbf{x}_i)}{\partial x_{ij}} \cdot E^{DH}(y_i|y_i > 0, \mathbf{x}_i) \\ &\quad + P^{DH}(y_i > 0|\mathbf{x}_i) \cdot \frac{\partial E^{DH}(y_i|y_i > 0, \mathbf{x}_i)}{\partial x_{ij}} \end{aligned}$$

For variables not included in the heteroscedastic equation $\partial\sigma_i/\partial x_{ij} = 0$ and the expressions can be simplified accordingly.

Discrete differences for both the hurdle and the double-hurdle model are calculated in case of factor variables. This is the discrete change in $P(y_i > 0)$,

$E(y_i|y_i > 0)$ and $E(y_i)$ when the value of the variable shifts from zero to one, holding all the other variables constant.

$$\begin{aligned}\frac{dP(y_i > 0)}{dx_{ij}} &= P(y_i > 0|x_{ij} = 1, \mathbf{x}_i) - P(y_i > 0|x_{ij} = 0, \mathbf{x}_i) \\ \frac{dE(y_i|y_i > 0)}{dx_{ij}} &= E(y_i|y_i > 0, x_{ij} = 1, \mathbf{x}_i) - E(y_i|y_i > 0, x_{ij} = 0, \mathbf{x}_i) \\ \frac{dE(y_i)}{dx_{ij}} &= E(y_i|x_{ij} = 1, \mathbf{x}_i) - E(y_i|x_{ij} = 0, \mathbf{x}_i)\end{aligned}$$

Marginal effects and discrete differences are obtained at the mean of the explanatory variables. Standard errors are calculated using the delta method, a common approximation appropriate in large samples. Results for the hurdle models are presented in Tables 9 and 10. Marginal effects for the double-hurdle models can be found in Tables 11 and 12

All in all, the effects do not substantially differ between the hurdle and the double-hurdle model. With respect to the relative wage of high-skilled workers ($\log(\frac{H}{M})$), I find a small negative and weakly significant effect on the probability to employ high-skilled workers. This is consistent with traditional microeconomic theory. If the wage level of high-skilled workers increases relative to that of medium-skilled workers, the probability to employ high-skilled workers decreases. However, the relative wage seems to have no effect on the conditional and unconditional mean of the share of high-skilled workers. The effect is also not present in case of the double-hurdle model or the share of low-skilled workers as dependent variable.

The relative wage of low-skilled workers ($\log(\frac{L}{M})$) is found to negatively affect the probability to employ high-skilled workers and the unconditional mean of the share of high-skilled workers. The other way around, it affects the probability to employ low-skilled workers and the unconditional mean of low-skilled workers positively. This seems to be counterintuitive at a first view but might be an indication of complex complementarities between high-skilled, medium-skilled and low-skilled workers. This effect is not robust, since the marginal effect in the double-hurdle model turns out not to be significantly different from zero.

Firm size ($\log(L_{2007})$) has in all models a positive impact both on the probability to employ at least one high-skilled worker and on the probability to employ at least one low-skilled worker. However, in the second hurdle, both

the share of high-educated workers and the share of low-educated workers are negatively correlated with firm size. This indicates that as firm size increases, the probability to employ at least one person of a specific skill group increases for all skill groups, but most of the jobs created when firm size increases require a medium level of education.

The coefficient concerning the physical capital stock ($\log(K)$) of the firm is consistent with the hypothesis of capital skill complementarity (Griliches, 1969). For the share of high-skilled employees a higher capital stock is related to a higher probability of employing high-skilled workers in both the hurdle model and the double-hurdle model. But no significant effect can be observed on the conditional or unconditional mean of the share of high-skilled workers. Furthermore, the effect on the probability to employ high-skilled workers is rather small in size.

For the share of low-skilled employees, I find a negative effect of the capital stock on the probability to employ low-skilled workers and on the unconditional mean of the share of low-skilled workers in both the hurdle and the double-hurdle model. The size of the effect does not differ much between the hurdle and the double-hurdle model. As for high-skilled worker, the effect is rather small in size. Putting these effects together, there seems to be an indication of capital-skill complementarity in young firms. However, the capital-skill complementarity seems to be not that important in determining the skill-structure of jobs created by new firms.

Table 9: Marginal effects of the hurdle model (share of high-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$\text{Log}(\frac{H}{M})$	-0.074	(0.056)	0.188	(0.189)	-0.157*	(0.085)
$\text{Log}(\frac{L}{M})$	-0.085*	(0.049)	-0.122	(0.134)	-0.116*	(0.070)
$\text{Log}(L_{2007})$	0.007	(0.015)	-0.312***	(0.084)	0.072***	(0.014)
$\text{Log}(K)$	0.002	(0.002)	-0.005	(0.004)	0.004*	(0.002)
<i>Human Capital - professional experience</i>						
Log(industry exp.)	0.006**	(0.003)	-0.008	(0.015)	0.012**	(0.005)
Entr. exp. (n. s.)	0.019*	(0.010)	0.002	(0.012)	0.025*	(0.014)
Entr. exp. (s.)	0.023***	(0.009)	0.003	(0.011)	0.032**	(0.012)
<i>Human Capital - highest educational degree⁽¹⁾</i>						
Without	-0.046**	(0.021)	0.040	(0.110)	-0.068***	(0.026)
Master craftsman	-0.031**	(0.015)	0.020	(0.026)	-0.046**	(0.020)
University degree	0.109***	(0.020)	0.041	(0.029)	0.144***	(0.025)
Ph.D.	0.258***	(0.047)	0.100**	(0.046)	0.304***	(0.056)
R&D	0.100***	(0.017)	0.029**	(0.012)	0.132***	(0.023)
Team	0.022	(0.017)	0.066**	(0.029)	0.019	(0.019)
Het. educ. degr.	-0.041**	(0.019)	-0.046**	(0.019)	-0.046**	(0.023)
<i>Year of foundation⁽²⁾</i>						
Founded in 2006	-0.001	(0.011)	-0.001	(0.011)	-0.001	(0.014)
Founded in 2007	-0.008	(0.011)	-0.002	(0.014)	-0.011	(0.016)
<i>Industry⁽³⁾</i>						
HT manuf.	0.099***	(0.024)	0.031	(0.047)	0.130***	(0.037)
Tech.-int. services	0.149***	(0.023)	0.055	(0.041)	0.189***	(0.033)
Software	0.162***	(0.036)	0.076	(0.056)	0.195***	(0.046)
Knowl.-int services	0.192***	(0.033)	0.029	(0.051)	0.254***	(0.046)
Low-tech manuf.	0.020	(0.017)	-0.026	(0.029)	0.034	(0.025)
Busin.-rel. serv.	0.071**	(0.034)	0.070*	(0.041)	0.081*	(0.044)
Cons.-rel. serv.	-0.031*	(0.018)	0.020	(0.052)	-0.046*	(0.024)
Construction	0.009	(0.024)	-0.005	(0.039)	0.013	(0.036)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 10: Marginal effects of the hurdle model (share of low-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$\text{Log}(\frac{H}{M})$	0.190	(0.142)	0.000	(0.071)	0.291	(0.191)
$\text{Log}(\frac{L}{M})$	0.151*	(0.084)	0.042	(0.051)	0.207*	(0.121)
$\text{Log}(L_{2007})$	-0.055**	(0.025)	-0.390***	(0.049)	0.142***	(0.016)
$\text{Log}(K)$	-0.006**	(0.003)	-0.002	(0.002)	-0.008**	(0.004)
<i>Human Capital - professional experience</i>						
Log(industry exp.)	-0.016***	(0.004)	-0.005	(0.004)	-0.022***	(0.006)
Entr. exp. (n. s.)	0.006	(0.017)	-0.015	(0.012)	0.015	(0.024)
Entr. exp. (s.)	-0.029	(0.019)	-0.003	(0.008)	-0.037	(0.024)
<i>Human Capital - highest educational degree⁽¹⁾</i>						
Without	0.156***	(0.046)	0.025**	(0.012)	0.188***	(0.059)
Master craftsman	-0.085***	(0.022)	-0.015*	(0.008)	-0.106***	(0.029)
University degree	-0.117***	(0.019)	-0.019***	(0.006)	-0.146***	(0.026)
Ph.D.	-0.155***	(0.028)	-0.056***	(0.018)	-0.190***	(0.040)
R&D	-0.044***	(0.017)	-0.001	(0.010)	-0.058**	(0.023)
Team	-0.061***	(0.019)	0.044***	(0.013)	-0.101***	(0.024)
Het. educ. degr.	0.056**	(0.027)	0.046**	(0.022)	0.049	(0.032)
<i>Year of foundation⁽²⁾</i>						
Founded in 2006	-0.004	(0.014)	0.011	(0.008)	-0.011	(0.020)
Founded in 2007	-0.037**	(0.016)	0.003	(0.008)	-0.050**	(0.021)
<i>Industry⁽³⁾</i>						
HT manuf.	-0.088***	(0.034)	-0.046***	(0.011)	-0.098**	(0.049)
Tech.-int. serv.	-0.087***	(0.034)	-0.023**	(0.011)	-0.106**	(0.047)
Software	-0.048	(0.042)	-0.041***	(0.012)	-0.044	(0.059)
Knowl.-int serv.	-0.142***	(0.049)	-0.002	(0.009)	-0.187***	(0.064)
Low-tech manuf.	-0.042	(0.039)	-0.003	(0.016)	-0.054	(0.050)
Busin.-rel. serv.	0.045	(0.050)	0.012	(0.016)	0.053	(0.066)
Cons.-rel. serv.	0.064	(0.056)	0.033***	(0.011)	0.066	(0.071)
Construction	-0.090**	(0.036)	-0.040***	(0.008)	-0.103**	(0.051)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 11: Marginal effects of the double-hurdle model (share of high-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$\text{Log}(\frac{H}{M})$	-0.067	(0.059)	0.167	(0.173)	-0.148	(0.097)
$\text{Log}(\frac{L}{M})$	-0.081	(0.052)	-0.200	(0.122)	-0.092	(0.078)
$\text{Log}(L_{2007})$	0.040***	(0.010)	-0.269***	(0.044)	0.124***	(0.013)
$\text{Log}(K)$	0.002	(0.002)	-0.004	(0.004)	0.004*	(0.002)
<i>Human Capital - professional experience</i>						
Log(industry exp.)	0.008**	(0.003)	-0.007	(0.012)	0.014***	(0.005)
Entr. exp. (n. s.)	0.015	(0.009)	-0.001	(0.012)	0.021*	(0.012)
Entr. exp. (s.)	0.020**	(0.008)	0.007	(0.011)	0.027**	(0.011)
<i>Human Capital - highest educational degree⁽¹⁾</i>						
Without	-0.036*	(0.018)	0.046	(0.101)	-0.053**	(0.022)
Master craftsman	-0.022	(0.015)	0.016	(0.024)	-0.034*	(0.019)
University degree	0.107***	(0.024)	0.047*	(0.027)	0.142***	(0.029)
Ph.D.	0.270***	(0.051)	0.102**	(0.041)	0.324***	(0.056)
R&D	0.089***	(0.016)	0.034***	(0.013)	0.117***	(0.021)
Team	0.022	(0.015)	0.054***	(0.018)	0.023	(0.019)
Het. educ. degr.	-0.040***	(0.014)	-0.042**	(0.017)	-0.048***	(0.017)
<i>Year of foundation⁽²⁾</i>						
Founded in 2006	-0.001	(0.010)	-0.001	(0.011)	-0.001	(0.013)
Founded in 2007	-0.009	(0.009)	-0.006	(0.013)	-0.012	(0.013)
<i>Industry⁽³⁾</i>						
HT manuf.	0.093***	(0.026)	0.040	(0.054)	0.120***	(0.031)
Tech.-int. serv.	0.148***	(0.029)	0.057	(0.046)	0.190***	(0.031)
Software	0.175***	(0.044)	0.068	(0.060)	0.220***	(0.047)
Knowl.-int. serv.	0.168***	(0.046)	0.033	(0.056)	0.223***	(0.047)
Low-tech manuf.	0.013	(0.021)	-0.022	(0.035)	0.022	(0.026)
Busin.-rel. serv.	0.093**	(0.038)	0.056	(0.047)	0.115**	(0.047)
Cons.-rel. serv.	-0.027	(0.017)	0.001	(0.051)	-0.039*	(0.021)
Construction	0.010	(0.021)	0.003	(0.046)	0.014	(0.028)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 12: Marginal effects of the double-hurdle model (share of low-skilled workers)

Variable (x_j)	$\frac{\partial E(y)}{\partial x_j}$		$\frac{\partial E(y y>0)}{\partial x_j}$		$\frac{\partial P(y>0)}{\partial x_j}$	
$\text{Log}(\frac{H}{M})$	0.190	(0.158)	0.028	(0.071)	0.259	(0.204)
$\text{Log}(\frac{L}{M})$	0.159*	(0.093)	0.059	(0.054)	0.196	(0.126)
$\text{Log}(L_{2007})$	0.016	(0.021)	-0.329***	(0.045)	0.220***	(0.017)
$\text{Log}(K)$	-0.008**	(0.003)	-0.003	(0.002)	-0.010**	(0.004)
<i>Human Capital - professional experience</i>						
Log(industry exp.)	-0.017***	(0.004)	-0.007	(0.004)	-0.021***	(0.006)
Entr. exp. (n. s.)	-0.013	(0.017)	-0.014	(0.013)	-0.012	(0.019)
Entr. exp. (s.)	-0.030	(0.021)	-0.001	(0.009)	-0.037	(0.025)
<i>Human Capital - highest educational degree⁽¹⁾</i>						
Without	0.154***	(0.043)	0.024*	(0.012)	0.182***	(0.051)
Master craftsman	-0.092***	(0.022)	-0.017*	(0.009)	-0.111***	(0.026)
University degree	-0.127***	(0.017)	-0.023***	(0.006)	-0.154***	(0.021)
Ph.D.	-0.160***	(0.022)	-0.064***	(0.019)	-0.194***	(0.028)
R&D	-0.038**	(0.017)	-0.002	(0.010)	-0.047**	(0.020)
Team	-0.036*	(0.020)	0.038***	(0.013)	-0.060***	(0.023)
Het. educ. degr.	0.065**	(0.026)	0.044**	(0.021)	0.062**	(0.028)
<i>Year of foundation⁽²⁾</i>						
Founded in 2006	0.008	(0.016)	0.010	(0.007)	0.006	(0.019)
Founded in 2007	-0.031*	(0.017)	0.004	(0.008)	-0.041**	(0.021)
<i>Industry⁽³⁾</i>						
HT manuf.	-0.115***	(0.025)	-0.045***	(0.011)	-0.134***	(0.032)
Tech.-int. serv.	-0.083***	(0.028)	-0.016*	(0.010)	-0.101***	(0.037)
Software	-0.072**	(0.033)	-0.039***	(0.012)	-0.080*	(0.043)
Knowl.-int serv.	-0.118***	(0.044)	0.002	(0.009)	-0.151***	(0.055)
Low-tech manuf.	-0.036	(0.039)	-0.003	(0.014)	-0.045	(0.048)
Busin.-rel. serv.	0.042	(0.048)	0.018	(0.014)	0.046	(0.058)
Cons.-rel. serv.	0.066	(0.053)	0.034***	(0.010)	0.069	(0.065)
Construction	-0.109***	(0.026)	-0.035***	(0.008)	-0.130***	(0.035)

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, standard errors in parentheses. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Specific human capital has a significant influence on the employment structure within a newly established firm. The probability to employ high-skilled workers is larger for founders with longer industry experience. On the other hand, the probability to employ low-skilled workers becomes smaller as industry experience increases. Likewise, the unconditional mean of the share of high-skilled (low-skilled) workers is larger (smaller) the more industry experience a firm's founders have accumulated. But it turns out that the effect is very small in size.

Entrepreneurial experience is only found to have an influence on the demand for high-skilled employees and not on the demand for low-skilled employees. If a founder was successful as an entrepreneur, i.e. his previous business(es) still exist(s), the probability to employ high-skilled workers increases by 3 percentage points. Likewise, the unconditional share of high-skilled workers increases by about two percentage points. The size of the effect is very similar regardless the model used. Even if a founder has entrepreneurial experience which was not successful, i.e. the previous business(es) has (have) been either closed voluntary or become insolvent, the hurdle model predicts a higher share of high-skilled workers compared to founders who do not have any entrepreneurial experience. However, the positive effect of unsuccessful entrepreneurial experience on the skill-structure of new firms' employees is not robust when using the double-hurdle model.

The structure of jobs created in new firms is largely determined by the generic human capital as measured by the educational degree of the founders. As described in section 4.2, I can distinguish five different categories of formal education. Vocational training serves as point of reference. All effects are calculated as compared to firms which are established by founders with vocational training. Compared to firms founded by persons who completed vocational training, firms founded by persons without any professional training employ a smaller fraction of high-skilled workers. This effect is driven by their significantly lower probability of employing high-skilled workers (-7 percentage points). On the other hand, founders who have not completed any professional training have a significant higher demand for low-skilled workers. The probability to employ low-skilled workers is about 19 percentage points higher for founders without any professional training (as compared to founders with vocational training). Since the positive effect on the share of

low-skilled workers (16 percentage points) is so much higher than the negative effect on the share of high-skilled workers (-5 percentage points), a missing professional education negatively affects the demand not only for high-skilled, but also for medium-skilled workers.

Also firms founded by persons who completed professional school (*master craftsman*) are found to demand a lower share of high-skilled workers. But, unlike the badly educated founders, they also employ a lower fraction of low-skilled workers. This means that founders with a master's craftsman diploma rely, as compared to founders with vocational training, much more on the work of medium-skilled workers.

A university degree raises the probability of employing high-skilled workers by about 14 percentage points. Given these founders employ high-skilled workers, they also employ a significantly larger share of high-educated workers in case of the double-hurdle model⁴. All in all, the share of high-skilled workers is about 10 percentage points higher in start-ups of founders with a university degree. The effect is even larger if the founders have completed postgraduate studies. Compared to founders with vocational training their unconditional share of high-skilled workers is about 26 percentage points higher. On the other hand, founders with completed university studies have a lower probability of employing low-skilled workers. They also employ a smaller share of low-skilled workers than founders with vocational training given they employ at least one low-skilled person. The same effect is found for founders who completed postdoctoral studies (*Ph.D.*) and for founders who completed professional school (*master craftsman*). For founders who have completed a postdoctoral degree the effect is almost double the effect of master craftsmen (see Tables 10 and 12). Since shares add up to one, the effect of a university degree or a postgraduate degree on the demand for medium-skilled workers can be estimated by comparing the direction and size of the effect on the low-skilled and high-skilled workers. Since the effect of a university degree on the share of high-skilled workers and the effect of a university degree on the share of low-skilled workers are opposite in direction but approximately of equal size, having a university degree seems to have no influence on the share of medium skilled workers. This is not true in case of postgraduate studies. The effect of having completed postgraduate studies on the share of high-skilled workers (26 percentage points) in absolute values is much larger

⁴The conditional effect is insignificant in the hurdle model.

than the effect of postgraduate studies on the share of low-skilled workers (-16 percentage points). Hence, firms founded by persons who completed their doctoral studies employ also a smaller fraction of medium-skilled workers.

The hypothesis of a skill-biased technical change is fully supported for newly established firms. If a firm conducts R&D continuously, both the probability of employing high-skilled workers and the conditional share of high-skilled employees are positively affected. The probability to employ high-skilled workers increases by about 13 percentage points, the conditional share of high-skilled workers increases by 3 percentage points and the unconditional share of high-skilled workers increases by 10 percentage points. Furthermore, the probability of employing low-skilled workers is significantly lower in firms with continuous R&D (-6 percentage points). Accordingly, the unconditional share of low-skilled workers is smaller (-4 percentage points) in firms which conduct R&D continuously. When comparing the direction and the size of these two effects, not only low-skilled workers but also medium-skilled workers suffer from ongoing technological change. This result is in line with the results of Jacobebbinghaus and Zwick (2002) who investigated mature firms and find that technological change not only reduces relative demand for low-skilled workers, but also reduces relative demand for medium-skilled workers.

Let us now have a short look on the control variables. The team dummy has a positive influence on the conditional share of high-skilled workers. The probability of employing low-skilled workers is negatively related to the team dummy. However, there is a positive relationship of founding within a team of founders and the conditional share of low-skilled workers. The overall effect on the unconditional share of low-skilled workers is negative. Interestingly, if there is heterogeneity in the educational degrees of the founders within the team, demand for high-skilled workers is negatively affected. Both the probability of employing high-skilled workers and the conditional and unconditional share of high-skilled workers is lower if the firm is founded by persons who hold different educational degrees. On the other hand, relative demand for low-skilled workers is positively affected by the heterogeneity of educational degrees within the team of founders.

Firm age is not found to have an influence on the share of high-skilled workers. However, in the first year of their operations firms employ a smaller

fraction of low-skilled workers.

Not surprisingly, the structure of jobs differs largely between industries. Retail and wholesale firms serve as reference category. Firms operating in research- and knowledge intensive industries such as high-tech manufacturing, technology-intensive services, software and knowledge-intensive services employ a significantly larger share of high-skilled workers and a significantly smaller share of low-skilled workers. Consumer-related services employ less high-skilled workers than retail and wholesale firms. Relative demand for high-skilled workers is found to be significantly higher in business-related services as compared to retail and wholesale. Since the share of low-skilled workers is significantly lower in construction, these firm rely more on medium-skilled workers than retail and wholesale firms.

Comparing the hurdle and the double-hurdle model (Table 9 vs. Table 11 and Table 10 vs. 12), the results turn out to be rather robust regardless the corner solution model chosen. When comparing the sum of predicted shares ($\hat{S}_H + \hat{S}_L$), the double-hurdle model performs slightly better than the hurdle model. In the double-hurdle model, only one observation is predicted to employ more than 100 percent high- and low-skilled workers. But the sum of predictions exceeds 100 percent for 14 observations in the hurdle model. Figure 1 displays two histograms of the sum of predicted shares of the hurdle and double-hurdle model, respectively.

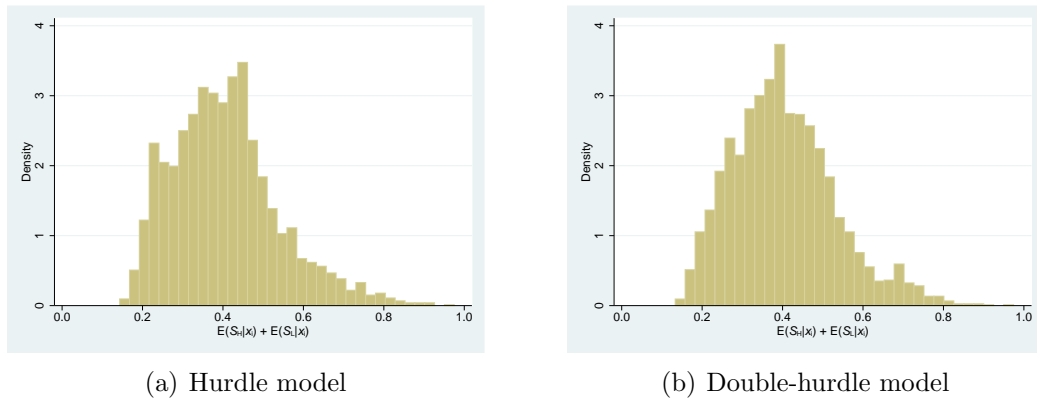


Figure 1: Sum of predicted shares ($\hat{S}_H + \hat{S}_L$) for the hurdle model (left) and the double-hurdle model (right)

Note: Observations with $\hat{S}_H + \hat{S}_L > 1$ are excluded.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

5 Conclusions

Skills and productive knowledge embodied in a person, commonly known as human capital, has been widely acknowledged in economics to be an important factor of production. In entrepreneurship research the human capital of the founders has been found to be a major predictor of young firms' survival and firm performance. Furthermore, labor demand is largely influenced by entrepreneurs' human capital when labor is treated as homogeneous.

In this paper, I investigate the effect of the specific and generic human capital of a firm's founders on heterogeneous labor demand of young firms. It turns out that the educational degree of the founders considerably determines the qualification structure of the workforce in young firms. The results suggest that both a high level of specific human capital and a high level of generic human capital are related to skill upgrading in young firms. Moreover, I find evidence that a skill-biased technical change is relevant even for very young firms. Skills and physical capital prove to be complements. However, this effect is rather small. Most of the effects turn out to be robust in all corner solution outcome models estimated. The study contributes to the literature by investigating heterogeneous labor demand of newly established firms and by introducing the concept of the importance of human capital into a framework of heterogeneous labor demand.

Two major issues when investigating heterogeneous labor demand, organizational change and internationalization, could not be addressed in this study. While organizational change is less relevant for young firms, further research might address the question of heterogeneous labor demand of "born globals".

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A Appendix

Table 13: Classification of research- and knowledge-intensive industries

NACE Rev. 1.1 (WZ 2003)	Description
Cutting edge technology industries	
23.30	Processing of nuclear fuel
24.20	Manufacture of pesticides and other agro-chemical products
24.41	Manufacture of basic pharmaceutical products
24.42	Manufacture of pharmaceutical preparations
29.60	Manufacture of weapons and ammunition
30.02	Manufacture of computers and other information processing equipment
32.10	Manufacture of electronic valves and tubes and other electronic components
32.20	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy
32.30	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods
33.10	Manufacture of medical and surgical equipment and orthopaedic appliances
33.20	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment
33.30	Manufacture of industrial process control equipment
35.30	Manufacture of aircraft and spacecraft
High technology industries	
24.13	Manufacture of other inorganic basic chemicals
24.14	Manufacture of other organic basic chemicals
24.16	Manufacture of plastics in primary forms
24.17	Manufacture of synthetic rubber in primary forms
24.51	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
24.61	Manufacture of explosives
24.63	Manufacture of essential oils
24.64	Manufacture of photographic chemical materials
24.66	Manufacture of other chemical products n.e.c.
25.11	Manufacture of rubber tyres and tubes
25.13	Manufacture of other rubber products
26.15	Manufacture of and processing of other glass, including technical glassware
29.11	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
29.12	Manufacture of pumps and compressors
29.13	Manufacture of taps and valves
29.14	Manufacture of bearings, gears, gearing and driving elements
29.24	Manufacture of other general purpose machinery n.e.c.
29.31	Manufacture of agricultural tractors
29.32	Manufacture of other agricultural and forestry machinery
29.41	Manufacture of portable hand held power tools

Continued on next page...

NACE Rev. 1.1 (WZ 2003)	Description
29.42	Manufacture of other metalworking machine tools
29.43	Manufacture of other machine tools n.e.c.
29.52	Manufacture of machinery for mining, quarrying and construction
29.53	Manufacture of machinery for food, beverage and tobacco processing
29.54	Manufacture of machinery for textile, apparel and leather production
29.55	Manufacture of machinery for paper and paperboard production
29.56	Manufacture of other special purpose machinery n.e.c.
30.01	Manufacture of office machinery
31.10	Manufacture of electric motors, generators and transformers
31.20	Manufacture of electricity distribution and control apparatus
31.40	Manufacture of accumulators, primary cells and primary batteries
31.50	Manufacture of lighting equipment and electric lamps
31.61	Manufacture of electrical equipment for engines and vehicles n.e.c.
31.62	Manufacture of other electrical equipment n.e.c.
33.40	Manufacture of optical instruments and photographic equipment
34.10	Manufacture of motor vehicles
34.30	Manufacture of parts and accessories for motor vehicles and their engines
35.20	Manufacture of railway and tramway locomotives and rolling stock
Technological services	
64.3	Telecommunications
72	Computer and related activities (72.2 Software consultancy and supply)
73.1	Research and experimental development on natural sciences and engineering
74.2	Architectural and engineering activities and related technical consultancy
74.3	Technical testing and analysis
Knowledge-intensive services	
73.2	Research and experimental development on social sciences and humanities
74.11	Legal activities
74.12	Accounting, book-keeping and auditing activities; tax consultancy
74.13	Market research and public opinion polling
74.14	Business and management consultancy activities
74.4	Advertising

Source: KfW/ZEW Start-Up Panel 2008 based on Legler and Frietsch (2006). Remark: Differentiation according to the classification NACE Rev. 1.1 of the Statistical Office of the European Communities.

Table 14: Hurdle models of heterogeneous labor demand (high-skilled employees)

	Share of high-skilled employees								
	(1) First stage		(2a) Second stage		(2c) Second stage				
	Probit		Truncated normal		Log-linear				
	coeff.	se	coeff.	se	coeff.	se			
$Log(\frac{H}{M})$	-0.785*	(0.427)	0.195	(0.196)	0.278	(0.200)	0.257	(0.165)	
$Log(\frac{L}{M})$	-0.578*	(0.347)	-0.127	(0.139)	-0.230	(0.184)	-0.180	(0.143)	
$Log(L_{2007})$	0.358**	(0.068)	-0.335***	(0.090)	-0.507***	(0.080)	-0.293***	(0.093)	
$Log(K)$	0.022*	(0.012)	-0.005	(0.004)	-0.005	(0.005)	-0.005	(0.004)	
Miss log(K)	0.180	(0.176)	-0.051	(0.048)	-0.069	(0.063)	-0.061	(0.055)	
<i>Human Capital - professional experience</i>									
Log(industry exp.)	0.059**	(0.025)	-0.008	(0.015)	-0.009	(0.022)	-0.007	(0.015)	
Entr. exp. (n. s.)	0.120*	(0.063)	0.005	(0.025)	0.024	(0.033)	0.008	(0.029)	
Entr. exp. (s.)	0.151***	(0.056)	0.007	(0.027)	0.022	(0.034)	0.011	(0.028)	
<i>Human Capital - highest educational degree⁽¹⁾</i>									
Without	-0.438*	(0.226)	0.073	(0.185)	0.112	(0.287)	0.128	(0.163)	
Master craftsman	-0.246**	(0.113)	0.045	(0.056)	0.076	(0.079)	0.044	(0.063)	
University degree	0.646***	(0.102)	0.097	(0.062)	0.146*	(0.083)	0.128**	(0.060)	
Ph.D.	1.002***	(0.147)	0.167**	(0.066)	0.233***	(0.088)	0.199***	(0.063)	
R&D	0.543***	(0.079)	0.059**	(0.023)	0.084**	(0.035)	0.071**	(0.030)	
Team	0.092	(0.092)	0.141***	(0.054)	0.207***	(0.065)	0.120**	(0.055)	
Het. educ. degr.	-0.239*	(0.127)	-0.100**	(0.045)	-0.135*	(0.076)	-0.110**	(0.055)	
Founded 2006	-0.006	(0.073)	-0.000	(0.026)	0.004	(0.036)	0.002	(0.029)	
Founded 2007	-0.054	(0.082)	-0.026	(0.033)	-0.044	(0.035)	-0.037	(0.029)	
<i>Industry⁽³⁾</i>									
HT manuf.	0.526***	(0.126)	0.053	(0.082)	0.060	(0.130)	0.076	(0.102)	
Techn.-int. serv.	0.728***	(0.106)	0.077	(0.078)	0.110	(0.116)	0.120	(0.093)	
Software	0.716***	(0.135)	0.127	(0.092)	0.159	(0.126)	0.170*	(0.101)	
Knowl.-int. serv.	0.881***	(0.125)	0.041	(0.092)	0.058	(0.131)	0.060	(0.104)	
Low-tech manuf.	0.158	(0.110)	-0.070	(0.079)	-0.137	(0.122)	-0.053	(0.095)	
Business-rel. serv.	0.341**	(0.162)	0.090	(0.082)	0.130	(0.117)	0.142	(0.094)	
Cons.-rel. serv.	-0.255*	(0.152)	0.006	(0.103)	-0.044	(0.161)	0.008	(0.113)	
Construction	0.063	(0.172)	0.004	(0.072)	-0.025	(0.125)	0.013	(0.094)	
Constant	-2.460***	(0.291)	0.922***	(0.254)	-0.135	(0.249)	-0.270	(0.192)	
σ_i	Wald test on joint sign. of var. in \mathbf{w}_i ($\chi^2(11)$)								
$Log(\sigma)$			68.04***	[0.000]	410.85***	[0.000]	111.69***	[0.000]	
λ			-2.163***	(0.372)	-1.843***	(0.175)	-1.721***	(0.166)	
							0.629***	(0.221)	
ll			-1037		-1086		-1056		
Observations			2988		2988		2988		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 15: Hurdle models of heterogeneous labor demand (low-skilled employees)

	Share of low-skilled employees								
	(1) First stage Probit		(2a) Second stage Truncated normal		(2b) Second stage Log-linear		(2c) Second stage Box-Cox		
	coef.	se	coef.	se	coef.	se	coef.	se	
$\text{Log}(\frac{H}{M})$	0.762	(0.501)	0.000	(0.073)	0.033	(0.092)	0.034	(0.082)	
$\text{Log}(\frac{L}{M})$	0.542*	(0.318)	0.043	(0.052)	0.090	(0.073)	0.059	(0.066)	
$\text{Log}(L_{2007})$	0.373***	(0.041)	-0.413***	(0.051)	-0.546***	(0.065)	-0.284***	(0.069)	
$\text{Log}(K)$	-0.022**	(0.010)	-0.002	(0.002)	-0.003	(0.002)	-0.004**	(0.002)	
Miss log(K)	-0.347***	(0.113)	-0.027	(0.022)	-0.046	(0.034)	-0.048*	(0.026)	
<i>Human Capital - professional experience</i>									
Log(industry exp.)	-0.057***	(0.015)	-0.005	(0.004)	-0.008	(0.006)	-0.008*	(0.004)	
Entr. exp. (n. s.)	0.040	(0.063)	-0.031	(0.027)	-0.042	(0.040)	-0.031	(0.030)	
Entr. exp. (s.)	-0.098	(0.063)	-0.007	(0.018)	-0.003	(0.027)	-0.004	(0.019)	
<i>Human Capital - highest educational degree⁽¹⁾</i>									
Without	0.477***	(0.151)	0.046**	(0.021)	0.058*	(0.031)	0.039	(0.025)	
Master craftsman	-0.285***	(0.079)	-0.037*	(0.020)	-0.051*	(0.029)	-0.048**	(0.024)	
University degree	-0.392***	(0.071)	-0.051***	(0.016)	-0.075***	(0.025)	-0.065***	(0.019)	
Ph.D.	-0.562***	(0.142)	-0.125***	(0.047)	-0.235**	(0.105)	-0.151***	(0.059)	
R&D	-0.155**	(0.062)	-0.002	(0.021)	-0.004	(0.028)	0.000	(0.020)	
Team	-0.269***	(0.066)	0.095***	(0.027)	0.136***	(0.037)	0.062**	(0.026)	
Het. educ. degr.	0.136	(0.087)	0.081**	(0.037)	0.095*	(0.054)	0.063*	(0.037)	
<i>Year of foundation⁽²⁾</i>									
Founded 2006	-0.028	(0.052)	0.027	(0.018)	0.038	(0.025)	0.033*	(0.019)	
Founded 2007	-0.134**	(0.057)	0.003	(0.018)	0.006	(0.023)	0.011	(0.018)	
<i>Industry⁽³⁾</i>									
HT manuf.	-0.266*	(0.139)	-0.108***	(0.035)	-0.159***	(0.051)	-0.132***	(0.041)	
Techn.-int. serv.	-0.288**	(0.134)	-0.039**	(0.020)	-0.050*	(0.027)	-0.051**	(0.022)	
Software	-0.118	(0.160)	-0.077***	(0.024)	-0.114***	(0.036)	-0.102***	(0.031)	
Knowl.-int. serv.	-0.546**	(0.217)	-0.009	(0.024)	-0.022	(0.037)	-0.014	(0.028)	
Low-tech manuf.	-0.144	(0.136)	0.005	(0.032)	-0.003	(0.045)	-0.004	(0.034)	
Bus.-rel. serv.	0.137	(0.169)	-0.011	(0.036)	-0.006	(0.048)	0.005	(0.037)	
Cons.-rel. serv.	0.170	(0.181)	0.039*	(0.021)	0.061**	(0.030)	0.047**	(0.024)	
Construction	-0.282*	(0.146)	-0.081***	(0.018)	-0.119***	(0.023)	-0.105***	(0.019)	
Constant	-0.227	(0.337)	1.366***	(0.075)	0.461***	(0.097)	0.246**	(0.096)	
σ_i	Wald test on joint sign. of var. in \mathbf{w}_i ($\chi^2(11)$)								
$\text{Log}(\sigma)$			203.32***	[0.000]	133.94***	[0.000]	42.85***	[0.000]	
λ			-2.486***	(0.118)	-2.226***	(0.139)	-2.178***	(0.150)	
ll			-1732		-1920		-1828		
Observations			2988		2988		2988		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 16: Tobit models of heterogeneous labor demand

	Share of high-skilled employees			Share of low-skilled employees		
	Tobit	P-Tobit	se	Tobit	P-Tobit	se
$Log(\frac{H}{N})$	-0.450	-0.010	(0.312)	0.467*	0.037	(0.283)
$Log(\frac{L}{N})$	-0.461*	-0.387	(0.279)	0.310	0.062	(0.218)
$Log(L_{2007})$	0.292***	0.042	(0.038)	0.222***	-0.299***	(0.025)
$Log(K)$	0.013	-0.002	(0.009)	-0.010	-0.003*	(0.006)
Miss $log(K)$	0.114	-0.056	(0.126)	-0.181**	-0.042*	(0.075)
<i>Human Capital - professional experience</i>						
Log(industry exp.)	0.041***	0.040**	(0.016)	-0.046***	-0.007*	(0.006)
Entr. exp. (n. s.)	0.081*	0.089	(0.049)	0.061	-0.029	(0.043)
Entr. exp. (s.)	0.101**	0.094	(0.041)	-0.055	-0.004	(0.036)
<i>Human Capital - highest educational degree⁽¹⁾</i>						
Without	-0.252	0.078	(0.185)	0.329***	0.039*	(0.088)
Master craftsman	-0.189**	-0.164*	(0.086)	-0.203***	-0.044*	(0.054)
University degree	0.542***	0.540***	(0.076)	-0.292***	-0.065***	(0.048)
Ph.D.	0.737***	0.634*	(0.091)	-0.425***	-0.166***	(0.093)
R&D	0.360***	0.219	(0.062)	-0.076**	-0.007	(0.039)
Log(team size)	0.101	0.052	(0.067)	-0.086**	0.061**	(0.035)
Het. educ. degr.	-0.230***	-0.169	(0.079)	0.135**	0.074**	(0.053)
<i>Year of foundation⁽²⁾</i>						
Founded 2006	0.100**	0.119***	(0.051)	-0.018	0.033*	(0.040)
Founded 2007	-0.046	0.011	(0.065)	-0.026	0.009	(0.042)
<i>Industry⁽³⁾</i>						
HT manuf.	0.378**	0.640	(0.187)	-0.218**	-0.132***	(0.104)
Techn.-int. serv.	0.576***	0.826	(0.180)	-0.369***	-0.049**	(0.110)
Software	0.559***	0.880**	(0.207)	-0.187*	-0.095***	(0.111)
Knowl.-int. serv.	0.601***	0.826	(0.182)	-0.486***	-0.019	(0.162)
Low-tech manuf.	-0.067	0.330	(0.208)	-0.094	-0.002	(0.113)
Busin.-rel. serv.	-0.374	0.254	(0.269)	0.036	0.004	(0.116)
Cons.-rel. serv.	-0.361	-0.141	(0.270)	0.200*	0.047**	(0.113)
Construction	0.100	0.187	(0.206)	-0.216	-0.099***	(0.132)
Constant	-1.978***	-1.245**	(0.287)	-0.152	1.258***	(0.215)
σ_i						
Wald test on joint sign. of var. in w_1 ($\chi^2(11)$)	100.94***	368.01***	[0.000]	277.25***	52.80***	[0.000]
$Log(\sigma)$	0.126	0.058	(0.125)	0.240***	-2.292***	(0.082)
p		0.502	(0.333)	0.402***		(0.026)
ll	-1291	-1275		-2333	-1988	
Observations	2988	2988		2988	2988	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

Table 17: Box-Cox double-hurdle model of heterogeneous labor demand

	Share of high-skilled employees			Share of low-skilled employees		
	Hurdle 1	Hurdle 2	se	Hurdle 1	Hurdle 2	se
$\text{Log}(\frac{H}{L})$	-0.721	0.173	(0.479)	0.638	0.025	(0.535)
$\text{Log}(\frac{L}{M})$	-0.344	-0.224*	(0.385)	0.508	0.051	(0.330)
$\text{Log}(L_{2007})$	0.689***	-0.264***	(0.117)	0.713***	-0.300***	(0.056)
$\text{Log}(K)$	0.021*	-0.005	(0.012)	-0.027**	-0.002	(0.012)
Miss $\log(K)$	0.160	-0.056	(0.186)	-0.415***	-0.030	(0.139)
<i>Human Capital - professional experience</i>						
Log(industry exp.)	0.071***	-0.007	(0.027)	-0.050***	-0.007*	(0.015)
Entr. exp. (n. s.)	0.140**	-0.007	(0.068)	0.017	-0.025	(0.072)
Entr. exp. (s.)	0.137**	0.017	(0.057)	-0.137*	-0.002	(0.071)
<i>Human Capital - highest educational degree⁽¹⁾</i>						
Without	-0.547**	0.083	(0.245)	0.483***	0.039**	(0.167)
Master craftsman	-0.291***	0.031	(0.111)	-0.319***	-0.036*	(0.081)
University degree	0.632***	0.109*	(0.115)	-0.393***	-0.058***	(0.078)
Ph.D.	1.051***	0.167***	(0.167)	-0.490***	-0.123***	(0.166)
R&D	0.510***	0.069***	(0.087)	-0.158**	-0.004	(0.075)
Team	-0.031	0.106**	(0.108)	-0.419***	0.069***	(0.086)
Het. educ. degr.	-0.244*	-0.087**	(0.133)	0.069	0.076**	(0.095)
<i>Year of foundation⁽²⁾</i>						
Founded 2006	-0.016	0.005	(0.078)	-0.069	0.030*	(0.056)
Founded 2007	-0.007	-0.046	(0.102)	-0.174***	0.009	(0.063)
<i>Industry⁽³⁾</i>						
HT manuf.	0.484***	0.093	(0.162)	-0.175	-0.123***	(0.157)
Techn.-int. serv.	0.776***	0.102	(0.135)	-0.255*	-0.042**	(0.143)
Software	0.786***	0.136	(0.155)	-0.082	-0.077***	(0.167)
Knowl.-int. serv.	0.889***	0.065	(0.159)	-0.542**	-0.012	(0.219)
Low-tech manuf.	0.229*	-0.041	(0.130)	-0.131	-0.005	(0.142)
Busin.-rel. serv.	0.517**	0.069	(0.210)	0.158	0.002	(0.179)
Cons.-rel. serv.	-0.215	-0.053	(0.180)	0.145	0.038**	(0.191)
Construction	0.025	0.043	(0.205)	-0.290*	-0.084***	(0.149)
Constant	-2.828***	-0.210	(0.279)	-0.429	0.260***	(0.348)
σ_i^2	Wald test on joint sign. of var. in \mathbf{w}_1 ($\chi^2(11)$)					
$\text{Log}(\sigma)$	49.99***	[0.000]		91.59***	[0.000]	
λ	-1.859***	(0.376)		-2.462***	(0.144)	
	1.201***	(0.276)		1.433***	(0.173)	
<i>Observations</i>						
II	1027			-1752		
	2988			2988		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered standard errors in parentheses, p-values in brackets. References: (1) vocational training; (2) founded 2005; (3) retail and wholesale.

Source: KfW/ZEW Start-Up Panel 2008, author's calculations.

A.1 Double-hurdle model

The d1-ml procedure in Stata makes use of analytical derivatives of the log-likelihood function. The first derivatives are given as follows:

$$\begin{aligned}\frac{\partial \log L}{\partial \boldsymbol{\gamma}} &= \sum_0 -\frac{\phi_1 \Phi_2}{1 - \Phi_1 \Phi_2} \mathbf{z}_i + \sum_+ \frac{\phi_1}{\Phi_1} \mathbf{z}_i \\ \frac{\partial \log L}{\partial \boldsymbol{\beta}} &= \sum_0 -\frac{1}{\sigma_i} \frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \mathbf{x}_i + \sum_+ \frac{1}{\sigma_i} \frac{y_i - \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \mathbf{x}_i \\ \frac{\partial \log L}{\partial \boldsymbol{\alpha}} &= \sum_0 \frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \cdot \frac{\mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \mathbf{w}_i + \sum_+ \left[\left(\frac{y_i - \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \right)^2 - 1 \right] \mathbf{w}_i,\end{aligned}$$

with $\phi_1 = \phi(\mathbf{z}_i' \boldsymbol{\gamma})$, $\phi_2 = \phi(\frac{\mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i})$, $\Phi_1 = \Phi(\mathbf{z}_i' \boldsymbol{\gamma})$, $\Phi_2 = \Phi(\frac{\mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i})$ and $\sigma_i = \sigma \cdot \exp(\mathbf{w}_i' \boldsymbol{\alpha})$.

A.2 The Box-Cox double-hurdle model

The Box-Cox hurdle model was first presented by Jones and Yen (2000) and is based on Cragg's (1971) double-hurdle model with the dependent variable transformed. Hence, compared to the double-hurdle model one more parameter, the transformation parameter λ has to be estimated. The transformation relaxes the normality assumption of unobserved errors on which the standard double-hurdle model is built. Similarly to Cragg's double-hurdle model the model is specified by two latent variables.

$$\begin{aligned}d_i^* &= \mathbf{z}_i' \boldsymbol{\gamma} + \epsilon_i, & \epsilon_i &\sim \mathcal{N}(0, 1), & i &= 1, 2, \dots, n, \\ y_i^* &= \mathbf{x}_i' \boldsymbol{\beta} + u_i, & u_i &\sim \mathcal{N}(0, \sigma^2), & i &= 1, 2, \dots, n,\end{aligned}$$

where u_i and ϵ_i are independently distributed.

The observed dependent variable is transformed as follows:

$$y_i^T = \begin{cases} \frac{y_i^\lambda - 1}{\lambda} & \text{if } \lambda \neq 0 \\ \ln(y_i) & \text{if } \lambda = 0 \end{cases}$$

The Box-Cox double-hurdle model is then given by

$$y_i^T = \begin{cases} y_i^* & \text{if } y_i^* > \frac{1}{\lambda} \text{ and } d_i^* > 0 \\ 0 & \text{if } y_i^* \leq \frac{1}{\lambda} \text{ or } d_i^* \leq 0, \end{cases}$$

and the log-likelihood of the Box-Cox double-hurdle model is

$$\begin{aligned} \text{Log}L &= \sum_0 \ln \left[1 - \Phi(z_i' \gamma) \Phi \left(\frac{\frac{1}{\lambda} + \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \right) \right] \\ &+ \sum_+ \ln \left[\Phi(z_i' \gamma) y_i^{\lambda-1} \frac{1}{\sigma_i} \phi \left(\frac{y_i^T - \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \right) \right]. \end{aligned}$$

The first order derivatives are derived analytically:

$$\begin{aligned} \frac{\partial \text{Log}L}{\partial \gamma} &= \sum_0 -\frac{\phi_1 \Phi_2}{1 - \Phi_1 \Phi_2} \mathbf{z}_i + \sum_+ \frac{\phi_1}{\Phi_1} \mathbf{z}_i \\ \frac{\partial \text{Log}L}{\partial \boldsymbol{\beta}} &= \sum_0 -\frac{1}{\sigma_i} \frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \mathbf{x}_i + \sum_+ \frac{1}{\sigma_i} \frac{y_i^T - \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \mathbf{x}_i \\ \frac{\partial \text{Log}L}{\partial \boldsymbol{\alpha}} &= \sum_0 \left[\frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \frac{\frac{1}{\lambda} + \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \right] \mathbf{w}_i + \sum_+ \left[\left(\frac{y_i^T - \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \right)^2 - 1 \right] \mathbf{w}_i \\ \frac{\partial \text{Log}L}{\partial \lambda} &= \sum_0 \frac{1}{\sigma_i \lambda^2} \frac{\phi_2 \Phi_1}{1 - \Phi_1 \Phi_2} \\ &+ \sum_+ \left[-\left(\frac{y_i^\lambda [\lambda \log(y_i) - 1] + 1}{\sigma_i \lambda^2} \right) \left(\frac{y_i^T - \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i} \right) + \log(y_i) \right], \end{aligned}$$

with $\phi_1 = \phi(\mathbf{z}_i' \boldsymbol{\gamma})$, $\phi_2 = \phi\left(\frac{\frac{1}{\lambda} + \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i}\right)$, $\Phi_1 = \Phi(\mathbf{z}_i' \boldsymbol{\gamma})$, $\Phi_2 = \Phi\left(\frac{\frac{1}{\lambda} + \mathbf{x}_i' \boldsymbol{\beta}}{\sigma_i}\right)$ and $\sigma_i = \sigma \cdot \exp(\mathbf{w}_i' \boldsymbol{\alpha})$.