Are Health Professionals Better Off in Foreign Industries? – On Inter-Industry Wage Differentials and Job-Related Ability*

Sofie J. Cabus[†]

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Abstract

This paper explores wage differentials of graduates in nursery, midwifery, or care, who have to make a choice of employment at the start of their career. We focus on the potential switch the respective graduates can make from the life sciences and health sector to other, foreign sectors, and its effect on wages. We theoretically embed this switch in the skill-weights approach of Lazaer (2009). The empirical strategy benefits from data on abilities necessary to perform in the job. Owing to iterative one-to-one matching, we make graduates homogenous with respect to their background characteristics and abilities. The results are in line with the model predictions of Lazaer: health professionals, who voluntary leave LSH, can earn significant higher wages of +2.33 percent.

Keywords: Health Professionals; Job Match; Nursery; Mobility; Wage Differentials;

Jel: I18; I21; I28; J23

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†Top Institute for Evidence Based Education Research, Maastricht University, Kapoenstraat 2, 6200 MD Maastricht, the Netherlands, s.cabus@maastrichtuniversity.nl.

1 Introduction

The chronic lack of employable workers in the life sciences and health industry[1], often referred to as recruitment bottlenecks, is worrisome, and will become problematic, as in most developed countries population ageing increasingly put stress on the demand for health care services (Hurd, 1973; Jones and Gates, 2004; Heitmueller and Inglis, 2007; Cedefop, 2010; Maestad et al., 2010; World Health Organization, 2011). The LSH industry may well suffer from bad image problems, relative to other industries, so that the industry is not able to attract individuals in health and welfare education or training. For instance, Taylor (2007) argues that nurses are underpaid, relative to other industries, as LSH professionals and associates have to work hard and irregular hours, and face, in some cases, life threatening risks on the job (see also Shields and Ward, 2001; Shields, 2004; Yildirim and Aycan, 2008).[2] It is in this respect that we particularly focus on the inter-industry wage differential of graduates in the field of nursery or midwifery. The central question of this paper is then: can an individual, with nursing credentials, but who is not employed in the LSH industry but in 'foreign' industries, earn higher wages than a nurse in LSH employment?

The literature: wage differentials and job-related ability

The previous literature on wage differentials focused on differences in earnings by gender (e.g. Groshen, 1991; Jones and Gates, 2004); by race or ethnicity (e.g. Lam and Liu, 2002; Heywood and Halloran, 2004; Heywood and Parent, 2012); by health status (e.g. Johnson and Lambrinos, 1985; and Kidd et al., 2000); or by type of education program (e.g. Booton and Lane, 1985; Gill and Leigh, 2003). This paper focuses on inter-industry wage differentials for apparently similar workers, a topic on which we find old and recent theoretical and empirical studies. We start with the early work of Dickens and Katz (1987). They have analyzed the differences in wages for both union and nonunion workers across time, countries and industries. The authors argue the persistency of these wage differentials, even after controlling for individual background characteristics and job location. Dickens and Katz (1987) also show that individuals who switch from low to high paying industries receive a considerable share of the industry wage premium. They conclude that job-related ability and work experience may play an important role in explaining the persistency of the observed differences in wages, aside from differences in job quality or compensating wage differentials.

Krueger and Summer (1986) confirm these findings of Dickens and Katz. Their work is mainly on the inter-industry wage structure. They argue that: *"[...] the wage structure is very similar for different types of workers. Certain industries pay all types of workers high wages and others paying all types of workers relatively low wages* (p.2)*."* Krueger and Summer (1986) conclude

[1] The Life Science and Health industry will be further abbreviated by the 'LSH industry'.

[2] In addition, professions as nursery and midwifery are considered female professions and, thus, less attractive to men (Maestad et al., 2010).

that the competitive labor market model, in which firms compete against each other, (and which should impose competitive wages,) should be modified in order to explain the observed inter-industry wage variations. They argue for a non-competitive explanation dealing with 'efficiency wages' and 'rent-sharing' between firms and workers.

Gibbons and Katz (1992) present in their work two different explanations with respect to wage differentials between industries. On the one hand, they argue that the underlying worker population between distinct industries may substantially differ with respect to unobserved job-related ability, so that differences in worker productivity drives the observed wage differential, and not the type of industry (see also Roy, 1951). On the other hand, Gibbons and Katz (1992) argue that, if it is possible to construct a research design wherein apparently similar workers can be compared, that 'true' wage differentials can be observed, in essence, as a result of: (1) compensating wage differentials; (2) rent-sharing; and (3) effeciency wages. Note that these two explanations are also similar to those put forth by Krueger and Summer (1986).[3]

A more recent study of Handy and Katz (1998) provides an example with respect to inter-industry wage structure differences. The authors examine the differences in wages between nonprofit organizations and corporations. Overall, the authors observe lower wages in the nonprofit sector than in the for-profit sector. Handy and Katz (1998) argue that the observed wage differentials are actually advantageous for the nonprofit sector, as it generates consumer trust and self-selection of employees in managerial positions. This selectivity is called positive, as it attracts desirable workers in nonprofits compared to for-profits. Melly (2005) also describes wage differentials between public and private sector employees in Germany. She explores these wage differentials by gender and by educational attainment. The author argues that women have higher differences in wages between the public sector and the private sector than men. Melly (2005) also observes that, compared to the private sector, wages in the public sector are more equally distributed across different educational levels.

Theoretical model: a skill-weights approach

Relatively new in explaining inter-industry wage differentials, is the skill-weights approach of Lazaer (2009). Lazaer (2009) modeled a skill-weights approach for understanding wage differences between stayers (those who stay in the industry) and leavers (those who switch industry).[4] Contrary to the previous literature presented above, the starting point of Lazaer's theory is that nursing credentials signal two types of skills: (1) general skills; and (2) industry-specific skills. The former type of skills can be used in the LSH and the foreign industry, whereas

[3] Having both explanations empirically tested, Gibbons and Katz (1992) conclude that there is no theoretical model in the literature that is able to motivate their estimated wage differentials between industries.

[4] Note that we adapt his general theory directly to the choice of working in the LSH industry. Thus, Lazaer (2009) did not use nursery as an example in his work.

the latter only contribute to the productivity at the LSH industry.[5] The skills-weights approach puts forth that not all industries attach the same weight to the skills an individual acquired in his (school) career. For instance, the LSH industry attaches high weights to health and welfare skills, such as taking blood from a patient. These skills are considered irrelevant in foreign industries (e.g. a nurse who would a saleswoman in a department store). Hereby, Lazaer (2009) offers a novel explanation for the existence of bottleneck professions, namely: individuals with nursery credentials switch to foreign industries in case their weighted general skills pay-off more in foreign industries than seniority in LSH. We will test this hypothesis in this paper.

Empirical strategy: iterative one-to-one matching models

Estimating inter-industry wage differentials induce problems of self-selection of individuals into LSH employment (Rubin, 1974). For instance, women are more likely than men to become nurse or midwife (Jones and Gates, 2004). Individuals may have an entirely different motivation to work in LSH, simply based on gender, race or ethnicity, or cultural differences. However, we argue that these determinants of motivation also play a key role in enrolling in health and welfare education or training necessary to perform in an LSH job. The probability that an individual will start in an LSH profession depends on studying in the field of health and welfare, and these individual probabilities to enroll in health and welfare education or training reflect the (initial) motivation of students to go into LSH (see also Botelho et al., 1998). Thus, comparing only individuals with credentials in nursery or midwifery, already enhances comparability between these health professionals in different industries (this is also confirmed in Section 4).

Nonetheless, selectivity bias can still occur at the start of employment: individuals can diverge from their initial thought of going into LSH and, consequently, apply for work in foreign sectors. This decision to 'switch' may be associated with, for instance, individual background characteristics (e.g. gender, ethnicity, ability, and motivation), on the one hand, or regional variation in employment opportunities (i.e. the number of vacancies, the availability of hospitals, and structure of the LSH industry) (e.g. Booton and Lane, 1985; Elliot et al., 2007), on the other hand. We deal with the former type of selectivity by using iterative one-to-one matching models. Here, the idea is that individuals with nursery or midwifery credentials who work in the LSH industry are matched, based on observed background characteristics and job-related abilities, with individuals having the same credentials, but who are not in the LSH industry.[6] We deal with the latter type of selectivity by using regional fixed effects models. These fixed effects models are particularly useful within the scope

[5] Lazaer (2009, p.914) argues in this respect: *"Firm-specific human capital raises the productivity of the worker at the current firm, but not elsewhere, setting up a bilateral monopoly situation between the worker and firm."*

[6] Job-related abilities will be expressed by an index measuring general and industry-specific skills (see Section 4).

of industry-related effects on regional variation in employment opportunities, which are considered difficult to change in the short run (e.g. the availability of hospitals).

To conclude, the previous literature indicated the ignorability of reversed causality owing to the inelastic labor supply of nurses (Phillips, 1995; Askildsen et al., 2003; Shields, 2004; Di Tommaso et al., 2009).

Empirical application: the Netherlands

This paper explores the employment decision of graduates in the field of nursery, midwifery, or care in the Netherlands. The LSH industry in the Netherlands is an interesting case study for at least three reasons. First, the life sciences and health industry is a 'top industry': it captures about 14.9 percent of the Dutch Gross Domestic Product (i.e. an investment per capita of about €5,392); the industry is considered an important employer giving work to 178,435 nurses and 43,630 life sciences and health professionals (Central Bureau of Statistics, 2012); and the total revenue of the life sciences and health industry is estimated at 17.7 billion euros in 2010 (Dutch life sciences outlook, 2012; Statistics Netherlands, 2011).

Second, the Amsterdam Economic Board argue in their 'Human Capital Agendas' that *managing talent* will play a critical role in innovation and growth of the life sciences and health industry (see Amsterdam Economic Board, 2012). In this respect, the LSH industry formulates three goals: (1) to develop new or change old education or training programs in accordance with the development of the LSH industry; (2) to foster close cooperation between modern LSH activities, the companies in the industry (regional or national), and LSH education or training programs; and (3) to improve job attractiveness of the LSH industry.

Third, government officials recently policy measures in order to cut health care costs in 2014 (rijksoverheid.nl, 2013). If government officials and policy makers would make the LSH industry less attractive, relative to other industries, then this calls for an in-depth research on the consequences for (the attractiveness of) employment in the LSH industry.

We use repeated cross-section data on the school-to-work decision of about 6,000 graduated nurses, midwives or care professionals working in the Netherlands in different sectors over the period 2003 to 2011. The data consist of (1) individual characteristics and job-related (cap)abilities of individuals; (2) educational features as type of education, educational program, field of education, and level of education; and (3) job characteristics as hourly wages, job hours, job search, field of the job, level of the job, skill use and skills short to perform in the job, and self-reported job match.

The results indicate that health professionals, who voluntary leave LSH, earn higher wages equal to +2.33 percent significant at 5 percent level. The estimated wage differentials for health professionals who got dismissed are not significant.

This paper shows that the skill-weights approach of Lazaer (2009) offers valuable insights into the financial reasons to drop out of LSH employment.

This paper proceeds as follows. In Section 2, we elaborate on the skill-weight approach as discussed in Lazaer (2009). The empirical analysis will be described in Section 3. We discuss the data and provide descriptive statistics in Section 4. Section 5 presents the results, and Section 6 concludes.

2 Theoretical Model

2.1 Quit, stay, or layoff

Every nurse has two types of skills. Let A denote the general skills, and B the industry-specific skills. Thus, every nurse has a skill set (A,B). The weights attached to the skill set of the nurse in the LSH industry is denoted by λ_1, whereas the weights attached to skills in the foreign (F) industry is denoted by λ_2.[7]

Consequently, the skill-weights approach imply that:

$$\begin{aligned} &\lambda_1 A + (1-\lambda_1)B \text{ , the output of a nurse in the LSH industry,} \\ &\lambda_2 A + (1-\lambda_2)B \text{ , the output of a nurse in the F industry.} \end{aligned} \tag{1}$$

Nurses are paid according to their output in each industry.

There are two periods $t \in \{1,2\}$. In the second period ($t = 2$), a nurse can make a decision between staying in the LSH industry or leaving to the F industry. Lazaer (2009, p.917) defines the wages (W_2) a nurse can earn in the second period as:

$$\begin{aligned} W_2 &= \frac{1}{2}\left\{[\lambda_1 A + (1-\lambda_1)B] + [\lambda_2 A + (1-\lambda_2)B]\right\} , \\ &= B + \frac{1}{2}(\lambda_1 + \lambda_2)(A - B). \end{aligned}$$

A nurse can earn W_2, irrespectively whether she stays or she leaves. As such, if a nurse decides to stay in LSH, λ_2 will be rewarded as 'seniority'. The expression $(A - B)$ denotes the difference between general and industry-specific skills. Thus, we can specify the wage of an individual who stays and who leaves as (Lazaer, 2009, p.920):

$$W_{stay} = B + \frac{1}{2}(\lambda_1 + E(\lambda_2|\lambda_2 < \lambda_1)(A - B) , \tag{2}$$

$$W_{quit} = B + \frac{1}{2}(\lambda_1 + E(\lambda_2|\lambda_2 > \lambda_1)(A - B). \tag{3}$$

[7] $\lambda \sim U[0,1]$ follows a uniform distribution.

The skill-weights approach predicts that nurses only quit in case they would do better elsewhere. The inter-industry wage differential between voluntary leavers and stayers can then be expressed as (Lazaer, 2009, p.924):

$$\begin{aligned} W_{quit} - W_{stay} &= \frac{1}{2}[E(\lambda_2|\lambda_2 > \lambda_1) - E(\lambda_2|\lambda_2 < \lambda_1)](A - B) \ , \\ W_{quit} - W_{stay} &> 0. \end{aligned} \tag{4}$$

Here, the estimated wage differential is unambiguously positive.[8] The decision rule to quit, thus, depends on the different, higher weight attached, by the employer in the F industry, to the general skills A of nurses, and compared to the LSH industry. Consequently, seniority will have a lower monetary value (i.e. $E(\lambda_2|\lambda_2 < \lambda_1)$) than the general skills of a quitter (i.e. $E(\lambda_2|\lambda_2 > \lambda_1)$). Otherwise, a nurse would stay in LSH.

An employer can also dismiss a nurse, so that the wage differential is equal to (Lazaer, 2009, p.924):

$$\begin{aligned} W_{layoff} - W_{stay} &= \frac{1}{2}[\lambda_L + \bar{\lambda} - \lambda_1 - E(\lambda_2|\lambda_2 < \lambda_1)](A - B) \ , \\ W_{layoff} - W_{stay} &< 0 \ , \end{aligned} \tag{5}$$

where λ_L denotes the fallback position to accept leisure, and $\bar{\lambda}$ the average wage offer for the skill set (A,B) on the foreign labor market (i.e. $E(\lambda)$). The estimated wage differential is expected to be negative for nurses who got dismissed.[9]

2.2 Recruitment bottlenecks

The skill-weights approach offers an interpretation in the rise (and fall) of recruitment bottlenecks, namely: *"[...] wage loss associated with job turnover is greater in very thin markets than in very thick markets (Lazaer (2009, p.925)."* The concept of thick markets indicates that the total number of vacancies available in the industry, relative to other industries, is large, so that industry-specific skills become more general. Thus, in the extreme case that there would only be one industry, the LSH industry, and no other industries, having nursery credentials would become obvious for an individual to connect with the labor market, so that these skills are considered general. Consequently, if the LSH industry is thick, then nurses get more offers from which they can choose. In this extreme case, $(A - B)$ is equal to zero and one would not estimate a wage differential ($W_{quit} - W_{stay} = 0$). However, in case the market is very thin, industry-specific

[8] Note that specific skills B are cancelled out from equation (4) when substracting W_{stay} from W_{quit}.

[9] In case $W_{layoff} - W_{stay} > 0$, the nurse would choose to leave in the second period to the F industry. This case is possible, but less likely.

skills are not transferable to other, foreign industries. In the extreme case that there would be one industry, the LSH industry, wherein nursery credentials are suitable, among many other foreign industries, health and welfare education or training becomes a risky investment. The average wage offer $\bar{\lambda}$ on the foreign labor market for an individual who heavily invested in B, and not in A, will be relatively low compared to individuals who heavily invested in A, and not in B. The likelihood that a nurse, who got dismissed from LSH, will have to accept a job offer in the foreign industry below his/her level in order to be employed, increases with decreasing market thickness. Thus, the thinner the market, the higher the risk of investment in B in terms of bad labor market outcomes. Thin markets are, therefore, prone to recruitment bottlenecks.

3 Empirical Strategy

3.1 Iterative one-to-one matching

Consider an individual $i \in \{1, 2, ...N\}$ who studied in the field of nursing, midwifery, or care. Having studied in this field is a necessary condition in order to work as nurse, midwife or related health (associate) profession. At time $(t = 1)$, the graduated individual has to make a decision to stay in LSH, or to switch industry. Assume that the decision of the individual is based on the attractiveness of LSH at time t, relative to other sectors. We express the level of attractiveness by the hourly wages (y_i) one can earn when working in a particular industry.

Let I denote a treatment indicator that takes the value of 0 if individuals choose to stay in LSH; and 1 if otherwise. We then may write the average treatment effect of the treated as (see Cameron and Trivedi (2005):

$$\begin{aligned} E(y_{1i}|I &= 1) - E(y_{0i}|I = 0)\ , \\ &\text{if} \quad \text{studied health profession} = 1\ , \end{aligned} \tag{6}$$

where y_{1i} denotes the wages observed for a treated student, and y_{10} the wages observed for a control student.

We can rewrite equation (6) as:

$$\begin{aligned} \Pr(y_{1i} - y_{0i}|I &= 1) + \{\Pr(y_{0i}|I = 1) - \Pr(y_{0i}|I = 0)\}\ , \\ &\text{if} \quad \text{studied health profession} = 1. \end{aligned} \tag{7}$$

The first term denotes the average treatment effect of the treated, and the second term the bias that may be estimated owing to self-selection of graduates into LSH employment. Self-selection gives rise to omitted variables bias, in case selection on observable and unobservable variables takes place. In order to deal with selection into LSH employment, we consider the functional form of the labor market outcome 'wages':

$$y_i \sim f(\alpha_i; \nu_i; \xi_i; X_{ji}). \tag{8}$$

Equation (8) argues that the level of the wages one can earn in the labor market depends on: (innate) ability α_i; education ν_i; experience ξ_i; and a vector of individual, family and neighborhood characteristics. From this functional form of y_i we can argue that untreated students are comparable to treated students, when they have, on average, the same level of innate ability, education and experience. And also based on their background characteristics, they are, on average, the same. As such, if treated and untreated students are comparable as previously argued, wages differentials can only be explained by the hourly wages (y_i) one can earn when working in different occupations (i.e. LSH, or not).[10] Wage differentials can, thus, be defined as the difference in wages of comparable, homogenous individuals (with respect to $\alpha_i; \nu_i; \xi_i; X_{ji}$) working in different industries.

An important step in our empirical strategy is to make treated and untreated students, on average, comparable with respect to: $\alpha_i; \nu_i; \xi_i; X_{ji}$. Therefore, we propose to match individuals, who studied in the field of nursing, midwifery, or care, and who are in LSH employment, to individuals, who studied in the field of nursing, midwifery, or care, but who work in foreign industries. We use iterative one-to-one matching of treated individuals to untreated individuals based on observed individual characteristics X_{ji} and a set of abilities necessary to perform in the job (denoted by A_{li}) (see Section 4 for more information on the validity and reliability of the set of abilities used in this paper). These abilities are partly endowed, have been formed by education in schools, and also by experience on the job (e.g. internships). Therefore, ν_i and ξ_i can also be expressed as the value added of schooling.

We perform 500 one-to-one matching iterations in total, each time using a random sorting of the data. We argue that, under the assumption that the set of abilities measured is sufficiently informative with respect to the individuals (cap)abilities to perform well in the job, and disregarding the school an individual graduates from, we are able to capture differences between control group and treatment group with respect to: $\alpha_i; \nu_i; \xi_i$.[11] Of course, differences between schools with respect to the (quality of) education offered to their pupils exist, and experiences gained in LSH employment can substantially differ between job markets. As a result, owing to one-to-one matching, job-related ability in control group and treatment group can be equally distributed at the country-level.

However, between regions, one may still find substantial heterogeneity in the distribution of job-related ability. Therefore, we also condition on the variation

[10] Note that, if treated and untreated students are, on average, comparable, their reservation wage should also be, on average, comparable. In this case, the problem of censored observations is ignorable (see Cabus and Haelermans, 2013).

[11] Owing to one-to-one matching based on job-related abilities, the distribution of job-related abilities are, on average, the same for treated and matched untreated students. Note that we can test for this latter assumption to hold (see Section 5).

in attractivenss of industries between municipalities (m_k, with $k \in \{1, 2, ..., K\}$). Employment rates can differ between cities in the Netherlands, among other reasons, because of the availability of hospitals, clinics, pharmacy, and other LSH business-related activities. Regional variation can bias the results, as students who have a keen interest in studying in the field of nursery, midwifery, or care, and, consequently, in being employed in a good hospital or care center, are likely to, for example, perform their internship in this good hospital in order to increase their chances on the LSH job market. The attractiveness of LSH employment can substantially differ between municipalities, among other reasons, because of the availability of hospitals, clinics, pharmacy and other LSH related businesses.

Thus, selectivity can play an important role at the regional level. It can be argued that the availability of (or the competition between) LSH businesses may have a direct impact on: (1) the students composition in nursery or midwifery; (2) the wages one can earn when working in LSH; and (3) LSH employment.

We deal with regional variation in selectivity (i.e. regional variation in employment opportunities) by using regional fixed effects models. Fixed effects models grasp features of the municipality that are considered fixed (municipality-specific) and, as such, features that are not easily to alter in the short run (e.g. the availability of hospitals or health education programs). Regional fixed effects models also controls for regional variation in the wage rate, and, consequently, the (attractiveness of the) LSH industry within that region compared to other sectors. Consequently, fixed effects models account for regional variation in the underlying student population who graduated in nursery, midwifery, or care.

To conclude, we discuss the problem of reversed causality. The previous literature indicates the inelastic labor supply of nurses (Phillips, 1995; Askildsen et al., 2003; Shields, 2004; Di Tommaso et al., 2009). Consequently, a rise (or fall) in the wage rate does not, or only to small extent, affect nurses' employment decision. Therefore, the problem of reversed causality can be ignored.

3.2 Multivariate regressions

After having performed the iterative on-to-on matching, the multivariate regression estimates the difference in wages between comparable, homogenous workers in the different industries. We now construct a weighted standardized index of requested job-related ability r_i by using principal components analysis (in Section 4, we show that, owing to rich data on job-related ability, r_i is valid and reliable). We then may write:

$$\begin{aligned} y_i &= cte + \beta I_i + \gamma r_i + \theta \left(I \times r_i \right) + \varepsilon_{m_k i}, \\ &\text{if} \quad \text{studied health profession} = 1. \end{aligned} \tag{9}$$

y_i denotes the log of hourly wages; I_i the treatment indicator; r_i requested job-related ability; $(I \times r_i)$ the interaction between the treatment indicator and requested job-related ability; and $\varepsilon_{m_k i}$ the error term. Further note that, in equation (**??**), the municipalities' average wage rates are controlled for by including indicators of m_k into the regression (i.e. fixed effect model). Regional fixed effects models also cluster the standard error at m_k and, consequently, robust standard errors $\varepsilon_{m_k i}$ are presented in this and each subsequent job-related ability model.

The estimate of θ denotes the wage differential. θ captures the variance in wages that cannot be explained by differences between nurses working in different industries. We control for requested job-related ability (or, in other words, requested skills), so that positive differences in wages are not attributable to asking more skills (or productivity), but to the different weights attached to the same skills (see Section 2).

3.3 Industry mobility – the ability-productivity mismatch

In the final phase of the empirical strategy, we wish to distinguish between nurses who changed industry because they got dismissed, or because they quitted. First, we also construct a weighted standardized index of own job-related ability a_i by using principal components analysis (in Section 4, we show that, owing to rich data on job-related ability, a_i is valid and reliable). Second, we measure the difference between job-requested abilities (denoted by r_i), on the one hand, and job-related abilities (denoted by a_i), on the other hand. We then indicate quit and layoff as[12]:

$$r_i < a_i, \text{ if quit,} \tag{10}$$

$$r_i > a_i, \text{ if layoff.} \tag{11}$$

Note that the difference between requested and own job-related abilities also measures the level of job (mis)match. The value of 0 indicates a good job match, and all values $\neq 0$ a certain level of mismatch. In conclusion, we estimate equation (9) seperately for nurses who quitted and for nurses who got dismissed.

4 Data and descriptive statistics

We use repeated cross section data of the Dutch higher vocational school leaving monitor (HBO) over the period 2003 to 2011. All individuals ($N = 6,848$) in our sample studied nursery or midwifery. We track three broad categories of health professions for graduates who wish to be employed in LSH, namely: (1)

[12] The idea is that, if a nurse quitted LSH, general skills are highly weighted ($\lambda_2 A$) in the foreign job, and industry-specific skills are lowly weighted ($(1 - \lambda_2)B$) (see also Section 2) A horizontal ability-productivity mismatch then arise, as the nurse will not be able to apply the industry-specific skills B in the foreign job. After switching, he/she can become overskilled for the job in the foreign industry ($r_i < a_i$), or underskilled ($r_i > a_i$). The former case is more likely for nurses who quitted LSH, whereas the latter case is more likely for nurses who got dismissed.

nursery and midwifery professionals; (2) life sciences and health professionals; and (3) life sciences and health associate and other professionals.

4.1 Univariate analysis

Table 1 and Table 2 summarize the descriptive statistics of the variables: (1) individual characteristics (i.e. age, gender, ethnicity and province of employment); (2) study program information (i.e. average grade, internship, and type of education); and (3) the questions with respect to own ability and requested ability for the job. We report the total number of observations, the mean values and differences between the mean values of the control group and the treatment group. The final column presents the T-values of an independent sample T-test. Overall, we observe only minor differences between treated and untreated individuals. Only with respect to type of study program, we observe significant mean differences between treated and untreated individuals. For instance, in the treatment group, there are significant fewer individuals who studied in part-time programs, and significant more individuals who studied in full-time and dual programs. And, on average, untreated individuals are about three years older than treated individuals.

With respect to own job-related abilities, 6 out of 17 items have significant T-values (5 percent level), namely: (1) the ability to apply field-specific knowledge in practice (Tg-Cg= $0.1; T = 4.66$); (2) the ability to take decisive action (Tg-Cg= $-0.07; T = -2.72$); (3) the ability to come up with new ideas and solutions (Tg-Cg= $-0.1; T = -4.74$); (4) the ability to cooperate productively with others (Tg-Cg= $0.097; T = 4.67$); (5) the ability to mobilize the capacities of others (Tg-Cg= $-0.08; T = -3.48$); (6) the ability to perform your work without supervision (Tg-Cg= $-0.055; T = -2.59$). Note that the differences between the treatment group and the control group are rather small.

Not surprisingly, we find 11 out of 17 items with respect to requested job-related abilities to be significantly different between the control group and the treatment group (see Table 2). Requested abilities to perform well in the job, thus, significantly differs between employment in LSH and other sectors. The highest mean difference between the control group and the treatment group is observed with respect to the question: ability to apply field-specific knowledge in practice (Tg-Cg= $0.330; T = 12.06$). This finding indicates that employment in LSH asks for vocational, practical-oriented skills.

4.2 Two measures of ability

We construct two measures of ability, namely: (1) own job-related ability; and (2) requested job-related ability. Therefore, we use factor analysis (i.e. principal component analysis) in order to reduce the dimension of having 17 items measuring ability into only 1 variable. Table 4 and Table 5 present the results for the two related ability measures. Note that we have standardized the items, and only retain the first component constructed by the factor analysis.

The own job-related ability measure has an eigenvalue of 6.2169 ($\rho = 0.3657$); the average inter-item correlation is 0.3120; and the scale reliability coefficient Cronbach's alpha is equal to 0.8852. The requested job-related ability measure has an eigenvalue of 7.5401 ($\rho = 0.4436$); the average inter-item correlation is 3980; and the scale reliability coefficient Cronbach's alpha is equal to 0.9183. From these statistics, we conclude that the own job-related ability measure as well as the requested job-related ability measure are valid and reliable.

Figure 2 and Figure 3 plot the distribution of both ability measures by LSH employment; relative to other sectors. The Kolmogorov Smirnov test shows that own job-related ability is equally distributed between sectors ($KS = 0.0296; P = 0.468$). However, this is not the case with respect to requested job-related ability ($KS = 0.1037; P = 0.0000$).[13]

4.3 Bivariate analysis

Figure 1 presents the cumulative percent share of graduated health professionals as nurse, midwife, care or associates with related health and/or life sciences credentials in LSH employment; relative to other sectors. Note that the employment rates are cumulative over the age of the respondent (X-axis), and that we present each time the cumulative percent shares by LSH employment (*health*=1) or not (*health*=0); gender; migrant status (i.e. migrant versus not a migrant); and type of study program (i.e. the full-time program, the part-time program, or the dual program). The cumulative percent share can also be expressed as duration time (i.e. the age at which the respondent starts in a job as midwife, nurse, care, or other (associate) health profession). For instance, we observe a longer duration for taking up a job in other sectors than in LSH. By the age of 30, 77.7% of graduated health professionals has a job in LSH, whereas only 64.5% has a job in other sectors.

Next, consider the employment rates by health and gender. We observe that males, on average, start working at an older age than females. This is mainly because they are older (33 year-olds) at the start of their LSH employment compared to females (27 year-olds). The same discrepancy in age is observed when individuals choose not to work in LSH; namely 35 year-olds (males) compared to 30 year-olds (females).

The overal picture of the cumulative percent shares by health and migrant status is somewhat blurred. We observe that Dutch native students have the shortest duration time to get employed in LSH. In total 78.4 percent of native Dutch health professionals is employed in LSH by the age of 30, compared to 64.2 percent (native Dutch graduates) and 67.9 percent (ethnic minority graduates) in other than LSH professions.

A greater disparity between the cumulative percent shares is observed by health and type of study program. The longest duration time is observed for individuals who studied nursery, midwifery, care or related health professions

[13] Note that, by using one-to-one matching in Section 5, we are able to create equally distributed groups with respect to requested job-related ability ($chi - squared = 0.0526; P - value = 0.231$).

in the part-time program. By the age of 30, only 20.4 percent of part-time graduates has employment in LSH. This percent share can be compared to 94.9 percent (full-time program) and 76.8 percent (dual program). This great disparity can largely be explained by age differences of individuals enrolled in the different type of study programs. The mean age at the start of employment is 24.5 (*health*=1) and 25.2 (*health*=0) among graduates of the full-time program; 39.3 (I=0 and I=1) among graduates of the part-time program; and 29.7 (*health*=1) and 32.2 (*health*=0) among graduates of the dual program.

5 Results

5.1 Determinants of the LSH employment decision

Table 3 presents the results of the probit discrete choice model. It estimates the likelihood to be in LSH employment conditional on observed background characterstics and a set of own job-related abilities.[14] Note that the responses on the ability questions are standardized.

We observe that the likelihood to be in LSH employment significantly increases with: year of the survey; average grade in the final year of nursery or midwifery education; having done internships; following the dual program; the ability to apply field-specific knowledge in practice; the ability to distinguish main priorities from side issues; and the ability to cooperate productively with others. Contrary, the probability that a graduate will work in the LSH industry significantly decreases with: age; following the part-time study program; the ability to work within budget/plan/guideline; the ability to come up with new ideas and solutions; the ability to mobilize the capacities of others; and the ability to perform your work without supervision. Surprisingly, no significant differences are found between males/females and Dutch native/ethnic minority groups. We argue from this evidence on gender and ethnicity that selectivity may have taken place at the start of education (i.e. whether or not study health or welfare education), so that we do not observe selectivity with respect to gender and ethnicity at the start of employment.

5.2 Estimated wage differentials

The results of four models are summarized in Table 6. Each model is estimated by using regional fixed effects. Robust standard errors are presented between brackets. We present four subsequent models, namely: the results from an approach using pooled ordinary least squares (pooled OLS)[15] without iterative one-to-one matching in Model 1; and the results from the approach using iterative one-to-one matching in Model 2 to Model 4. In Model 1 and Model 2,

[14]The probit results including requested job-related ability (LD Model) and both own and requested job-related ability (JM Model) are available upon request.

[15]Note that the OLS estimates are pooled over the years 2003-2011.

we do not distinguish between 'quit' and 'layoff'. We only estimate the wage differential for quitters in Model 3, and only for nurses who got dismissed in Model 4.

First, consider the results of the estimate of $\hat{\beta}$. The estimate of $\hat{\beta}_1$ is equal to +0.0284 significant at 5 percent level in Model 1. This estimate drops to insignificant values once appropriately accounted for observed background characteristics in Model 2 to Model 4.

Next, consider the association between job-requested ability and wages. We find that the estimate of $\hat{\gamma}$ is equal to +0.0025, and not significant in Model 1. This finding is robust in the other models.

Third, the estimate of interest is the wage differential. In Model 1 ($\hat{\theta} = +0.0201$) is significant at 1 percent level. Controlling for underlying differences in the population between 'stayers' and 'switchers', the wage differential slightly drops to ($\hat{\theta} = 0.0187$) significant at 1 percent level in Model 2. The estimate of ($\hat{\theta}_{quit} = +0.0233$) is significant at 5 percent level in Model 3, while the estimate of ($\hat{\theta}_{layoff} = +0.0137$) is not significantly different from zero. These findings are in line with the model predictions of Lazaer (2009) (see Section 2).

5.3 Robustness checks for $\hat{\theta}_{quit}$

We provide two robustness checks in total for $\hat{\theta}_{quit}$. The full model estimation results are available upon request. First, in line with the critiques from Di Tommaso et al. (2009), we control for several other than monetary aspects of the job, namely: (1) type of contract; (2) the size of the organization wherein the individual works; (3) tasks of supervision; (4) months unemployed before the first job; (5) whether the job has good career opportunities; (6) and satisfaction with currect work. The estimate of $\hat{\theta}_{quit}$ slightly drops to +1.73 percent, and does not lose its significance at 5 percent level.

Second, conform the skill-weights approach of Lazaer (2009), we use the infuence of 'seniority' on wages (see Section 2).An appropriate robustness check would then be to control for age in the multivariate regression. As such, we re-estimate $\hat{\theta}_{quit}$ controlled for age. Note that, owing to iterative one-to-one matching, there are no age differences between stayers and quitters (Tg-Cg= $0.119; T = 0.25$). The results indicate that an increase in age indeed is associated with higher wages (+0.0184). The estimate of $\hat{\theta}_{quit}$ is now equal to +0.0045, and no longer significant.

6 Conclusion and Policy Discussion

This paper contributes to the previous literature on inter-industry wage differentials and job-related ability. We apply the skill-weights approach of Lazaer (2009) on the potential switch graduates in nursery, midwifery, or care, can make from the life sciences and health industry to other, foreign sectors, and estimate its effect on wages. The skill-weights approach argues that nurses will leave voluntary the LSH industry for a job outside LSH, in case the returns to skills in LSH is lower than the returns to skills in foreign industries. This inter-industry wage differential is then the result of the difference in weighting general and industry-specific skills between foreign and LSH industries. Or else, a positive wage differential is the result of the difference between the monetary reward of highly weighted general skills and lowly weighted industry-specific skills in foreign industries (i.e. the returns to skills in foreign industries when leaving LSH) and the monetary reward of seniority in LSH (i.e. the returns to skills in LSH when staying in LSH)

The empirical strategy benefits from unique data on abilities necessary to perform in the job. These job-related abilities are the direct result of innate ability and individuals' background characteristics, on the one hand, and education in school and experience on the job, on the other hand. Owing to iterative one-to-one matching, we make graduates homogenous with respect to their background characteristics and abilities. The empirical strategy also deals with regional variation in employment opportunities in LSH, and argues ignorability of reversed causality. The results from the estimated wage differentials are in line with the model predictions of Lazaer (2009): nurses who quit LSH voluntary earn, on average, higher (+2.33 percent) wages in other, foreign industries. With respect to nurses who got dismissed, we do not find a significant wage differential.

This paper also provides valuable insights into the rise of recruitment bottlenecks by using the concept of market thickness. Thick markets provide more job offers, and, thus, more job mobility, than thin markets. In general, risk-averse people will have the propensity to obtain a diploma that put high weights on learning skills vital for employment in the 'thick markets'. In knowledge societies, such as the Netherlands, thick markets arise for skill-intensive jobs, and recruitment bottlenecks are heavily associated with low end (industry-specific) vocational education or training (for a policy discussion on skill utilization in EU-27, see cedefop.europa.eu). The LSH industry behaves as a rather thin market. As individuals with nursery credentials cannot, or only to limited extent, apply their industry-specific skills in other than LSH industries, the potential switch a nurse can make directly implies the loss of suitability of industry-specific skills, and, consequently, the loss of investment in industry-specific education and training. Studying health and welfare education or training largely involves the acquisition of industry-specific skills, and to lesser extent, the acquisition of general skills (Hirsch and Schumacher, 2012). The study, therefore, can be considered hazardous for people who are uncertain about the discounted value of health and welfare education or training. For instance, people who consider the question whether they can manage family with nursery work (Yildirim and Aycan, 2008). Further research should focus on the decision to study health and welfare education or training in order to better understand the discrepancy between the perceived and actual discounted value of health and welfare education or training.

Our findings, embedded in the skill-weights approach, also argue the chronic nature of recruitment bottlenecks in LSH. Seniority and skills' payoff is embedded in the industry structure, and, therefore, not easily to alter in the short run (for a discussion, see also Gibbons and Katz, 1998). The policy discussion in this respect is twofold: on the one hand, nurses are underpaid and unions are fighting for wage increase (for a discussion, see also Taylor, 2007). On the other hand, health care costs are rising and policymakers wish to cut costs also through freezing, or even lowering wages of health professionals. The LSH industry may well find its solution in the demand for informal care. Dutch policymakers already discuss the evolution from a 'welfare state' to a 'participation society', a society wherein every individual takes up its responsibility in caring for sick or senior family members or friends in order to cut in health care costs (King Willem-Alexander's speech from the throne, Prinsjesdag September 17th 2013, see rijksoverheid.nl). However, it is in this respect that Heitmueller and Inglis (2007) discuss substantial wage losses of informal care givers as a result of non-labor market participation.

7 Tables and figures

Table 1: Descriptive statistics of the treated and untreated individuals with respect to individual and program characteristics (before matching).

	Obs.Cg	Mean.Cg	Obs.Tg	Mean.Tg	(Tg-Cg)	T-value
Individual Characteristics						
age	1,114	30.8	5,734	28.2	-2.7	-9.6
gender (male=1)	1,114	0.147	5,734	0.117	-0.030	-2.8
non-Western migrant	1,114	0.052	5,734	0.045	-0.007	-1.0
Western migrant	1,114	0.029	5,734	0.027	-0.002	-0.3
not a migrant	1,114	0.919	5,734	0.928	0.009	1.0
Study program information						
grades	1,037	7.373	5,220	7.381	0.008	0.5
study program					0.000	
full time program	1,114	0.509	5,734	0.581	0.072	4.5
part time program	1,114	0.320	5,734	0.169	-0.151	-11.9
dual program	1,114	0.171	5,734	0.250	0.079	5.7
internship(yes=1)	1,112	0.945	5,722	0.969	0.024	4.0
Job province						
Groningen	1,114	0.074	5,734	0.059	-0.014	-1.8
Friesland	1,114	0.057	5,734	0.055	-0.001	-0.2
Drenthe	1,114	0.037	5,734	0.024	-0.013	-2.6
Overijssel	1,114	0.060	5,734	0.067	0.007	0.9
Gelderland	1,114	0.120	5,734	0.122	0.001	0.1
Utrecht	1,114	0.070	5,734	0.101	0.030	3.2
Noord-Holland	1,114	0.121	5,734	0.119	-0.002	-0.2
Zuid-Holland	1,114	0.217	5,734	0.219	0.002	0.1
Zeeland	1,114	0.018	5,734	0.018	0.000	0.1
Noord-Brabant	1,114	0.161	5,734	0.147	-0.014	-1.2
Limburg	1,114	0.054	5,734	0.059	0.005	0.7
Flevoland	1,114	0.012	5,734	0.011	-0.001	-0.3

Table 2: Descriptive statistics of the control group (Cg) and the treatment group (Tg) with respect to own and requested abilities (before matching).

	Obs.Cg	Mean.Cg	Obs.Tg	Mean.Tg	Tg-Cg	T-value
own abilities (scale 1 to 5): ability to...						
apply field-specific knowledge in practice	1,052	3.754	5,478	3.855	0.101	4.66
use ICT	1,053	3.678	5,469	3.698	0.020	0.77
communicate in foreign languages	1,048	2.856	5,478	2.881	0.025	0.73
gather information	1,051	3.961	5,479	3.976	0.016	0.74
recognize problems and opportunities	1,054	3.988	5,493	3.981	-0.007	-0.35
draw connections	1,052	3.994	5,479	3.979	-0.015	-0.74
distinguish main priorities from side issues	1,053	3.891	5,482	3.908	0.018	0.85
reason logically	1,053	4.045	5,456	4.032	-0.014	-0.67
work within budget/plan/guideline	1,051	3.610	5,455	3.558	-0.052	-1.9
work well under pressure	1,055	4.034	5,478	4.060	0.027	1.15
take decisive action	1,057	3.843	5,473	3.778	-0.066	-2.72
come up with new ideas and solutions	1,055	3.933	5,470	3.825	-0.108	-4.74
learn new things	1,056	4.153	5,464	4.175	0.021	1.02
make meaning clear to others	1,055	3.990	5,479	4.020	0.030	1.33
cooperate productively with others	1,050	4.134	5,474	4.231	0.097	4.67
mobilize the capacities of others	1,055	3.778	5,476	3.694	-0.083	-3.48
perform your work without supervision	1,052	4.306	5,476	4.250	-0.055	-2.59
requested abilities (scale 1 to 5)						
apply field-specific knowledge in practice	1,063	3.666	5,550	3.996	0.330	12.06
use ICT	1,057	3.402	5,533	3.427	0.025	0.78
communicate in foreign languages	1,060	2.042	5,539	2.270	0.228	6.56
gather information	1,061	3.734	5,547	3.835	0.100	3.56
recognize problems and opportunities	1,064	4.038	5,547	4.119	0.081	3.16
draw connections	1,059	3.990	5,542	4.155	0.164	6.51
distinguish main priorities from side issues	1,064	3.926	5,545	4.022	0.096	3.94
reason logically	1,062	3.952	5,522	4.067	0.115	4.72
work within budget/plan/guideline	1,060	3.547	5,527	3.544	-0.003	-0.08
work well under pressure	1,065	4.095	5,544	4.269	0.174	6.74
take decisive action	1,065	3.872	5,536	3.895	0.023	0.83
come up with new ideas and solutions	1,065	3.834	5,528	3.826	-0.008	-0.28
learn new things	1,064	3.811	5,529	3.976	0.165	5.8
make meaning clear to others	1,061	4.116	5,522	4.150	0.034	1.39
cooperate productively with others	1,065	4.118	5,543	4.251	0.133	5.43
mobilize the capacities of others	1,064	3.861	5,547	3.914	0.053	2.01
perform your work without supervision	1,064	4.323	5,548	4.338	0.015	0.66

Table 3: Results of a Probit Regression.

		Log pseudolikelihood=-7175.49				Number of obs=5564 Wald chi2(26)=171.55 Prob > chi2=0 Pseudo R2=0.0443
$I = 1$	Coef.	Robust Std. Err.	z	P>z	[95% Conf.Interval]	
qyear	-0.002	0.008	-0.20	0.841	-0.018	0.014
age	0.008	0.003	2.32	0.021	0.001	0.015
Gender (male=1)	0.080	0.070	1.14	0.253	-0.057	0.217
(Not a migrant=1)						
non-Western migrant	-0.036	0.104	-0.35	0.727	-0.240	0.168
Western migrant	-0.039	0.131	-0.30	0.767	-0.296	0.218
edugrade	-0.011	0.021	-0.52	0.602	-0.051	0.030
internship	-0.261	0.118	-2.22	0.027	-0.491	-0.030
(full time program=1)						
part-time program	0.243	0.078	3.13	0.002	0.091	0.395
dual program	-0.182	0.060	-3.03	0.002	-0.299	-0.064
own abilities (standardized)						
apply field-specific knowledge in practice	-0.120	0.026	-4.67	0.000	-0.171	-0.070
use ICT	0.008	0.026	0.30	0.763	-0.043	0.058
communicate in foreign languages	-0.014	0.024	-0.57	0.567	-0.060	0.033
gather information	0.007	0.028	0.26	0.796	-0.047	0.061
recognize problems and opportunities	-0.019	0.032	-0.60	0.551	-0.082	0.044
draw connections	0.023	0.033	0.70	0.483	-0.042	0.089
distinguish main priorities from side issues	-0.052	0.031	-1.69	0.091	-0.112	0.008
reason logically	0.038	0.031	1.21	0.228	-0.024	0.099
work within budget/plan/guideline	0.041	0.025	1.67	0.095	-0.007	0.089
work well under pressure	-0.035	0.030	-1.15	0.249	-0.094	0.024
take decisive action	0.028	0.031	0.90	0.367	-0.033	0.089
come up with new ideas and solutions	0.099	0.031	3.23	0.001	0.039	0.158
learn new things	-0.014	0.029	-0.49	0.625	-0.070	0.042
make meaning clear to others	-0.036	0.030	-1.19	0.232	-0.095	0.023
cooperate productively with others	-0.118	0.028	-4.15	0.000	-0.174	-0.062
mobilize the capacities of others	0.080	0.027	2.94	0.003	0.027	0.134
perform your work without supervision	0.081	0.029	2.82	0.005	0.025	0.137
constant	2.386	16.438	0.15	0.885	-29.831	34.603

Table 4: Measure of own ability using principal component analysis: validity and reliability coefficients.

own abilities (scale 1 to 5): ability to...	Own ability	Unexplained
apply field-specific knowledge in practice	0.2352	0.6560
use ICT	0.1747	0.8102
communicate in foreign languages	0.0907	0.9488
gather information	0.2415	0.6374
recognize problems and opportunities	0.2776	0.5211
draw connections	0.2851	0.4945
distinguish main priorities from side issues	0.2661	0.5597
reason logically	0.2798	0.5134
work within budget/plan/guideline	0.1857	0.7857
work well under pressure	0.2613	0.5757
take decisive action	0.2594	0.5816
come up with new ideas and solutions	0.2600	0.5797
learn new things	0.2447	0.6278
make meaning clear to others	0.2646	0.5648
cooperate productively with others	0.2382	0.6472
mobilize the capacities of others	0.2251	0.6849
perform your work without supervision	0.2553	0.5947
Average interitem correlation:	0.3120	
Number of items in the scale:	17	
Cronbach's alpha	0.8852	

Table 5: Measure of requested ability using principal component analysis: validity and reliability coefficients.

requested abilities (scale 1 to 5)	Req. ability	Unexplained
apply field-specific knowledge in practice	0.2308	0.5984
use ICT	0.1769	0.7640
communicate in foreign languages	0.0938	0.9336
gather information	0.2470	0.5399
recognize problems and opportunities	0.2683	0.4571
draw connections	0.2870	0.3787
distinguish main priorities from side issues	0.2734	0.4363
reason logically	0.2799	0.4093
work within budget/plan/guideline	0.1806	0.7539
work well under pressure	0.2426	0.5563
take decisive action	0.2544	0.5119
come up with new ideas and solutions	0.2602	0.4893
learn new things	0.2697	0.4514
make meaning clear to others	0.2739	0.4343
cooperate productively with others	0.2352	0.5827
mobilize the capacities of others	0.2457	0.5446
perform your work without supervision	0.2253	0.6173
Average interitem correlation:	0.3980	
Number of items in the scale:	17	
Cronbach's alpha	0.9183	

Figure 1: Cumulative percent share of graduated individuals in a job as nurse, midwife, care or associate life science and/or health professions (Note 1: X-axis denotes the time of analysis in years since birth and Y-axis the cumulative percent share. Note 2: Based on the Kaplan-Meyer estimator over the period 2003 to 2011.)

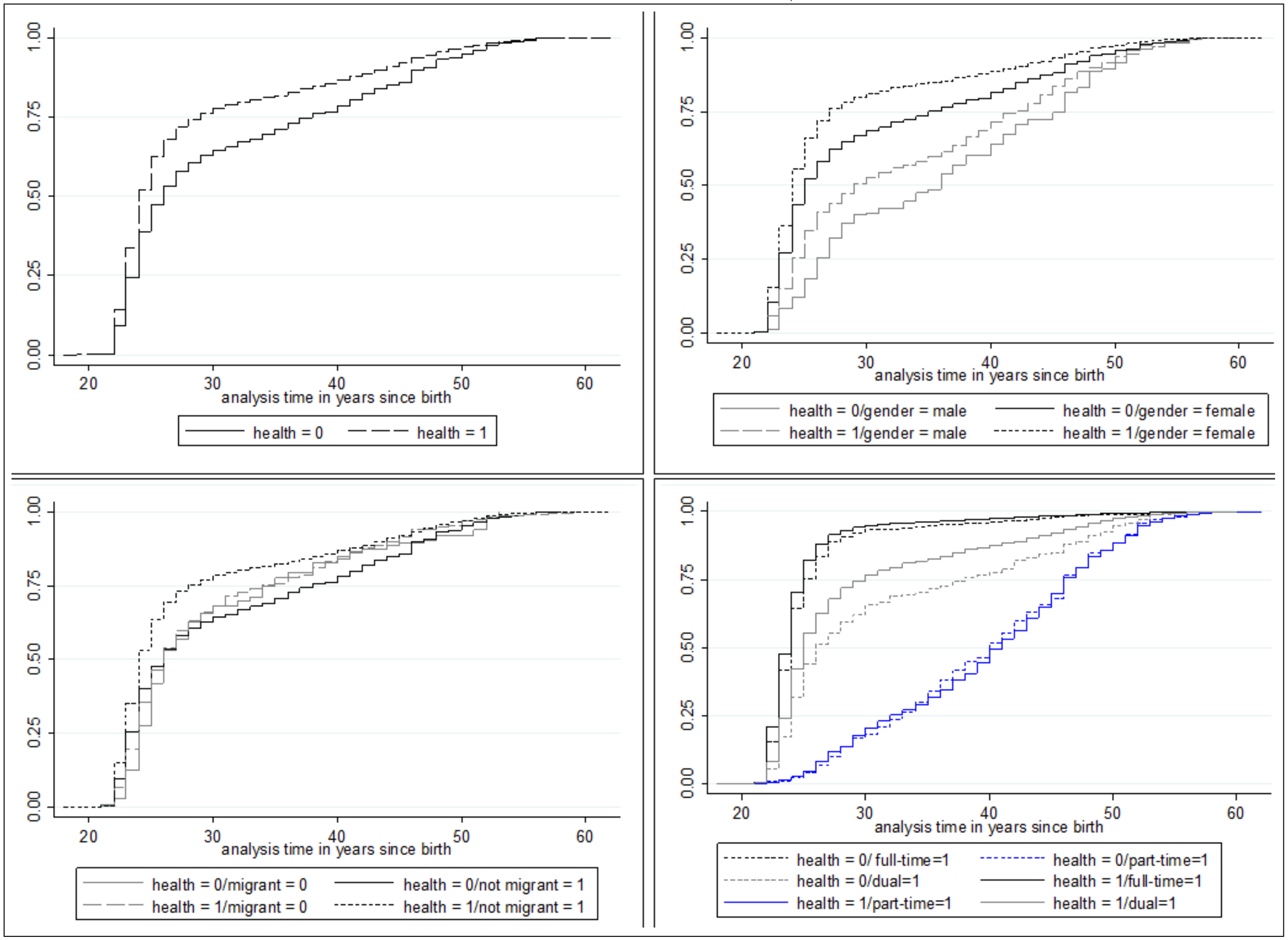

Table 6: Estimation output of the Labor Demand Model (outcome variable = log wages).

	FULL Model 1		FULL Model 2		QUIT Model 3		LAYOFF Model 4
Employment (F=1) ($\hat{\beta}$)	0.0284	**	0.0147		0.0254		0.0290
	(0.0140)		(0.0212)		(0.0350)		(0.0339)
Requested skills ($\hat{\gamma}$)	0.0025		0.0032		0.0098		0.0022
	(0.0016)		(0.0059)		(0.0096)		(0.0079)
Wage differential ($\hat{\theta}$)	0.0201	***	0.0187	***	0.0233	**	0.0137
	(0.0041)		(0.0070)		(0.0110)		(0.0138)
Matching variables	Characteristics Study program Own abilities		Characteristics Study program Own abilities		Characteristics Study program Own abilities		Characteristics Study program Own abilities
Specification	OLS		NNM 500 0.01		NNM 500 0.01		NNM 500 0.01
Std.error	Cl(jcity) 321		Cl(jcity) 241		Cl(jcity) 195		Cl(jcity) 172
Obs.	5,540		1,518		828		690

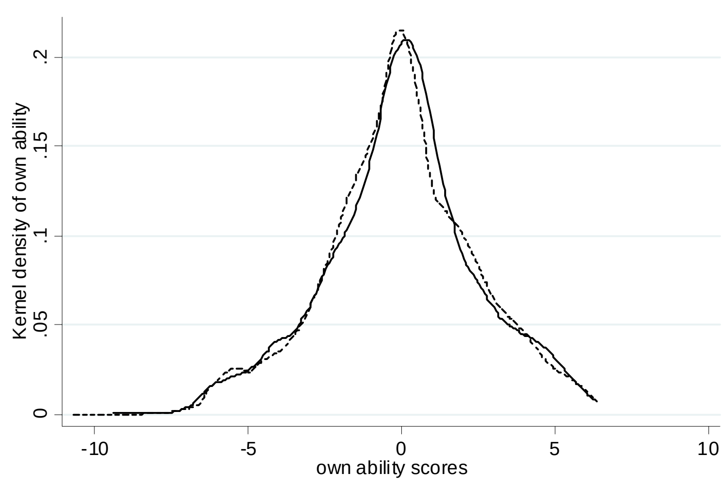

Figure 2: Kernel density of own ability scores by LHS employment (dotted line); and foreign industries (solid line). (Note: The Kolmogorov-Smirnov test points to equal distributions (chi=0.0296; P-value=0.468).

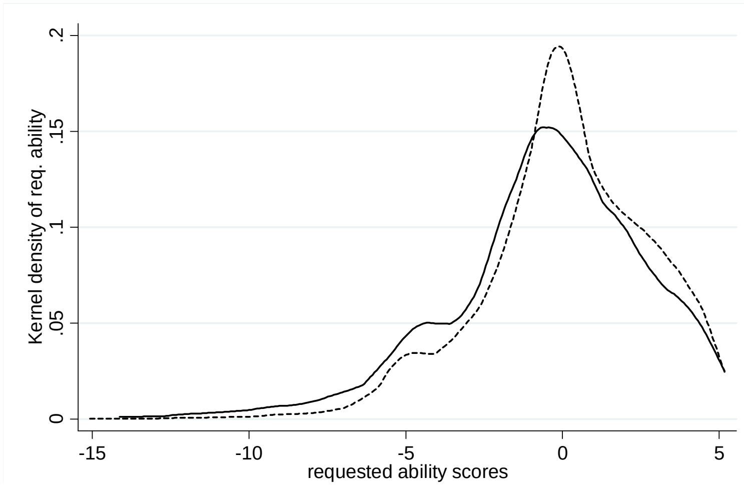

Figure 3: Kernel density of requested ability scores by LHS employment (dotted line); and foreign sectors (solid line). (Note: The Kolmogorov-Smirnov test points to unequal distributions (chi=0.1037; P-value=0.0000).

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