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The Skill Balancing Act:

Determinants of and Returns to Balanced Skills

Elisabeth Bublitz[1] & Florian Noseleit[2]

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Abstract:

Entrepreneurs are found to have balanced skill sets and most have worked in small firms before starting their own business. In light of this, we compare the skill sets of employees working in businesses of different size to the skill sets of entrepreneurs using a rich data set on the applied skills of individuals. This data set allows us to construct an indicator that measures skill balance in the quantity (skill scope) and quality (skill level) dimension. Our results show that employees working in large businesses tend to have a lower skill balance than those working in small businesses; yet, the skill balance of entrepreneurs remains the largest. The impact of human capital formation on skill balance also varies among employees of different business sizes and entrepreneurs. Finally, the estimated returns to balanced skills are largest for entrepreneurs whereas, for employees, these returns decrease as business size increases. However, we find no relationship between balancing skills at lower skill levels and income, indicating that both dimensions—skill level and skill scope—are relevant. We end by discussing the policy implications that can be drawn from our results in regard to skill balance.

JEL classification: J24, J31, L26, M13
Keywords: entrepreneurship, returns to human capital, balanced skill set, jack-of-all-trades

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1. Introduction

A person very skilled in one dimension may be highly regarded and well paid. However, the individual who attains the same level of competence across a range of skills (here referred to as "skill balancing" or "balanced skills") may have an advantage over someone who is very good at only one thing but no so skilled in other fields. Balanced skills have been investigated in the case of entrepreneurs but not for employees working at businesses of different size. However, before starting their own business, most entrepreneurs have worked as salaried employees in small firms, suggesting that skill balance could also play a role for this group. In addition, income is expected to increase with skill levels but it is unknown whether a certain threshold needs to be crossed before individuals will benefit from balanced skills. This paper investigates the skill balancing act of entrepreneurs and employees to better understand what distinguishes one group from the other, and to discover if having a balanced skill set is beneficial and, if so, how individuals can be helped to acquire one.

The idea that entrepreneurs are multi-skilled individuals who try to balance their skill levels was first formalized by Lazear (2004, 2005). According to Lazear's jack-of-all-trades hypothesis, because "a chain is only as strong as its weakest link," entrepreneurs will only be as successful as their lowest skill level will allow. The reasoning behind this theory is twofold. First, having balanced skills means there is no weakest "link" that will break the chain of performance and income. Second, due to their greater responsibility and the higher number of tasks they need to perform, successful entrepreneurs either already have or need to develop a larger skill balance than do individuals working for others. In other words, entrepreneurs tend to be generalists; employees tend to be specialists.

Entrepreneurs often have worked in small, often young, firms before starting their own business (see, e.g., Parker, 2009b; Wagner, 2004). Employees of small firms are likely to be assigned a variety of tasks because of a lower division of labor, thereby requiring these workers to have a wider scope of skills. It follows that increasing firm size leads to a higher degree of specialization, and thus a workforce composed of individuals with smaller, less balanced skill sets. Accordingly, skill balance in small firms would be achieved through the skill balance on the individual level. For large firms, even complex projects could be managed without skill balance at the individual level, by employing, for each required task, individuals with similar skill levels.

In the extant research on balanced skills, employees are usually considered a homogeneous group of specialists, disregarding varying skill characteristics or the influence of firm size on job requirements. One exception, however, is Lee (2005), who finds that in certain occupations, employees are rewarded for having balanced skills. Also, the jack-of-all-trades—an individual with a set of already acquired skills—has not yet been matched with the skills that an individual actually applies on the job. According to Lazear's (2009) skill-weights approach, the specificity of human capital is generated by the degree to which a skill is needed in a job, thereby forming a firm-specific profile. Nonetheless, in the research on balanced skills, firm size has to date been a minor issue, while in the skill-weights approach, balanced skills have not been explicitly addressed. Furthermore, although monetary benefits can be an incentive for individuals to increase their skill balance, few approaches address the question of how much and, especially, where it pays to be a jack-of-all-trades (Åstebro and Thompson, 2011; Hartog et al., 2010; Lee, 2005). In addition, little is known about the effect that a balanced skill set has on personal income when applied skills (controlling for skill scope and skill levels) are considered.

To close these gaps in research, we investigate the (I) determinants of and (II) returns to balanced skills. We use an indicator that is able to account for two dimensions of skill balance: quantity (skill scope) and quality (skill level). In contrast to previous work on balanced skills, we consider the heterogeneity of employees working in businesses of various sizes. In the first part of the paper, we investigate which firm size requires more generalists than specialists and consider differences between the number of skills applied on the job by paid employees and by entrepreneurs. Next, we take a closer look at the relationship between balanced skills and formal, non-formal, and informal education. In the second part of the paper, we focus on the returns to skill balancing for entrepreneurs and employees, while at the same time exploring how varying the skill level affects the returns to skill balance.

The data used for our empirical analysis come from the "Qualification and Career Survey 2005/2006," which covers a representative sample of the working population in Germany. This survey allows us to distinguish between entrepreneurs and employees in different sizes of business and also contains information on the skill requirements of both groups in their current jobs. It provides details on job histories, job characteristics (such as income), and firm properties. We deviate from traditional measures of the jack-of-all-trades, which have not directly measured skills even though Lazear's theory focuses on them, and instead use an indicator that measures applied skills in the quantity (skill scope) as well as quality (skill level) dimensions, thus ensuring that we can determine what people really do, not what they might be able to do.

Our investigation into the *determinants of balanced skills* reveals that the average number of applied expert skills is significantly larger for entrepreneurs than it is for employees, which is in line with the findings of other research. With regard to firms, we show that the number of applied skills is negatively related to firm size for the lower three quartiles of the wage distribution. However, when looking only at the upper 25 percent, the number of skills reported by small business employees is not significantly higher than that reported by large business employees. Next, we look at the role of human capital, measured in educational degrees, work experience, and continuing education. Our findings show that entrepreneurs' skill balance benefits from tertiary education, continuing education, and entrepreneurial work experience. For employees, tertiary education, vocational training, and professional training as a master craftsman are positively related to skill balancing. Work experience shows a positive effect that declines over time; however, it is significant only for businesses with fewer than 20 employees. For a sample of employees who had never changed their employer, we find some evidence that workers in small businesses apply more skills on the job when their tenure (length of employment in one firm) is higher than the tenure of employees who just started working in a small business. On the contrary, employees in large businesses with long tenure tend to apply fewer skills than employees who recently joined a large business. These results could be driven by selection and/or learning processes; however, the data do not allow us to distinguish between the two. When investigating *returns to balanced skills*, we find that balancing skills at a lower skill level does not affect income, while a balancing at a higher skill level is rewarded with positive returns. For higher skill levels, our estimated returns to balanced skills are largest for entrepreneurs (vs. employees of any sized business). For employees, we find decreasing returns to balanced skills as business size increases.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature dealing with the jack-of-all-trades approach. From this we derive our research hypotheses regarding the determinants of and returns to balanced skills for employees and entrepreneurs. In Section 3 we introduce the data set and our empirical strategy. The results of our analyses and a discussion of them can be found in Section 4. Section 5 concludes.

2. Theory

In this section, we first look at the factors firm size and human capital formation as both may influence learning and therefore a process of skill balancing (see Figure 1). Skill balance is always measured in the two dimensions: skill scope and skill level. In the second part, we not only look at the returns to balanced skills for different groups, but also check whether controlling for skill level changes our results.

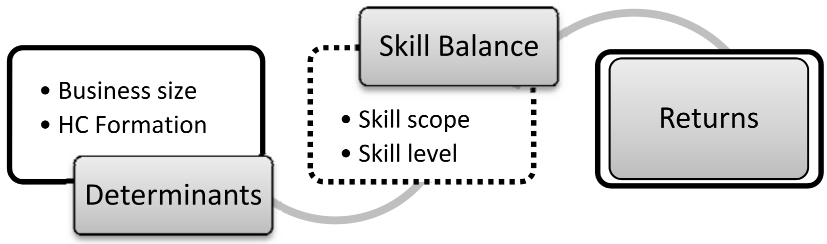

Figure 1: The determinants of and returns to balanced skills

2.1 Determinants of Balanced Skills

2.1.1 Business Size

Of particular interest for entrepreneurship research is Lazear's description of an entrepreneur who has a balanced set of skills (Lazear 2004, 2005), often known as "jack-of-all-trades." Entrepreneurs do not master every possible skill, but focus instead on achieving equal competence in each. Entrepreneurs are contrasted with individuals who decide to work as paid employees because, due to their specialization, this is how they maximize their earnings. The idea behind Lazear's model is that entrepreneurs are limited by their weakest skill and, therefore, attempt to balance skills. This implies that they will invest in more than one skill but only in those with the lowest skill levels. In contrast, salary workers invest in an already strong skill to increase their specialization and maximize their payoff. According to Lazear's theory, the propensity to become an entrepreneur increases with more balanced skill levels. However, skill balance can be observed on an individual level and also on a firm level, which is why it is important to remember that this theory does not address team foundings where skill balance can be achieved by groups of specialists who complement each other. Evidence for the jack-of-all-trades hypothesis is also found by Wagner (2003, 2006) and Silva (2007).

However, simply attributing generalist skills to entrepreneurs and specialist skills to employees may set up a false dichotomy. First, differences in the intra-organizational ability to make use of labor division suggest that heterogeneity with respect to skill sets is relevant for employees as well as for entrepreneurs. This is especially true if substantial transaction costs do not allow for market-based substitutes. Second, tomorrow's entrepreneurs are often found in today's workforce. Several studies confirm a positive relationship between start-up rates and the share of employees working in small firms or the number of small firms among all firms in a region (see, e.g., Armington and Acs, 2002; Audretsch and

Fritsch, 1994; Elfenbein et al., 2010; Hyytinen and Maliranta, 2008; Wagner, 2004). Elfenbein et al. (2010) find that entrepreneurs with prior work experience in small firms are particularly successful compared to their counterparts who had worked in large firms. Parker (2009b) looks into why small firms appear to be such a fertile breeding ground for future entrepreneurs, finding support for the self-selection theory. Taking these findings into account, entrepreneurs appear to breed entrepreneurs. That small firms appear to play such a prominent role in producing entrepreneurs could mean that they have a direct influence on the skill set of employees; that is, they may foster skill balancing. Moreover, it could be that balanced skills are acquired on the job, and not by having worked a large number of different jobs. For instance, Elfenbein et al. (2010) find that small firm employees engage in a broader range of commercial activities. Lee (2005) investigates the skill balance of employees in different occupations and finds that there are important differences. These findings cast some doubt on the idea that all employees are specialists before they start working as entrepreneurs.

Becker and Murphy (1992) argue that the cost of coordinating a group of specialized workers grows as the number of specialists increases. They implement this in a model where teams grow larger and workers specialize more as human capital and technological knowledge increase. This process, in turn, would pose additional obstacles to small firms because they face tighter budgets than large firms and, hence, small firms are less likely to hire specialists. Therefore, if firm size affects the propensity to become an entrepreneur, a distinction between small and large firms should be made in the analysis of skill balance.

In related research, Lazear (2009) develops a model that allows firms to attach weights to skills. Instead of distinguishing between general and firm-specific human capital, all human capital is initially viewed as general but it becomes specific in how and to what extent it is used in firms. In this model, firm size is not explicitly addressed and it is left to further research to address how certain weighting patterns might be shared by firms. Extending this concept, we assume that small firms attach similar weights to all applied skills, while large firms focus on specialized skills and value these the most. Accordingly, small firms lean more toward skill balancing.

In sum, considering all the challenges faced by small enterprises, it appears likely that job descriptions in these firms would best be filled not by specialists but by individuals with diverse backgrounds. Therefore, it appears worthwhile to explore in more detail who works in small enterprises: generalists or specialists. It is conjectured that it is not only specialists who work as paid employees and a clearer distinction in the area of specialization and generalization could provide additional insight. Our first hypothesis is as follows (a summary of all hypotheses can be found in Figure 2).

H1 Entrepreneurs will have the highest skill balance, followed by small business employees, and then large business employees.

2.1.2 Human Capital Formation

The next step in our analysis is to look at potential sources of balanced skills for employees and entrepreneurs. Human capital formation can result in an improvement in skill level, skill scope, or both. However, a change in either skill level or skill scope will not necessarily lead to skill balance and, indeed, could result in even less balance.

In a sample of Swiss individuals, Backes-Gellner et al. (2010) examine whether there are systematic differences between the educational paths of employees and entrepreneurs. Instead of only deciding on the level of education, individuals can also choose different educational paths to get there. Their finding supports Lazear's concept of skill balance, as entrepreneurs display mixed and more balanced educational paths while employees opt for pure and more specialized educational paths. However, Backes-Gellner et al. use the likelihood of being an entrepreneur as the dependent variable instead of skill balance, thus implicitly assuming that entrepreneurs are jack-of-all-trades. Similar results regarding educational paths are found by Oberschachtsiek (2009) for the case of Germany. In comparison with Oberschachtsiek's jack-of-all-trades measure (number of roles or dummy variable if individual has experience in more than three distinct fields of competence), our indicator for balanced skills is more precise and explicitly measures skills. Therefore, our data allow us to more directly and precisely investigate the impact of formal education (e.g., university degree), non-formal education (adult/continuing education), and informal education (work experience) on skill balance. Our focus is on the influence of human capital, measured by the highest degree of education attained, instead of on the complete educational path. Most studies find that education levels of the self-employed are higher than those of employees (Parker 2009a; Robinson and Sexton 1994). It is likely that these higher education levels are also related to the degree of skill balance achieved.

First, *formal education* is expected to be positively related to a broad skill set applied at the workplace. This holds not only for employees, but also for entrepreneurs, as formal education may include the specific skills needed to run a business. However, the importance attached to balanced skills will be higher in small firms than in large firms. *Non-formal education*, i.e., continuing education within the firm context, may influence skill balance as well. Research has long shown that large firms invest more in on-the-job training; they also hire more able workers, presumably because it is less costly to train them (cf. Barron et al., 1987; Holtmann and Idson, 1991). Despite these firm-specific differences in investment in direct continuing education, on-the-job learning will occur in businesses of all sizes, but its focus will differ. Thus, the effect of continuing education is expected to be the smallest for large business employees, to be stronger for small business employees, and strongest of all for entrepreneurs. *Informal education*, i.e., work experience, is another important factor for human capital. Since experience is closely related to the tasks that need to be performed at the work place, differences regarding occupational status (i.e., entrepreneurs vs. employed) and the degree of intra-organizational labor division (i.e., small vs. large firms) are likely.

In the case of entrepreneurs, it might be expected that prior work and entrepreneurial experience allow them to acquire the (balanced) skills needed to exploit opportunities. Silva (2007) argues that unobserved tastes and capabilities, rather than diverse experience, stimulate skill accumulation and, therefore, that being a jack-of-all-trades is more a matter of innate ability, and less of an acquired skill. This means that entrepreneurs will have a broad skill set if they show certain innate traits. Stuetzer (2011) provides evidence for the endowment hypothesis as found by Silva and the investment hypothesis as put forward by Lazear, thus suggesting that both play a role for the skill balance of entrepreneurs. However, the cross-sectional character of our data does not allow testing whether it is unobserved tastes and capabilities, rather than general work and entrepreneurial experience, that are related to broad skill accumulation; detailed panel data would be needed to test for innate abilities.

Given that young and small firms produce more entrepreneurs, the question arises as to whether work experience in small firms additionally increases the chance of becoming an entrepreneur, perhaps due to an increase of skill balance that can be achieved in such firms. It could be that employees in these firms learn differently. Also, in the case of employees, one might expect that experience is positively associated with skill balance as long as the organizational background of the firm demands employees with a broad set of skills. As argued above, this demand should be especially prevalent in small businesses. For employees in large businesses, the expected relationship between experience and skill balance depends on the reward for a balanced skill set. Incentives here are lower, and experience is more likely to influence a process of specializing instead of balancing. However, employees in large firms could also have an incentive to invest in a broad skill set so as to be able to (1) switch to another organization that requires a different or broader skill set or (2) insure against structural changes that render parts of their skill portfolio obsolete. Therefore, we expect employees of both small and large firms to increase their skill balance with work experience, but to a lesser extent in large businesses because the incentive to specialize is stronger in those businesses. As regards the jack-of-all-trades approach, unlike before, we will now be able to observe whether individuals implement a "generalized human-capital investment strategy" (Lazear, 2004, p. 211) in a firm. From this we conclude the following.

> *H2 The positive effect of human capital formation on skill balance is highest for entrepreneurs, followed by small business employees, and then large business employees.*

2.2 Returns to Balanced Skills

2.2.1 The Effect of Balanced Skills on Income

After addressing the determinants of balanced skills, we want to find out how much skill balancing is worth. To date, the wage implications of being a jack-of-all-trades have not been thoroughly addressed. Lazear's (2005) model implies that returns to skill variety are positive for entrepreneurs but not for specialized employees. In an earlier version of his paper, Lazear (2003) describes implications for income in more detail, focusing on the distribution of earnings between entrepreneurs and specialists. A general background assumption in this line of research is described by Wagner as follows: "Entrepreneurs must have sufficient knowledge in a variety of areas to put together the many ingredients needed for survival and success in a business, while for paid employees it suffices and pays to be a specialist in the field demanded by the job taken" (Wagner, 2006, p. 2415). No reference is made to the size of the firm where employees work.

And yet, skill balancing could be just as advantageous for employees as it is for entrepreneurs. If it holds true that employees sometimes work as generalists (e.g., Lee, 2005), it is likely that for this group, ceteris paribus, payoffs should differ across firms. Building on our previous discussion, on average, the returns to balanced skills should be higher in small firms than in large firms; indeed, it is unclear if the returns are positive at all for workers in larger firms.

In their research, Åstebro and Thompson (2011) contrast the jack-of-all-trades approach with the taste-for-variety idea and connect this to the household income of individuals. The taste-for-variety idea predicts that entrepreneurs decrease their income with greater skill variety; the jack-of-all-trades approach expects that entrepreneurs with balanced skills have higher incomes. Åstebro and Thompson find that varied labor market experience (measured by the number of different professions and industries) increases the likelihood of becoming an entrepreneur but lowers household income for employees and, particularly, for entrepreneurs. Accordingly, this would support the taste-for-variety approach for entrepreneurs. Counterevidence is provided by Oberschachtsiek (2009), who finds that the number of task roles is more related to competence than to taste for variety.

From our perspective, the often employed variable "variety in occupational experience" is too rough a measure to detect jacks-of-all-trades. For example, occupational switches increase occupational experience but, on the other hand, decrease wages (Topel, 1991). The same holds for the variable "number of industries worked in." For instance, industry shocks increase the likelihood of switching industries, which results in a loss of industry-specific human capital. Again, this results in a wage decrease (cf. Neal, 1995; Parent, 2000).

Hartog et al. (2010) use a more sophisticated measure to investigate how ability levels affect individuals' earnings. Their measure is taken from a survey that assesses a total of five cognitive and social abilities.[3] They find that a higher dispersion of ability levels hurts the earnings of entrepreneurs but does not affect the earnings of employees. However, their measure focuses not on the number, but only on the level, of abilities. Further, they look at general abilities and not at which skills are actually applied on the job. Consequently, unbalanced ability levels will not affect individuals as long as they work as specialists; however, this could change if they work as generalists, which, according to Lee (2005), is the case in certain occupations. Further, it can be conjectured that for certain cases skill balance does not require ability balance and vice versa. This makes it difficult to compare this measure to others implemented in the literature.

We want to discover what the returns are from an additional skill applied on the job for both entrepreneurs and employees. In the end, there might be another force driving the payment for an additional skill which relies on our earlier hypotheses. In the case of employees, as firm size determines certain job requirements, it might also provide a different incentive structure. If small firms are more prone to hire generalists, then in these firms employees with more skills should be worth more. In comparison, if large firms are more likely to hire specialists, it would not be worthwhile for employees at these firms to increase their skill balance. Certainly, wage increases could also be followed by an increase in skill balance, but this does not change our assumption regarding differences between firm sizes. As to entrepreneurs, we expect them to receive comparatively higher rewards for their skills, as conveyed in our third hypothesis.

> *H3 Entrepreneurs will receive the highest returns for an increase in skill balance, followed by small business employees, and then large business employees.*

[3] Abilities measured are (1) verbal ability, (2) mathematical ability, (3) technical ability, (4) clerical ability or coding speed, and (5) social ability (Hartog et al. 2010).

2.2.2 The Effect of Skill Level

Regarding returns, a higher education is known to be rewarded with higher wages but, to date, we do not know how skill levels affect returns to balanced skills. In his analyses, Lazear uses Stanford alumni data that allow him to compare the variety of individual study curriculums of graduates (Lazear, 2004) or the number of roles covered during job careers (Lazear, 2005). Wagner (2003) uses an earlier wave of the "Qualification and Career Survey" and thus focuses on the German labor market. In contrast to Lazear, he measures the amount of prior accumulated knowledge in terms of the number of different kinds of professional training undertaken after completing school and the number of times a change of profession occurred. In 2006, he also includes the number of professional fields. Similar variables were used by Åstebro and Thompson (2011) and Silva (2007). In general, all indicators are count variables and take on highest values for the group of self-employed.

Even though theory talks about skills, thus far measures have only picked up previously accumulated knowledge in different fields (knowledge scope) without accounting for the level of that knowledge. For example, only the number of roles was counted, regardless of whether knowledge levels were balanced. One year in marketing and five years in accounting were taken to have the same knowledge level, which is a contradiction to theory and practice. Both dimensions, skill level and skill scope, are needed to measure balance but have not yet been combined into one framework. As mentioned earlier, the skill-weights approach by Lazear (2009) allows firms to adjust the value attached to individual skills. If we assume that a firm considers a set of certain skills as equally valuable, earnings can be increased by either increasing the individual skill level and/or by adding an additional skill that the firm finds valuable.

Therefore, skill scope will continue to have an effect on the returns of employees as well as on those of entrepreneurs, but the size of this effect will also depend on the overall skill levels. Hence, we develop a two-dimensional concept for skill balancing that includes both skill scope and skill level and state our fourth hypothesis as follows.

> *H4 The returns to balanced skills of all groups are affected by skill scope and skill level.*

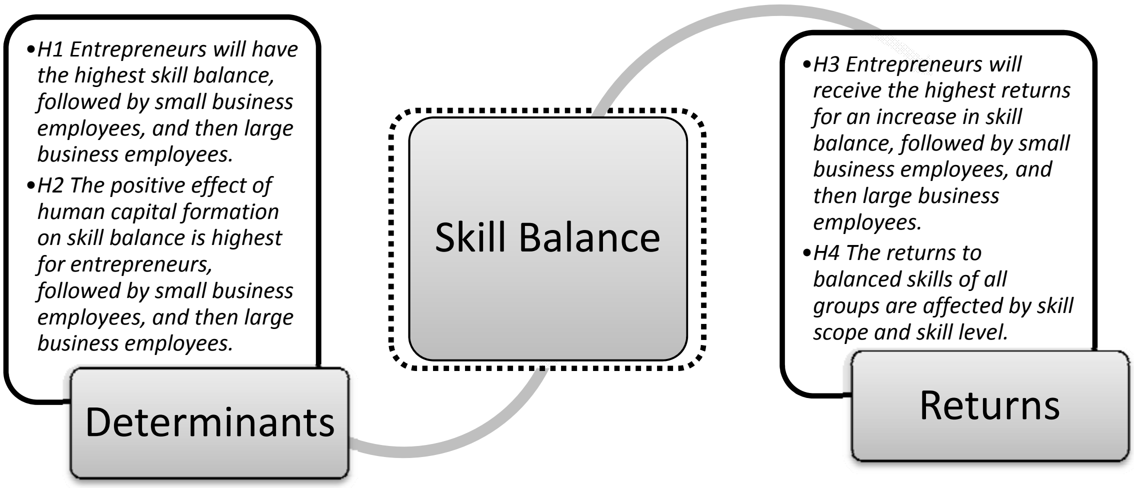

Figure 2: Predicted hypotheses

3. Data & Method

For our analysis we use the most recent wave of the Qualification and Career Survey, which was undertaken in 2005/2006 by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA). This wave includes a random sample of 20,000 people who belong to the active labor force in Germany. In addition to individual-specific data, the survey includes information on job histories, job characteristics (such as income), and job skill requirements. It is therefore useful for our purposes because it allows us to link the number of applied job skills of an individual with personal and business-specific characteristics.

For the empirical analysis, we select all employees who work in manufacturing industries and who answered all relevant questions. For the group of entrepreneurs, we also consider only those active in manufacturing on a full-time basis, thus including only full-time self-employed with an average monthly income of at least 1000 €. We restrict our analysis to manufacturing industries since several skills used in our analysis are more common in manufacturing than in services (e.g., manual skills or technology). Therefore, the limitation to manufacturing industries is more driven by characteristics of the survey design and its skill measure than by theoretical considerations that the proposed relationships are valid only for manufacturing and not services. Table A 1 in the Annex reports summary statistics, including the distribution of employees across business size.

Our data includes information on the self-employed, who will be used as a proxy for entrepreneurs, as also done by Wagner (2003) in proving the jack-of-all-trades hypothesis. According to Parker (2009a), self-employment can be regarded as the closest approximation to entrepreneurship. A shortcoming of the data is that the (self-reported) earnings of the self-employed and employees are gross earnings. Especially in the case of the income equations estimated in the next section, this could lead to biased results because of the progressive income tax and structural tax differences between the self-employed and employees. Furthermore, income under-reporting by entrepreneurs may be a problem in survey data, even when survey interviewers assure that all data are treated in strict confidence.

As mentioned earlier, we use a two-dimensional concept for skill balance that includes both skill scope and skill level. Another novelty of our indicator is that we do not look at how previously acquired skills are rewarded because, due to job changes and new job requirements, the skills applied on the job also differ. Instead, we consider only skills that are required by and therefore applied on the job. This approach is unique in the jack-of-all-trades literature. Our indicator further provides us with a clearer measure for pecuniary incentives for skill balancing.

To this end, we chose the survey question that explicitly asks respondents to list and assess all skills that they use in their current position (for an overview of all nine skills, see Figure 3). This avoids the problem of employees listing everything they have ever learned and done. Hence, skills are job and firm specific. Further, skills are ranked according to level of proficiency (expert, basic, none), which allows controlling for skill level. Note, however, that the individual perceptions of what qualifies as expert skill, for example, may vary.

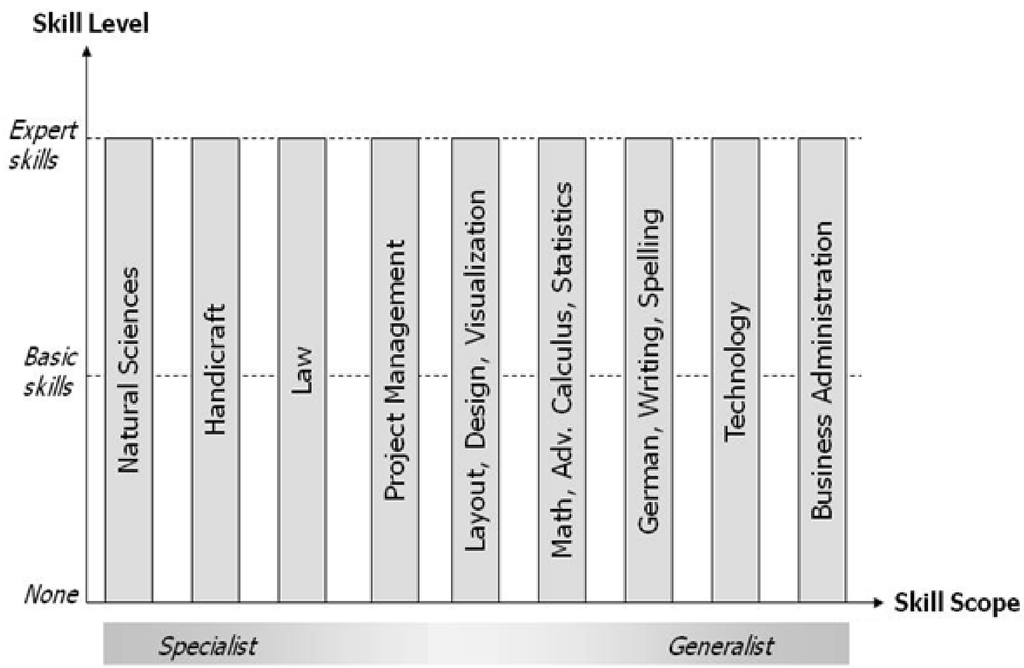

Figure 3: Two-dimensional indicator for skill balance (random order of all nine skills)

We construct a variable that counts all applied expert skills. To find out whether certain skills should be clustered, we run a factor analysis. The result shows that each skill should be used separately. In fact, the percentage of variance for the single skills that cannot be explained by common factors is relatively high. The lowest percentage of variance not explained by common factors is 0.55 for expert technical skills, while the average percentage is 0.71. This suggests that each skill is measured reliably in the current skill variable, and not by any of the other skill variables (for a correlation of the single skills, see Table A 1 in the Annex). We start with expert skills as the dependent variable; later on, we run additional regressions for basic skill levels. In our analysis, individuals will always balance their skills in the quality (skill level) and quantity (skill scope) dimension. To account for this, we allow only one dimension, here skill scope, to vary. Since we take into account only expert skills, it can be assumed that these are balanced with regard to their level. An increase of our count variable, and thereby of the skill scope dimension, will therefore increase skill balance and reflect a generalizing of skills.

Looking at the skills listed by respondents in the survey, it is obvious that knowledge in natural sciences, statistics, and technology are likely to be combined on the job. However, this does not necessarily mean that the persons with these skills are generalists; they could very well be, for example, specialized biologists. Hence, we move away from the idea that specialists are experts in only one skill and instead introduce a scale that allows specialists to increase skill scope without immediately becoming generalists, or, in other words, jacks-of-all-trades. Further, this scaling leaves room to distinguish between different degrees of generalization, as done in our theoretical arguments for firm size. This means that not everyone with more than one skill is a generalist, and further we will focus on marginal changes. As regards balanced skills, this also means that specialists could balance the skill levels of their specialties without achieving balance in the skill scope dimension. The distribution of skills for the employees and the self-employed is documented in Table A 3 in the Annex.

4. Results

In the following subsections, we investigate the on-the-job skill application of employees and entrepreneurs. First, we test for differences in the number of applied skills between employees of varying business size classes and entrepreneurs. Next, possible sources of skill balancing are investigated. Finally, we look at the returns to balanced skills to gain a broader understanding of underlying mechanisms fostering or inhibiting a change in the application of skills. Here, the effect of skill levels is also addressed.

4.1 Determinants of Balanced Skills

4.1.1 Business Size

Looking at the average number of expert skills used in the workplace, we observe a significant difference between the self-employed and employees. Figure 4 presents the number of skills for the self-employed and employees with and without tertiary education. Formal education is positively related to skill balancing for both groups, a finding that will be investigated in detail in the following section. Furthermore, the indicator for skill balance of the self-employed is higher in both cases. This result is in line with several studies that also find more balanced skill sets for entrepreneurs (see, e.g., Lazear, 2004, 2005; Wagner, 2003, 2006). Generally speaking, one could say that the self-employed are "jack-of-more-trades" than employees. Again, keep in mind that applying more than one skill is not considered equivalent to being a generalist.

Next, we investigate how employees' expert skills used in the workplace differ across business size. To account for composition effects, such as an unequal distribution of abilities across businesses, we compare expert skills between different businesses sizes within quartiles of the wage distribution. Research shows that wages serve as a good proxy for employee ability (cf. Ingram and Neumann 2006), and therefore reflect unobserved heterogeneity of abilities. Our categorization creates more homogeneous groups of individuals with regard to abilities and thus makes them more comparable across businesses. In fact, we find that within the first, second, and, albeit less pronounced, third quartile of the wage distribution, workers in small and medium-sized businesses tend to achieve a higher skill balance (see Figure 5). The difference in the number of skills is in almost all cases significantly higher for employees working in businesses with up to 20 employees in comparison to employees in the larger businesses. However, the pattern changes in the fourth quartile of the wage distribution (salary of 3600 € and more). We assume that the main reason for the little variation in the average number of expert skills over business size found in this quartile is that employees with managerial responsibility are more present within the upper quartile of the wage distribution. Due to their responsibilities and tasks on the job, these employees need a higher number of skills, regardless of business size, which is in line with extended definitions of entrepreneurship that include managerial positions (cf. Lazear, 2005).

In the next step, we run different regressions so as to include further controls that may influence the composition of the workforce as well as the number of skills used by the individual employee on the job. This lets us answer the question of whether employees in smaller firms and entrepreneurs tend to apply more expert skills compared to their counterparts in larger firms. Therefore, we include dummy variables for different business size groups, for industries, occupations (only for employees), and a dummy variable indicating whether someone is self-employed. As additional control variables we consider educational background, experience, continuing education, and gender. Table 1 reports the results for OLS and negative binomial regressions. The negative binomial regression is estimated because the dependent variable is a count variable. Columns 1 (OLS) and 2 (negative binomial) show the results for the total sample of employees and the self-employed in manufacturing.

As a central finding, we observe that the self-employed tend to use more expert skills at work compared to their dependently employed counterparts. This result is in line with earlier findings. We also observe that employees in small businesses tend to have a more balanced skill set compared to employees in large businesses. This suggests that large businesses are more specialized with respect to their labor inputs. In sum, our first hypothesis (H1)—that the self-employed have the biggest skill portfolio, followed by small business employees and then large business employees—is supported. However, when we look at the upper quartile of the wage distribution of employees, the differences are no longer as pronounced. Further research could investigate reasons for balanced skill sets. For example, is higher skill balance in small firm caused by a lack of financial resources for additional personnel, a desire of business owners to receive support in a variety of areas, or is it due to a small firm mentality, where everyone knows how to do almost everything?

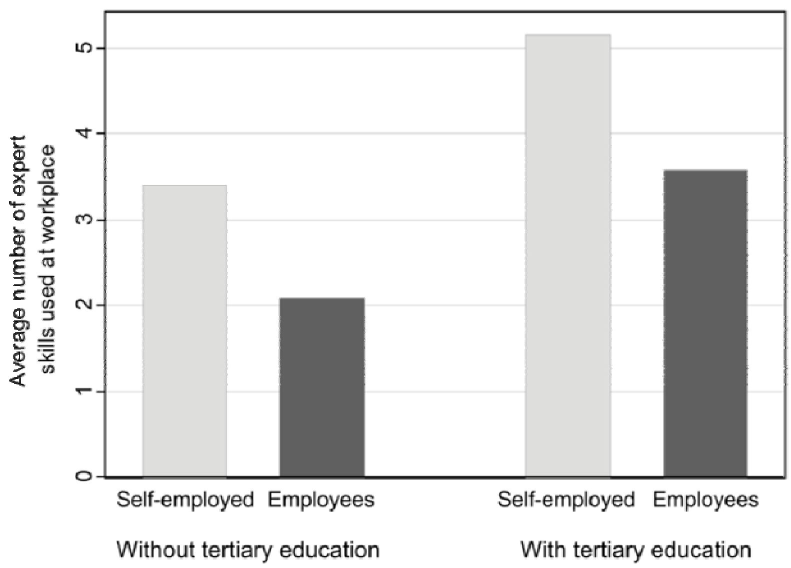

Figure 4: Average skill balance of employees and self-employed with higher and lower levels of formal education

Table 1: Regression results for skill balance of full sample (dependent variable: number of expert skills used on the job)

	OLS	NEGBIN
Self-employed	0.847***	0.251***
	(0.160)	(0.0450)
Size 1–19	0.243***	0.0977***
	(0.0761)	(0.0314)
Size 20–49	0.224***	0.0845**
	(0.0825)	(0.0343)
Size 50–249	0.188***	0.0700**
	(0.0687)	(0.0281)
Size 249–999	0.110	0.0404
	(0.0676)	(0.0276)
Size 1,000 or more	reference	reference
Vocational training (1 = yes)	0.438***	0.319***
	(0.0788)	(0.0579)
Tertiary education (1 = yes)	1.094***	0.552***
	(0.108)	(0.0619)
Master craftsman (1 = yes)	1.227***	0.605***
	(0.112)	(0.0625)
Continuing education (1 = yes)	0.0466	0.0239
	(0.0591)	(0.0233)
Work experience (log)	0.216*	0.0864*
	(0.126)	(0.0523)
Work experience squared	-0.0567**	-0.0237**
	(0.0266)	(0.0111)
Gender (1 = female)	-0.813***	-0.391***
	(0.0601)	(0.0298)
Constant	2.474***	0.697***
	(0.476)	(0.223)
Observations	5669	5669
R-squared	0.322	–
Loglikelihood	–	-10064

Notes: OLS and negative binomial regression. Robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. In the interests of brevity, we do not report the results for dummy variables indicating the occupational field (employees only) and industry.

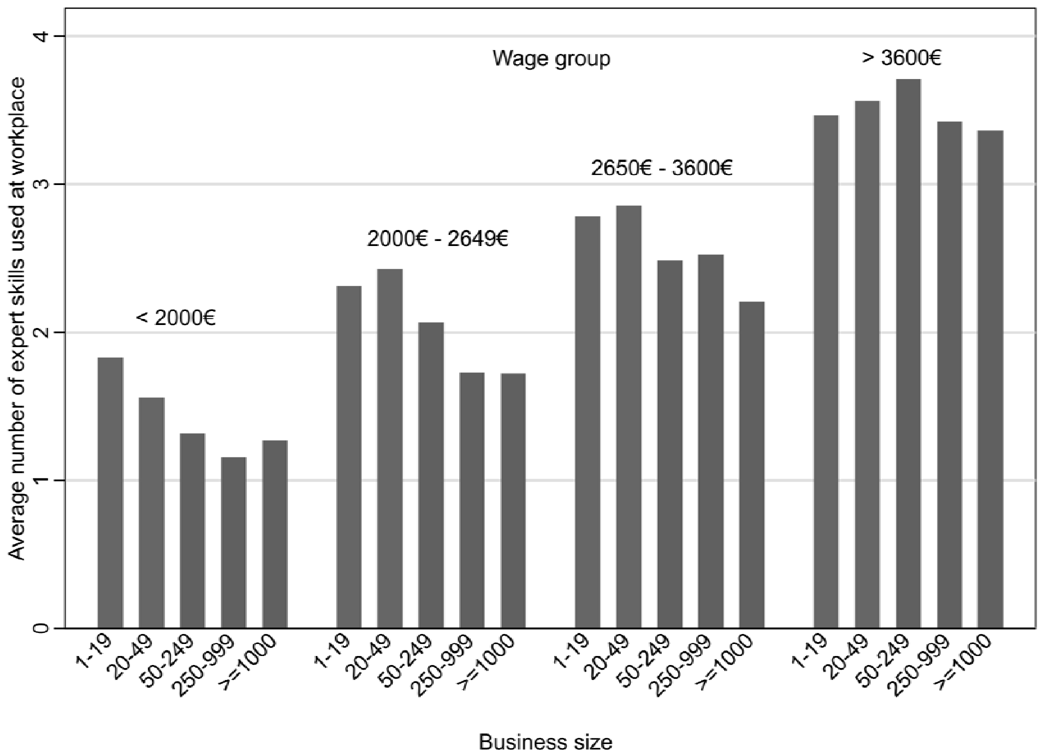

Figure 5: Average skill balance for different wage groups

4.1.2 Human Capital Formation

We now test how formal, informal, and non-formal education are related to generalist work practices of entrepreneurs and of employees working in businesses of different sizes. As shown earlier, human capital in the form of tertiary education increases skill balance (see Figure 4). Starting with the group of self-employed, Table 2 presents regression models (OLS and negative binomial) explaining a balanced skill set. The dependent variable is the number of expert skills frequently used in the workplace. The central explanatory variables refer to formal education, continuing education during the last two years, and general/entrepreneurial experience.

For the self-employed we find that those with tertiary education (vocational training and master craftsman are not significant) tend to apply a significantly greater number of expert skills, suggesting that this type of formal education is related to a balanced skill set. We also find a strong, significant, positive association between continuing education and skill balance. Interestingly, we find no evidence that general work experience is associated with the number of expert skills, but we do find that entrepreneurial experience (proxied by self-employment experience in the current business) of 10 to 15 years is positively related to skill balance at the 10 percent level. The self-employed with more than 15 years of entrepreneurial experience show an even stronger relation to the number expert skills.

One mechanism that may explain the higher likelihood to become self-employed with employment history in small businesses could be that work experience in small businesses is associated with a more balanced skill set. Table 3 presents separate models for employees in businesses of different size that explain the number of expert skills frequently used in the workplace by using a set of educational variables, general work experience, and a dummy indicating whether continuing professional education was acquired during the last two years.

Independently of business size, tertiary education has a positive effect on the number of expert skills applied in the workplace. Also, in most cases, vocational training and training as a master craftsman are significantly positively related, suggesting that training programs that require, in addition to formal theoretical (class) work, an immediate application of skills on the job are beneficial for a broad skill set, regardless of business size. These results suggest that formal education measured in different dimensions is relevant for balanced skills of employees. For continuing education, a weak positive effect at the 10 percent level is found only for employees in small businesses, not for employees working in businesses of larger sizes. Possibly, neither employees nor employers use continuing education as a way of improving skill balance but as a strategy to either bind employees to the firm (employer strategy) or as insurance against being laid off (employee strategy). With respect to general work experience, we find a positive relation to skill balance only for employees in small businesses. This positive relation is decreasing with experience, as indicated by the negative squared term. When we look at the size of the effect of the human capital variables of employees, we find a u-shaped relationship between firm size and the effect of formal education on skill balance.

Table 2: Regression results for skill balance of self-employed (dependent variable: number of expert skills used on the job)

	OLS Self-employed	NEGBIN Self-employed	OLS Self-employed	NEGBIN Self-employed
Vocational training	-0.169	0.00552	-0.295	-0.0126
(1 = yes)	(0.659)	(0.207)	(0.691)	(0.208)
Tertiary education	1.762**	0.453**	1.679**	0.443**
(1 = yes)	(0.679)	(0.199)	(0.733)	(0.204)
Master craftsman	-0.302	-0.0255	-0.585	-0.0754
(1 = yes)	(0.689)	(0.208)	(0.723)	(0.210)
Continuing education	1.697***	0.383***	1.820***	0.424***
(1 = yes)	(0.426)	(0.0834)	(0.439)	(0.0852)
Work experience (log)	-3.438	-0.762	-4.466	-1.001
	(5.396)	(1.096)	(5.362)	(1.098)
Work experience	0.608	0.136	0.670	0.148
squared	(0.867)	(0.178)	(0.854)	(0.176)
Less than 5 years S-E experience	reference	reference	reference	reference
5 to 10 years of S-E	–	–	0.114	0.0205
experience			(0.483)	(0.120)
10 to 15 years of S-E	–	–	0.992*	0.243*
experience			(0.541)	(0.132)
More than 15 years of S-E experience	–	–	1.144**	0.289**
			(0.523)	(0.121)
Gender (1 = female)	-0.672	-0.196	-0.591	-0.191
	(0.601)	(0.165)	(0.578)	(0.154)
Constant	7.344	2.617	7.466	3.023*
	(4.999)	(1.737)	(8.380)	(1.761)
Industry dummies	Yes	Yes	Yes	Yes
Observations	178	178	178	178
R-squared	0.409	–	0.440	–
Loglikelihood	–	-338.9	–	-335.7

Notes: OLS and negative binomial regression. Robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. In the interests of brevity, we do not report the results for dummy variables indicating the industry.

Table 3: Regression results for skill balance of employees of businesses of different sizes (dependent variable: number of expert skills used on the job)

	Size 1–19		Size 20–49		Size 50–249		Size 250–999		Size 1,000 or more	
	OLS	NEGBIN	OLS	NEGBIN	OLS	NEGBIN	OLS	NEGBIN	OLS	NEGBIN
Vocational training	0.773***	0.551***	0.359	0.219	0.357**	0.247**	0.241	0.240**	0.637***	0.449***
(1 = yes)	(0.164)	(0.130)	(0.222)	(0.141)	(0.178)	(0.118)	(0.155)	(0.109)	(0.217)	(0.173)
Tertiary education	1.074***	0.649***	0.969***	0.399***	0.812***	0.409***	0.834***	0.428***	1.272***	0.667***
(1 = yes)	(0.257)	(0.148)	(0.324)	(0.153)	(0.224)	(0.124)	(0.241)	(0.122)	(0.268)	(0.179)
Master craftsman	1.853***	0.948***	1.338***	0.523***	0.958***	0.456***	1.004***	0.504***	1.289***	0.691***
(1 = yes)	(0.247)	(0.141)	(0.350)	(0.162)	(0.252)	(0.129)	(0.235)	(0.123)	(0.278)	(0.180)
Continuing education	0.220	0.0923*	-0.0770	-0.0263	-8.08e-05	0.0104	-0.0232	-0.00643	-0.142	-0.0611
(1 = yes)	(0.136)	(0.0517)	(0.180)	(0.0692)	(0.128)	(0.0516)	(0.139)	(0.0553)	(0.136)	(0.0540)
Work experience (log)	0.570**	0.256**	-0.0223	-0.00194	0.0691	0.0345	0.299	0.119	0.0667	0.00399
	(0.278)	(0.128)	(0.313)	(0.124)	(0.313)	(0.124)	(0.251)	(0.103)	(0.276)	(0.102)
Work experience	-0.150**	-0.0670**	-0.0232	-0.0107	-0.0354	-0.0168	-0.0665	-0.0281	0.00501	0.00629
squared	(0.0600)	(0.0274)	(0.0672)	(0.0267)	(0.0632)	(0.0255)	(0.0550)	(0.0226)	(0.0604)	(0.0223)
Fixed-term contract	-0.585***	-0.266***	-0.517***	-0.236***	-1.044***	-0.530***	-0.891***	-0.448***	-0.723***	-0.313***
(1 = yes)	(0.162)	(0.0721)	(0.179)	(0.0836)	(0.130)	(0.0666)	(0.129)	(0.0676)	(0.131)	(0.0568)
Constant	-0.726	-22.47***	1.389***	-0.894	7.231***	2.360***	1.158**	-0.212	1.972***	0.510**
	(1.374)	(0.201)	(0.478)	(0.580)	(0.673)	(0.615)	(0.542)	(0.685)	(0.548)	(0.243)
Industry and occupation dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1078	1078	709	709	1388	1388	1146	1146	1171	1171
R-squared	0.313	–	0.385	–	0.358	–	0.404	–	0.356	–
Loglikelihood	–	-1800	–	-1191	–	-2411	–	-1969	–	-2061

Notes: OLS and negative binomial regression. Robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. For the sake of brevity, we do not report the results for dummy variables indicating the occupational field and industry.

Interesting differences show up when we compare the self-employed with employees. As regards formal education, tertiary education is the only variable that is significant for all groups. Vocational training and being a master craftsman have a significant positive effect on the skill balance of employees, but they have no effect on the skill balance of the self-employed. Possibly this has to do with an education level effect where the number of expert skills that the self-employed actually apply on the job, which is much higher than that of employees, is not effected by vocational training. Strohmeyer and Leicht (2000) also find that vocational training alone is not enough to meet the variety of challenges associated with self-employment. Being a master craftsman would have similar implications. In general though, this result shows that, for employees, expert skills can be acquired by lower levels of education, e.g., vocational training.

As to informal and non-formal education, general work experience is significant only for employees in businesses with fewer than 20 employees, so there appears to be a small firm effect for skill balance of employees. Variables that have significant positive effects only for entrepreneurs are continuing education and work experience as self-employed for more than 10 years. In particular the effect of continuing education implies that although employees might use continuing education, e.g., to specialize (which is why we find no significant effect for their group), the self-employed deliberately use it to increase their skill balance. Further, for the skills that the self-employed actually apply on the job, general work experience is no longer relevant, which could also be related to a education level effect that only specific entrepreneurial work experience affects the skill balance of the self-employed.

With respect to formal education, our results could lead one to say that the skill balance of the self-employed, which is on average significantly higher than that of employees, can benefit only from higher education, whereas employees' skill balance can still benefit from lower levels of education. This suggests that above a certain threshold, further skill balancing requires higher educational training (e.g., in law, math, and technology). On the one hand, the definition of what exactly an expert skill is might vary between the self-employed and employees, perhaps leading the latter to apply lower thresholds for expert skills. On the other hand, it is likely that a certain skill balance has already been achieved while working as an employee so that when transitioning into self-employment individuals need higher and more focused education to improve their skill balance. This idea is supported by the summary statistics where we see that, on average, the self-employed apply considerably more expert skills than employees (self-employed 3.86 vs. employees 2.37) which is in line with previous research (Parker, 2009a; Robinson and Sexton, 1994).

Based on these findings, Hypothesis 2 holds only for the self-employed because only for them a positive effect of human capital formation is found. In contrast to our hypothesis, the positive effect of formal human capital formation on skill balance shows a u-shaped relationship to firm size. Further, our regression results partially support that informal human capital formation is positively related to skill balancing in small businesses. Because of this only partial support, we further investigate the relationship between experience and skill balance by focusing on the role of job and firm-specific experience.

Since we only have cross-sectional data, it is not possible to observe the development of expert skills over time. However, since we do have information on the number of years a person worked for a company, we can check whether small businesses' employees, compared to large businesses' employees, acquire more expert skills as tenure (length of employment in one firm) increases. Accordingly, only those employees who have never switched jobs are considered. Furthermore, we exclude the upper quartile of the wage distribution in order to avoid a bias that might result from including management-level employees in large businesses (cf. Figure 5).

In our sample we have 473 individuals in manufacturing industries who have never changed jobs since their labor market entry and who belong to the three lower quartiles of the wage distribution. Due to the relatively small number of observations, we divide the sample into employees who work for businesses with less than 50 employees and those who work for businesses with more than 50 employees. In the small businesses (less than 50 employees) we have 156 observations; in the larger businesses (50 and more employees) we have 317 observations.

Figure 6 reports the average skill balance for workers of different business sizes and tenure groups. We observe that workers in large businesses achieve a higher skill balance than workers in small businesses if they have been working for three years or less for their employer. For the group of employees that have tenure of between four to eight years, we no longer observe a significant difference. Interestingly, workers who have been employed for more than 9 years in small businesses report significantly more expert skills than employees in large businesses. This finding suggests that employees who work for a longer period of time for a small business acquire a higher skill balance than do employees who work for a longer period of time in large businesses. However, at the very beginning of a career, employees in large businesses tend to have a higher skill balance compared to entrants in small businesses.

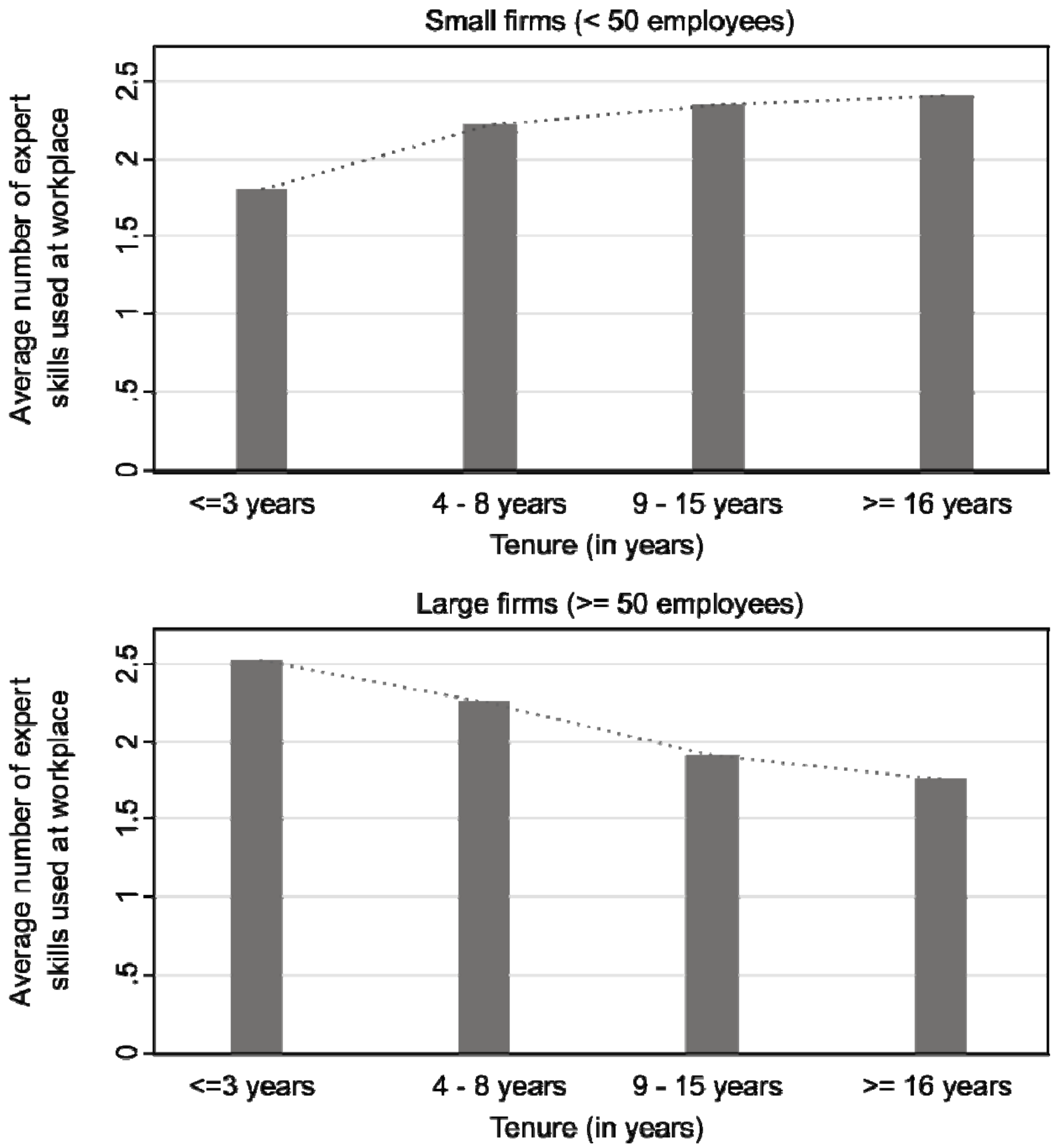

Figure 6: Average skill balance of employees in small and large businesses for tenure groups (omitting employees within the upper quartile of the wage distribution and employees who changed their employer)

Although these findings suggest that on-the-job learning might play an important role in generating a balanced skill set for employees in small businesses, we must be cautious about this interpretation due to the cross-sectional structure of the data. For example, small firms might release employees who do not meet broad skill requirements, resulting in a higher average number of skills for the remaining employees (selection over tenure). Or, the selection process could lead individuals to choose or be chosen by their employer based on skill set. If entrepreneurs-to-be intend to acquire a balanced skill set by working as paid employees, their optimal choice would be to work in small firms, that is, if our assumption is correct that more skills will be applied on such a job. Additionally, small firms might have a preference for employees with a more balanced set of skills. This mechanism supports our idea that employees in small firms should have a more balanced skill set than employees in large firms. With regard to large firms, a trend toward unbalanced skills on the part of individuals does not rule out that skill balance is achieved at the firm level; firm-level skill balance can be achieved by employing individuals who have the same level of skillfulness at different skills. However, we cannot disentangle the selection from the learning variable, and, also, we do not know what type of education would mainly drive these differences.

In summary, entrepreneurs' skill balance is positively related to human capital formation. Further, we find some empirical evidence that formal education is positively related to skill balancing for small business employees and that the effect first decreases with business size, but then increases again. Thus, we confirm that formal human capital formation is positively related to skill balance for all employees but the effect has a u-shaped relationship to firm size. Moreover, the empirical evidence suggests that small business work experience is positively related to skill balancing, while large business employees may specialize in certain fields with tenure. Therefore, Hypothesis 2 does not hold true for employees of large businesses. Although some results suggest that learning might play a role in explaining the differences in applied skills for labor market entrants in the lower three quartiles of the wage distribution, this evidence must be viewed with caution due to the nature of our data. Panel data are required before any firm conclusions can be drawn in this respect.

4.2 Returns to Balanced Skills

4.2.1 The Effect of Balanced Skills on Income

In this section, we look at whether, and if so, how, the applied skills of workers translate into individual earnings. Again, we focus on differences having to do with business size by analyzing returns to the expert skills of individuals employed in small and large businesses. We then compare these results to those obtained for the self-employed. Figure 7 plots the average skill balance of the self-employed and employees for different income groups. Both tend to show a higher skill balance in higher income groups compared to lower income groups. We also see that in all income groups, it is the self-employed who have the greatest skill balance.

Table 4 presents the results of the income regressions for employees in different business size classes as well as for the self-employed. We estimate the logarithm of the hourly income with OLS, where the hourly income is defined as the monthly gross income over the number of hours worked last month (including overtime). As an alternative to OLS, we applied TOBIT regression to account for the left-censoring of income but the results did not change substantially.

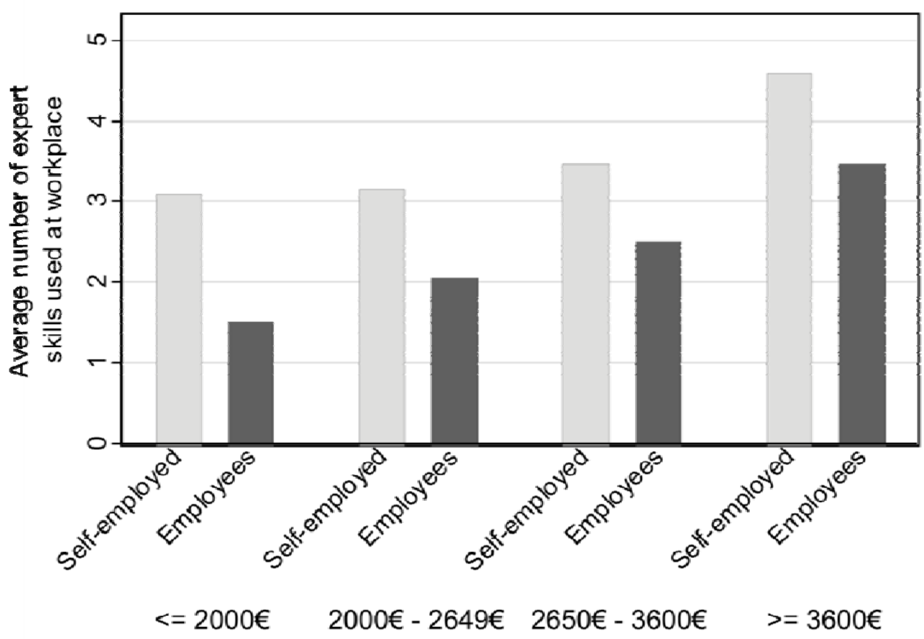

Figure 7: Average skill balance of employees and the self-employed for different income groups

The central explanatory variable is the number of expert skills used at work. Controls for educational background, work experience, gender, a dummy indicating whether an employee has a fixed-term contract, and a set of dummy variables for occupational background, regions, and industry complement the set of independent variables. For the self-employed, we include the experience of being self-employed instead of general work experience since the former turned out to be a better predictor for the income generated through self-employment (cf. Table 2).

Generally, the control variables have the expected signs. Female employees have significantly lower hourly wages, although this negative relationship is less pronounced in larger businesses. Work experience and formal education have a significant positive impact on wages, and employees with a fixed-term contract have significantly lower wages for nearly all business size classes. For the self-employed, we find that entrepreneurial experience is significantly positively related to income but we find no significant relationship between tertiary education and income, which is puzzling in light of our earlier results. Therefore, we tested a model without controls for industry and skill balance; in this model, tertiary education *is* significantly related to income. When including the skill balance variable again, tertiary education is no longer significant, indicating that entrepreneurial income benefits from tertiary education via skill balancing.

Table 4: Results of income regression (dependent variable: log of hourly income)

	Size 1–19	Size 20–49	Size 50–249	Size 250–999	Size 1,000 or more	Self-employed
No. of expert skills	0.0328***	0.0291***	0.0194**	0.0179**	0.0170***	0.0559**
	(0.00842)	(0.0102)	(0.00799)	(0.00753)	(0.00576)	(0.0240)
Vocational training (1 = yes)	0.167***	-0.0121	0.168***	0.127***	0.111**	-0.120
	(0.0553)	(0.0728)	(0.0366)	(0.0394)	(0.0472)	(0.160)
Tertiary education (1 = yes)	0.304***	0.194*	0.280***	0.341***	0.292***	-0.153
	(0.0752)	(0.114)	(0.0500)	(0.0562)	(0.0561)	(0.182)
Master craftsman (1 = yes)	0.235***	0.105	0.202***	0.170***	0.194***	-0.237
	(0.0672)	(0.0915)	(0.0452)	(0.0510)	(0.0546)	(0.159)
Continuing education (1 = yes)	0.00888	-0.0440	0.00584	0.0311	-0.0443	-0.0115
	(0.0302)	(0.0466)	(0.0259)	(0.0249)	(0.0291)	(0.102)
Work experience [A] (log)	0.348***	0.290***	0.282***	0.258***	0.142*	0.388**
	(0.0858)	(0.0902)	(0.0838)	(0.0880)	(0.0832)	(0.151)
Work experience squared [A]	-0.0512***	-0.0306	-0.0282*	-0.0197	0.00334	-0.0722*
	(0.0179)	(0.0200)	(0.0168)	(0.0174)	(0.0171)	(0.0382)
Fixed-term contract (1 = yes)	-0.0977***	-0.0921	-0.171***	-0.171***	-0.144***	–
	(0.0340)	(0.102)	(0.0461)	(0.0524)	(0.0528)	
Gender (1 = female)	-0.250***	-0.232***	-0.166***	-0.187***	-0.137***	-0.270*
	(0.0388)	(0.0541)	(0.0289)	(0.0302)	(0.0287)	(0.159)
Constant	2.151***	2.187***	1.941***	1.953***	2.406***	3.184***
	(0.132)	(0.162)	(0.267)	(0.150)	(0.243)	(0.397)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes [B]
Observations	1078	710	1389	1149	1172	172
R-squared	0.451	0.491	0.456	0.486	0.505	0.579

Notes: OLS regression with robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. For the sake of brevity, we do not report the results for dummy variables indicating the occupational field (only employees), industry and region. [A] The equation for self-employed uses, instead of general work experience, years of self-employment, which turned out to be a much better predictor for the earnings of the self-employed. [B] The income equation for the self-employed includes additional controls for firm size.

We also tested for possible non-linearities in the relationship between income and skill balancing by including a squared term of the skill balance variable. From this we discovered that the returns from increasing skill balance by one additional skill, which by definition is at the same skill level as already existent skills, are constant. This means, for the observed realizations of skill balance, that there is no limit point at which adding another skill to one's repertoire will have a decreasing return or a negative effect on income. In theory, this would occur once a maximum is reached and more balance would not increase payoffs, but we find no evidence for this in the data. Further, an increase in skill scope raises wages in all business size classes, while self-employed are rewarded with the highest returns for additional skills. In the group of employees, returns to balanced skills are largest for employees in businesses with less than 20 employees (3.28 percentage points for an additional skill used on the job). For all larger business size classes, we find a less pronounced but still positive relationship, with lowest returns to balanced skills for employees in businesses with more than 1,000 employees (1.7 percentage points for an additional skill used on the job).

These findings support our hypothesis that returns to balanced skills are highest for the self-employed, followed by small business employees, and then large business employees (H3). It is important to remember, of course, that these results address the returns to balanced skills and should not be taken to mean that actual wages are higher for employees of small businesses; generally speaking, employee wages are higher in larger businesses. One major shortcoming of our analysis is that, due to the nature of our data, we cannot control for selection into self-employment. Again, panel data are necessary for such a procedure.

4.2.2 The Effect of Skill Level

As a robustness test of our results on the influence of skill balance, we looked at the group of individuals that does not apply any expert skills. Nearly 20 percent of employees fall into this category; around 4 percent of the self-employed report that they apply none of the surveyed expert skills on the job. Nevertheless, these individuals might have a balanced set of basic skills and, therefore, we calculate a count of basic skills for those who report no expert skills. Again, a higher number of basic skills balances the skill set because it increases skill scope given that an individual applies no expert skills. The results of the income regressions, which include a variable that indicates a balancing of basic skills if expert skills are not present, are reported in Table A 4 in the Annex. Although we continue to find the same relationship between expert skill balance and income for both the self-employed and employees, we find no relationship between basic skill balance and income. This confirms that we were correct in choosing expert skills as the appropriate skill level for investigating skill balance. It also constitutes further support for the importance of control for skill levels because, otherwise, measured skill scope might be biased.

Hypothesis 4, which states that, in addition to skill scope, skill level has an effect on skill balance, can thus not be rejected. We can even identify a threshold (here, expert skills) that must be passed before employees, as well as the self-employed, will benefit from skill balance. This is in line with the education level effect that we found for human capital formation, which was that the skill balance of the self-employed can benefit only from higher education, whereas employees' skill balance can be positively affected by lower levels of education. Hence, this could be described as a two-stage level effect: education levels play a role in determining the skill level, which in turn affects returns. Therefore, individuals first need to invest in the education level that will allow them to increase the level and balance of their skills so that they can increase their income.

5. Conclusions

In this paper we investigate the concept of balanced skills from different perspectives. To our knowledge, extant literature on this topic focuses on entrepreneurs, with employees as the reference group. We contribute to this body of work by developing a refined indicator that allows measuring skill balance in two dimensions: quantity (skill scope) and quality (skill level).

We begin with possible *determinants of balanced skills*, namely, business size and human capital formation. First, we investigate differences in the skill balance of entrepreneurs and employees when different businesses sizes are taken into account. The results show that, in the three lower quartiles of the wage distribution, small business employees tend to apply a higher number of skills on the job than employees in larger businesses. Thus, they are more balanced with respect to skill structure than employees in larger businesses. Nevertheless, the self-employed have the highest skill balance.

As regards human capital formation, we find that formal education is beneficial for a balanced skill set both for employees in businesses of different size and for the self-employed. For employees, there is a u-shaped relationship between firm size and the effect of formal education on skill balance. Non-formal education, i.e., continuing education, has no significant effect on the skill balance of employees. For the self-employed, we find a strong and positive effect of entrepreneurial experience, instead of general work experience, and of continuing education on skill balance. Differences between the self-employed and employees appear to be driven by a education level effect according to which the skill balance of the self-employed can benefit only from higher levels of education, whereas the skill balance of employees can yet be positively influenced by lower levels of education.

This might be caused by the fact that the self-employed have, on average, more balanced skills than employees, which makes further skill balancing more difficult and, therefore, requires higher levels of education. When investigating the relationship between informal human capital and skill balance over time, we find some evidence that, for employees, work experience favors learning processes that balance skills in small businesses and results in specialization in larger businesses. However, this holds true only for a sample of employees who have never changed their employer. Also, our results could be driven by a selection process in which employees choose or are chosen according to their skill sets. However, the cross-sectional character of the data used in this study mandates a cautious interpretation and to be able to more precisely discover the sources of balanced skills, further research is required.

In the second part of the paper, we address *returns to balanced skills* and the role of skill levels. We present evidence that returns to balanced skills are highest for entrepreneurs, which supports Lazear’s (2004) argument that a balanced skill structure is more beneficial for this group. An additional expert skill (which balances the skill structure) applied on the job increases the salary of the self-employed by 5.59 percentage points. For employees, we find decreasing returns to balanced skills as business size increases. For example, the returns for an additional expert skill are 3.28 percentage points in small businesses with fewer than 20 employees; they are only 1.7 percentage points in large businesses with more than 1,000 employees. Furthermore, the income of all individuals is only affected by skill balance if skill levels are sufficiently high, meaning that skill level matters in addition to skill scope.

Our work contributes to the field by showing that the effect of skill balance is dependent on the skill level. Accordingly, entrepreneurial success is not only influenced by skill balance in the skill scope dimension but also by balance in the skill level dimension. Since entrepreneurial income benefits from tertiary education via skill balancing, educational programs should adjust to individual needs and promote the overall skill balance. Our analysis shows that the usual practice of simply categorizing employees as specialists, regardless of occupation and firm size, ignores the importance of skill balance for wages, and also fails to recognize the possible future entrepreneurial aspirations of this group. The results provide another explanation for why regions with many small firms produce a high number of entrepreneurs. Finally, work experience in small businesses, as well as in higher wage groups of large businesses, can be regarded as a qualification strategy for future entrepreneurs because these groups exhibit higher skill balance. In conclusion, the concept of balanced skills needs to be refined to account for our findings, for instance, by distinguishing between firm size, patterns of labor division, and strategies for balancing human capital. Our use of a two-dimensional indicator has revealed that jacks-of-all-trades remain important and can be found both among the self-employed and among employees.

One shortcoming of our work is that data on the income of the self-employed always suffers from problems that are discussed above, which are difficult to overcome. In addition, the survey used for this study emphasizes skills that are especially relevant for manufacturing industries, and hence the relevance of our concept for service industries is still to be tested. Also, organizations may be willing to pay for skills of workers that are currently not applied in the workplace in order to keep a broad knowledge base available. However, counterevidence shows that employers do not reward skills that are redundant in an occupation (cf. Nedelkoska and Neffke, 2010).

In the future, it would be interesting to test our hypotheses using panel data and consider selection into self-employment as well as into employment in various business sizes (especially employees in the upper wage quartile and managerial positions). In particular, further research could investigate labor mobility between different firm sizes in an effort to identify possible strategies of skill balancing.

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Annex

Table A 1: Summary statistics

Employees:

Variable	Mean	Std. Dev.	Min	Max
Hourly wage (log)	2.693826	.4902953	.0738226	5.569259
Size 1–19	.1962889	.3972257	0	1
Size 20–49	.1287975	.3350062	0	1
Size 50–249	.2526833	.4345904	0	1
Size 249–999	.2090231	.4066479	0	1
Size 1,000 or more	.2132072	.4096101	0	1
Expert skills used at work	2.36529	1.852479	0	9
Basic skills used at work	.5975987	1.491234	0	9
Vocational training (1 = yes)	.6427142	.4792436	0	1
Tertiary education (1 = yes)	.1875568	.3903934	0	1
Master craftsman (1 = yes)	.0944151	.292432	0	1
Work experience (log)	2.852997	.6497524	0	3.988984
Work experience squared	8.561695	3.2688	0	15.91199
Continuing Education (1 = yes)	.1471712	.3543087	0	1
Fixed-term contract (1 = yes)	.0674914	.2508939	0	1
Gender (1 = female)	.275241	.4466763	0	1

Self-employed:

Variable	Mean	Std. Dev.	Min	Max
Hourly income (log)	2.522582	.5036259	1.400622	3.831988
Expert skills used at work	3.855491	2.187952	0	9
Basic skills used at work	.2716763	1.276421	0	8
Vocational training (1 = yes)	.3872832	.4885433	0	1
Tertiary education (1 = yes)	.2485549	.4334297	0	1
Master craftsman (1 = yes)	.300578	.4598404	0	1
Work experience (log)	3.166456	.4233243	1.098612	3.931826
Work experience squared	10.20459	2.520128	1.206949	15.45925
Continuing education (1 = yes)	.150289	.3583918	0	1
Gender (1 = female)	.0867052	.2822194	0	1

Table A 2: Correlation of skills

		1	2	3	4	5	6	7	8	9
1	Natural Science	1								
2	Handicraft	0.054	1							
3	Law	0.125	0.025	1						
4	Project Management	0.258	-0.081	0.193	1					
5	Layout, Design, Visualization	0.135	-0.023	0.112	0.276	1				
6	Math, Adv. Calculus, Statistics	0.307	0.196	0.162	0.240	0.157	1			
7	German, Writing, Spelling	0.159	-0.087	0.189	0.286	0.234	0.235	1		
8	Technology	0.315	0.417	0.076	0.228	0.108	0.347	0.085	1	
9	Business Administration	0.006	-0.176	0.269	0.289	0.098	0.127	0.292	-0.076	1

Table A 3: Distribution of skills

Number of expert skills **(employees)**	Freq.	Percent	Cum.
0	1,064	19.35	19.35
1	920	16.73	36.09
2	1,124	20.44	56.53
3	997	18.13	74.66
4	650	11.82	86.49
5	392	7.13	93.62
6	213	3.87	97.49
7	104	1.89	99.38
8	29	0.53	99.91
9	5	0.09	100.00
Total	5,498	100.00	

Number of expert skills **(self-employed)**	Freq.	Percent	Cum.
0	8	4.62	4.62
1	14	8.09	12.72
2	23	13.29	26.01
3	42	24.28	50.29
4	30	17.34	67.63
5	19	10.98	78.61
6	13	7.51	86.13
7	10	5.78	91.91
8	8	4.62	96.53
9	6	3.47	100.00
Total	173	100.00	

Table A 4: Results of income regression including basic skills if no expert skills present (dependent variable: log of hourly income)

	Size 1–19	Size 20–49	Size 50–249	Size 250–999	Size 1,000 or more	Self-employed
No. of expert skills	0.0330***	0.0313**	0.0234***	0.0158*	0.0155**	0.0516**
	(0.00867)	(0.0130)	(0.00901)	(0.00867)	(0.00636)	(0.0253)
No. of basic skills	0.00116	-0.0192*	0.00733	-0.00567	-0.00142	-0.0223
(if no expert skills present)	(0.0131)	(0.0115)	(0.00873)	(0.00815)	(0.00671)	(0.0383)
Vocational training (1 = yes)	0.158***	0.0388	0.149***	0.112***	0.113**	-0.126
	(0.0551)	(0.0807)	(0.0368)	(0.0408)	(0.0468)	(0.153)
Tertiary education (1 = yes)	0.305***	0.349***	0.251***	0.338***	0.288***	-0.155
	(0.0762)	(0.118)	(0.0494)	(0.0573)	(0.0554)	(0.178)
Master craftsman (1 = yes)	0.223***	0.192*	0.179***	0.149***	0.192***	-0.235
	(0.0662)	(0.102)	(0.0450)	(0.0520)	(0.0535)	(0.154)
Continuing education (1 = yes)	0.00628	-0.0135	0.0103	0.0306	-0.0477*	-0.0119
	(0.0299)	(0.0467)	(0.0265)	(0.0248)	(0.0286)	(0.102)
Work experience[A] (log)	0.329***	0.285***	0.289***	0.272***	0.145*	0.391**
	(0.0862)	(0.0965)	(0.0845)	(0.0865)	(0.0829)	(0.151)
Work experience[A] squared	-0.0462**	-0.0281	-0.0299*	-0.0229	0.00195	-0.0725*
	(0.0179)	(0.0211)	(0.0169)	(0.0172)	(0.0171)	(0.0386)
Fixed-term contract (1 = yes)	-0.105***	-0.157*	-0.167***	-0.154***	-0.145***	–
	(0.0335)	(0.0922)	(0.0455)	(0.0528)	(0.0520)	
Gender (1 = female)	-0.251***	-0.220***	-0.178***	-0.199***	-0.130***	-0.282*
	(0.0382)	(0.0441)	(0.0291)	(0.0311)	(0.0287)	(0.161)
Constant	2.178***	1.896***	1.641***	1.309***	2.657***	3.072***
	(0.131)	(0.179)	(0.317)	(0.200)	(0.287)	(0.368)
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes[B]
Observations	1078	710	1389	1149	1172	172
R-squared	0.437	0.4052	0.4390	0.469	0.491	0.580

Notes: OLS regression with robust standard errors in parentheses. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level. For the sake of brevity, we do not report the results for dummy variables indicating the occupational field (only employees), industry, and region. [A] The equation for self-employed uses, instead of work experience, years of self-employment, which turned out to be a much better predictor for the earnings of the self-employed. [B] The income equation for self-employed includes additional controls for firm size.