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Schmollers Jahrbuch 135 (2015), 499 – 536
Duncker & Humblot, Berlin

Productivity Signalling and Further Training

Evidence on Absence Behaviour, Presenteeism and Overtime Hours of German Employees*

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Abstract

This paper pursues the argument that there is an incentive for employees to signal productivity in order to get further training in a firm. While usually both sides can benefit from this, firms are harmed if employees invest too much effort in potentially inefficient effort signals. Using representative survey data the paper empirically analyses whether different productivity signals increase the chances of further training for German employees. On the one hand, the results show that individuals who come to work when they are ill and who put up overtime hours can have higher chances to receive further training. On the other hand, it is found that individuals who report in sick are also more likely to receive further training. The observed relation suggests that only a moderate use of these effort signals is exerted. Therefore, negative consequences for firms due to effort spent in potentially inefficient effort signals might be modest.

JEL Code: M53, D03, I19

1. Introduction

Continuous, further, or intra-firm training, i.e., training during a period of employment, is an important tool of human resource management (HRM). The causes and effects of continuous training have been studied extensively in the existing literature. There are both fairly recent (Breuer / Kampkötter, 2013) and more extensive reviews (Blundell et al., 1996). From a firm perspective, it is usually found that continuous training increases employee productivity and motivation, while simultaneously reducing employee turnover. From an em-

* I want to thank Christian Pfeifer, an anonymous referee, the participants of the Colloquium on Personnel Economics 2014 in Cologne of the Brown Bag Seminar at University Tübingen, and of the Lüneburg Workshop in Economics 2015 for useful comments. Thanks for excellent research assistance go to Matthias Seckler. All errors remain mine.

ployee perspective, getting further training also has its benefits. Well-trained employees receive better payment, have higher chances of getting promoted and are less likely to be laid off. In this sense, both sides can potentially profit. Further training, however, comes at a cost. These costs are born by both sides and involve direct costs for training courses and indirect costs, such as the opportunity costs of being absent at work, the time spent for studying, etc. Furthermore, well-trained employees may have higher job aspirations a firm has to meet. Standard economic theory predicts that firms will not invest in general training at all and under-invest in specific training (Becker, 1962; Williamson, 1985). Empirical evidence, however, indicates that firms do invest in their workers' general training (Acemoglu / Pischke, 1998; Pischke, 2001). Evidence from laboratory experiments confirms underinvestment in specific training, but less than theory predicts (Fehr / Gächter, 2000).

A firm's decision of whom to train is non-trivial and often involves trade-offs. Extensive studies have been carried out, advising firms on which types of workers they should train, be it productive or unproductive workers, younger or older workers, tenured or newly hired workers, etc. Productive workers may benefit more from training while unproductive ones may stay behind and harm team performance without it. Younger workers may learn faster, but older workers may combine new skills from training with their life-long experience. New workers may be highly motivated, whereas tenured workers are less likely to quit, such that the firm has more benefit from the additional skills.

An important factor in the decision of who receives continuous training is the employees' performance, i.e., their effort. The direction of the effect is, however, unclear. On the one hand, employers may use the prospect of obtaining further training as an incentive device, or simply reward productive individuals (positive effect). On the other hand, training might be considered as more necessary by the employer when performance is low (negative effect). In the first case, a firm uses continuous training as a tool of motivation: an employee puts up increased effort, so the firm sponsors a further training course as a reward. Both sides benefit from this arrangement: the firm profits from higher effort by the employee, while the employee receives training as a reward, which can grant her / him, for example, higher skills or promotions (Pfeifer et al., 2013). In an ideal world, this behaviour can be interpreted as a gift-exchange (Akerlof, 1982). According to this view, firms might achieve higher profits by treating their workforce kindly (e.g., paying fair wages or handing out other financial or non-material benefits). Firms reciprocate positively to the employees' 'gift' of exerting higher effort. It has been shown that non-monetary gifts have a much stronger impact on reciprocity in employment relations than monetary gifts of equivalent value (Dur, 2009; Kube et al., 2012). Leuven et al. (2005) propose a model in which a firm invests the socially optimal amounts of general and specific training if the worker is sufficiently motivated by reciprocity. This mechanism is supported by empirical evidence. In a field

experiment with random assignment to a training programme Sauermann (2015) provides evidence that reciprocal workers have a significantly higher performance than their non-reciprocal peers after participation in the training course.

Observing effort or potential reciprocal behaviour in advance to choose optimal candidates for further training, however, is non-trivial in a world characterised by own interest and asymmetric information. Employees usually do not reveal their (lack of) effort, e.g., because they fear negative consequences. This paper provides fresh descriptive evidence on the relationship between training participation and effort proxies. The idea is that employees might try to signal high motivation and effort by (1) overtime hours, by (2) (not) calling in sick (absence behaviour / absenteeism) and by (3) showing up for work whilst being ill (presence behaviour / presenteeism).

There exist potential adverse effects of providing continuous training to individuals who use these effort signals. If employees have an incentive to signal motivation to increase their likelihood of getting continuous training, and if there are observable signals which do not necessarily correlate with actual performance, this can have negative consequences for the firm. Indeed, there are multiple ways to signal good performance that might actually harm the company. It can be argued that overtime, (the lack of) absence behaviour as well as presence behaviour may be undesirable from a firm perspective for a number of reasons. On the one hand, employees who attend work whilst being ill are characterised by a substantially reduced productivity compared to those who are well[1]. Additionally, there is the risk that sick employees showing up for work (presentees) spread their illness to other employees (Pichler / Ziebarth, 2015). Furthermore, presenteeism has a negative impact on future general health and increases the likelihood of more frequent sickness absence (for a more in-depth discussion on this topic, see Johns, 2010). On the other hand, it can be the case that employees who are ill might actually be able to work, albeit not full-time, if their disease is non-infectious (cf. Markussen et al., 2012). Calling in sick for minor reasons, therefore, may be a similarly bad signal as showing up for work with a contagious infection. Working overtime can have a number of negative effects on both the employees themselves and the firm, as well as on society as a whole (Caruso, 2006). First of all, overtime can prove costly for the firm if there are overtime bonuses[2]. Productivity decreases, errors and injuries during working time increase if working long hours prevents individuals from sleeping enough. It can be argued that if firms tolerate or even foster overtime and presence behaviour of employees, that have received or are going to receive continuous training, this reduces the

[1] Arguably, they have a higher productivity than someone not showing up for work at all.

[2] According to Hunt (2013), this is the case for about 50% of all German employees.

positive effects of firm-sponsored training on both, employee and firm performance.

The remainder of this paper is structured as follows. Section 2 will shortly sum up the research results of the literature strands this work combines: absence and presence behaviour, overtime hours, and the determinants of further training. Section 3 presents the data used and the empirical methods, along with descriptive statistics. The results from the empirical analysis will be presented in Section 4, while Section 5 concludes.

2. Literature Review

A recent paper, with a line of argumentation similar to this one, is by Kampkötter/Marggraf (2015). They study the effects of further training on absence behaviour and turnover probability based on personnel records of a large multinational company. They find that general training induces a decrease in turnover rates and absence behaviour. Their findings support the view that employees reciprocate training participation by increased effort and commitment[3].

2.1 Further Training

The determinants (and effects) of training have been studied extensively in the literature. Breuer/Kampkötter (2013) offer a recent, and Blundell et al., (1996) an extensive review. Several hypotheses emerge regarding the determinants of further training. For example, as regards age, there exists an inversely U-shaped propensity of training participation along the age curve, stipulated by Becker (1962): Since further training can be interpreted as an investment, the possibility of longer amortisation will induce firms to train younger employees. However, older employees often profit more from further training, as their formal education could need more of an update and their professional experience could make further training more effective. Following similar lines of argumentation, females, foreigners, and employees with a fixed-term work contract should get less further training because they are more likely to leave the company. The effect of formal education on further training depends on the type of company. Tenure is inversely related to further training. A higher occupational status is associated with more further training, while part-time workers should receive less of it. The paper of Grund/Martin (2012) is an example for a recent empirical study that uses state-of-the-art methodology. Using data from the German Socio-Economic Panel (GSOEP), they find that migration background, job status and firm size affect training decisions the most. In addition, they ob-

[3] See Fehr/Gächter (2000) and Sobel (2005) for reviews on reciprocity behaviour.

serve a general trend of rising training rates. Their results will later provide a benchmark to check the quality of our results. Other recent studies on Germany include Bellmann et al. (2011), who analyse the influence of regional determinants in addition to several determinants of further training at the establishment level. Applying multi-level random effects logit models to data based on the IAB-Establishment Panel 2001–2007, they show that whether an employer provides firm-sponsored training to a certain employee can be explained first and foremost by firm and individual determinants[4]: qualified employees get trained more and part-time employees get trained less. Collective bargaining agreements and works councils increase further training, as do innovations, a good business outlook, and firm size[5].

While the determinants of further training seem to be relatively undisputed, it remains unclear whether the relationships between further training and its effects (e.g. on wages or productivity) are causal. If this is the case, the investment in further training might benefit employees or firms deciding on HRM practices. A causal effect is questionable if there is a selection prior to training participation, i.e., if only the most productive and motivated employees are provided with continuous training, since, in this case, measuring the effect only captures the impact of (un-)observed employee heterogeneity. A number of recent studies has shown that due to this fact, it is not only important to control for a large number of potential covariates which determine both training and its potential effects, but also to make use of econometric modelling which allows for a causal interpretation of the results (see, e.g., O'Connel/Bryne, 2013, or Pfeifer et al., 2010).

In this context, Pfeifer et al. (2013) evaluate the effects of employer-provided formal training on employee suggestions for productivity improvement strategies and on promotions. In order to do so, they use personnel data of a German company based on which they are able to address issues such as training course heterogeneity and unobserved worker heterogeneity. They find that formal training increases the workers' likelihood of making suggestions and of receiving promotions, but only in the short term. Yet, the question whether such effects are consistent with the human capital argument that training increases workers' productivity or whether this represents reciprocal behaviour could not be tested.

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4 Only high regional unemployment is sometimes a significantly negative determinant of further training.

5 Similar effects have been shown by Stegmaier (2013), with a focus on the relationship between industrial relations and training.

2.2 Overtime Behaviour

Working overtime means that employees spend more time at their workplace than scheduled by the work contract. Overtime as a signal is not a new idea. Anger (2006, 2008) suggests this mechanism as an explanation for the positive relationship between overtime and future benefits. She applies an internal signalling model in which, by supplying unpaid overtime, a worker signals his value to the employer. Using data from the GSOEP, she indeed finds a positive signalling value of unpaid overtime, i.e., higher earnings for employees that work more than the time they are paid for. Also, examining personnel records of a large German company, Pfeifer (2010) has shown that more overtime is correlated with a higher promotion probability, especially in the last three months before the promotion occurs. Van der Meer / Wielers (2015), however, do not find any evidence on the proposition that unpaid overtime leads to extra wage growth using data from the Netherlands. They conclude that personnel policies should focus rather on the intrinsic motivation of personnel than on the extrinsic one.

Overtime can also have negative consequences. Caruso (2006) summarises the research that links long work hours to a wide range of risks to workers, families, employers, and the community. Employees working overtime have less time to recover, make more mistakes and are characterised by lower productivity, at least during the overtime hours. Sideeffects include delayed marriages and child bearing, as well as obesity in the workers' children, and hence pose a severe threat to social welfare. From an economic perspective, there has been a discussion on whether overtime regulation might have positive effects on employment (work share argumentation), but it has proven not to be the case (Oaxaca, 2014). Vecchio et al. (2013) use data on Australian employees within the health sector and find that unpaid overtime makes a significant contribution to the gender wage gap.

Also, negative consequences of overtime hours on individual health have been found. Dembe et al. (2005) show that overtime increases injuries and illnesses in the United States. Working in jobs with overtime schedules is associated with a 61 % higher injury hazard rate compared to jobs without overtime. Working at least 12 hours per day has a 37 % increased hazard rate and working at least 60 hours per week has a 23 % increased hazard rate. Apart from that, Härmä (2006) finds that insufficient sleep, long work hours and work stress may lead to cardiovascular illness. Griffiths et al. (2014) analyse the work hours of nurses in different European countries and find that nurses working longer hours are more likely to report poor or failing patient safety, poor quality of care, and more care activities left undone.

In the end, the economic literature mainly suggests that overtime as a signal for effort can have positive effects for the individual as well as for the firm. However, there might be cases where negative consequences prevail, especially if the maximum levels of overtime exceed those that are medically advised.

2.3 Absence and Presence Behaviour

There is long and well established literature on absenteeism. Beemsterboer et al. (2009) and Treble / Barmby (2011) provide extensive reviews of the literature on the determinants and effects of absence behaviour by employees. Pauly et al. (2002) show how sickness absence and presenteeism can have negative economic effects through reduced labour supply. In this literature, absence behaviour has long been considered as a signal for low productivity. A large number of studies use this variable as an effort proxy. These studies analyse potential shirking behaviour by employees who increasingly call in sick when their jobs are more protected or less monitored. Dionne / Dostie (2007), for example, show that there is a positive relationship between firm-level collective bargaining and absence. Ichino / Riphahn (2005) provide substantial evidence that employment protection fosters absence. Goerke / Pannenberg (2012) show that union members are more likely to be absent. Arnold et al. (2014) demonstrate that non-union representation in the form of works councils increases both individual sickness absence rates and a subjective measure of personnel problems due to sickness absence as perceived by a firm's management.

Also, much attention has been drawn on how the generosity of sick pay schemes fosters absence behaviour. Markussen et al. (2012) analyse the effect of a work-first strategy in the Norwegian sickness insurance system. They show that activation requirements, i.e., partial sickness insurance which involves some amount of working while being ill, can bring down benefit claims and may also reduce the likelihood that sickness absence leads to inactivity. Their findings are, however, restricted to the long-term ill with particular diagnoses, e.g., non-infectious diseases, which only constitute a small fraction of the total amount of sickness absence.

From this literature it is not clear, however, how productivity and absence behaviour are linked to each other. It may be the case that individuals who call in sick are less productive simply because their work remains undone. It may be the case that individuals call in sick because they are less productive inherently. In this case, they might stay home simply because their opportunity costs are smaller. Due to a lack of suitable data, e.g., linked-employer-employee panel data with information on absence and presence behaviour as well as their determinants such as subjective and objective health status, it is not yet possible to decide on the causal direction in this matter.

In comparison, presenteeism is a relatively under-investigated phenomenon. According to Johns (2010), presenteeism refers to attending work while being ill[6]. For a long time, it was assumed that work attendance equated to performance (see literature above). However, severe productivity losses due to

[6] Johns (2010) also gives and overview on the development of interest in the topic, its concepts and measurements.

health-related reasons may be caused by either workers showing up at work whilst being ill or workers choosing not to. As regards the negative effects of presence behaviour, they include reduced productivity (Schultz/Edington 2007), the possible spread of illnesses to other employees (Chatterji/Tilley 2002; Pichler/Ziebarth, 2015), a negative impact on the presentees' future health (Bergström et al., 2009) and increased sickness absence at later dates (Hansen/Andersen, 2009).

According to Gosselin et al. (2013), presenteeism seems more prevalent than absenteeism. This is surprising given that sickness absenteeism has been studied for a long time both theoretically and empirically. For sickness presenteeism, it is only known for a fact who might come to work ill, thanks to some determinant studies. But, due to a lack of theoretical work, it remains unknown why employees come to work while being ill. An overview of earlier studies analysing the determinants and effects of presenteeism is given in Johns (2010). The majority of studies on the determinants of presenteeism are based on data from Northern European countries. The most recent study to investigate the topic is Arnold (2015), using a large cross-sectional European data set. He finds that presenteeism is determined by similar characteristics as absenteeism (for recent studies, see Puhani/Sonderhof, 2010, and Ziebarth/Karlsson, 2010). When controlling for worker characteristics, however, Böckerman/Laukkanen (2009) find that sickness presenteeism is much more sensitive to working-time arrangements than sickness absenteeism. Also, they find that both phenomena are determined by the same characteristics, but in different directions.

The relationship between absence behaviour and presence behaviour has only been analysed recently. One of the few studies that provide evidence on both absenteeism and presenteeism from the same data is that of Bierla et al. (2013). They find that the attitude of employees is most important in explaining absence and presence behaviour, which in other words means that there remain a large number of unanswered questions that still need to be investigated. Hirsch et al. (2015) show, in a theoretical model, that presenteeism arises due to differences between workers in (health-related) disutility from workplace attendance. As these differences are unobservable to employers, the latter set wages that incentivise sick workers to attend work. Hirsch et al. (2015) test their hypothesis using the BIBB/BAuA employment survey. Arnold/de Pinto (2015) investigate how changes in work-related factors affect workers' absence and presence behaviour simultaneously. Hirsch et al. (2015) set up a theoretical model in which work-related characteristics not only affect a worker's absence decision, but also the individual-specific sickness definition, dropping previous studies' assumption on a substitutive relationship between absence and presence behaviour. Using European cross-sectional data, they find only few substitutive and complementary relationships, while the majority of the work-related characteristics is related only to one of the two illness states, absence behaviour or presenteeism.

As most of these studies use cross-sectional survey data, it is not yet clear from the literature on presenteeism whether people who come to work while being ill are more productive or whether they only want to signal high productivity.

3. Data and Method

3.1 Data and Statistics

This study analyses the relationship of absence behaviour, presence behaviour and overtime hours on continuous training, using the recent crosssection of the German BIBB/BAuA Employment Survey in 2012[7]. It is a representative sample of the working population in Germany that contains a variety of information on individual employees and their jobs. The survey is carried out in repeated cross-sections since 1979 in intervals of about five years and it is based on telephone interviews with up to 30,000 economically active individuals per cross-section (19,000 in the recent cross-section). The purpose of this representative employee survey is to describe employees and their jobs in a wide range of perspectives, e.g., to demonstrate trends and features of a changing work environment and to enable its empirical quantification.

The variables range from basic personal information such as age, education, job tenure and wages to job characteristics and working conditions. The data contain several variables describing the assignment, the content, and the attributes of an individual's job in detail[8]. Further variables refer to individual and household information, including a Kldb2010/1992 2-digit level job classification[9] as well as firm size and a NACE 2-digit level sector affiliation, regional information, location of the employee's workplace (German State) and some information about the firm the employee works in (e.g., size and business outlook). The sample used here is restricted to workers aged 19 to 62 years. Self-employed individuals are dropped from the sample, as they are of minor relevance for the analysis, likewise chronically ill and some other groups[10]. The regression sample comprises 12,405 individuals.

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[7] The full title of the dataset is: BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2012. See Hall et al. (2013) for further details.

[8] See also Rohrbach-Schmidt/Tiemann (2013) for a recent overview of the measurement of skills and tasks on the basis of the Qualification and Career Survey.

[9] This classification is based on the KldB 88 ("Klassifizierung der Berufe"), which is a classification of professions quite common in German datasets and literature. Contrary to the International Standard Classification of Occupations (ISCO), it is based on the actual type of professional activity, not on skill levels.

[10] Long-term illness is defined as stating to come to work ill more than 60 days or 30 times a year. Further drops include employees with unreasonable working times (<10 and >80 hours per week), employees with unreasonable overtime hours (overtime hours

For the study, three types of information are especially important. First, this survey is one of the rare cases where employees are asked, in addition to their absence behaviour, about their presence behaviour. Questions to employees include whether they have called in sick or worked while being ill during the last year and if so, how many times, and how many days[11]. As argued by Arnold (2015) and others, this questioning is relatively open, unlike categorical items widely used in the social medicine literature on absence behaviour. In addition, it does not encompass normative aspects. In the sample, 54.1% of all individuals have called in sick at least one day, summing up to 6.1 days on average (11.4 days for absentees). Regarding presenteeism, 58.3% of all individuals report presence behaviour at least once a year, and the average amount of days working ill in the sample is 7.4 (13.2 for presentees). These numbers are higher than those found in the literature, e.g., for presenteeism 40% incidence and 2.8/7 days on average in Arnold (2015) or an average of 5.2 days of sickness absence in Arnold/de Pinto (2015), both based on the European Working Conditions Survey. A histogram of employee absence and presence behaviour is presented in Figure A.1. It shows that a large share of employees come to work ill only for a couple of days and a couple of times per year. Similarly, the majority of employees have only some few sickness absence days. Note that all these figures exclude long-term ill.

Second, the data set has relatively good information on overtime hours. Individuals are asked what their contractual working time is and how many hours a week they worked on average[12]. From this measure, one can construct overtime hours. Additionally, one could analyse how overtime is remunerated, either monetarily or through less working time on other days. Individuals are also asked what their preferred working time was and how often their working hours came into conflict with their private life. In the sample, 55.1% of all individuals have overtime hours (on average). They have an average 3.6 overtime hours per week (6.6 hours for individuals with positive hours). Individuals with unrealistically high overtime hours (>40) are dropped. There is a lack of information on what the actual reason of a very high level of overtime is. It is reasonable to assume that individual effort has an impact, but there is a whole

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of more than the contractual working time or undertime hours more than half the contractual working time), marginally employed individuals, pupils, students and apprentices if they work less than 20 hours a week, and observations with missing covariates. Unfortunately, the possibility to work in a home office cannot be controlled for.

11 The items read as follows: "Did you stay home sick or have you called in sick in the last 12 months?" and "In the last 12 months, did you ever go to work although you should better have called in sick due to your state of health?", and (respectively) "How many times did that happen?", "How many workdays were that all in all?".

12 The items read as follows: "What are the weekly working hours in your job according to the agreement with your employer, excluding overtime?" and "And how many hours do you actually work per week, on average, including your side-line activities?".

range of potential alternative factors, such as formally working part-time on a full-time position or seasonal overtime. A histogram of overtime hours is also presented in Figure A.1.

Third, the study is especially focused on firm-sponsored training. By using the BIBB/BAuA Employment Survey, one can make use of detailed information on continuous training. Employees are asked whether they have attended one or more courses or seminars of continuous training during the past two years, whether they are planning to attend continuous training over the following two years and which type of course they are planning to attend. Finally, they are asked why they attend continuous training: to adopt a new activity, to stay in touch with professional developments or because of other reasons[13]. In the sample, 64.8% of employees have participated in continuous training in the past two years; among them 50.3% have taken several courses. Of all employees asked, 59.0% are planning to attend further training over the next two years. Among them, only 11.8% would do so because they are assigned a new task, 78.4% want to keep up, and 9.6% have other reasons. Employees state that they plan up to seven continuous training courses, with an average of 1.56 (2.63) courses for all employees (employees with at least one planned course). A histogram on the number of different courses an individual plans to attend them, a variable usually not available in other datasets, is presented in Figure A.1. A descriptive analysis of past and future continuous training participation is presented in Table A.1. Detailed information on the type of training courses planned is presented in Table A.3.

It can be seen that past and future training participation are correlated, such that employees with past training participation are ceteris paribus more likely to have further training planned in the future. However, this is mostly true for employees who want to keep up with work developments. An overview of all variables used in the analysis, including the control variables, can be found in Table A.2.

3.2 Empirical Strategy and Method

When analysing the relationship between overtime hours, presence behaviour and continuous training, causality is a non-trivial topic. From a naïve perspective, one would start by assuming that management has to decide on whom

[13] The items read as follows: „Did you attend one or several courses or seminars of continuing vocational training in this period? Please consider courses or seminars which are still ongoing, as well. This includes courses or seminars held in the company.“, “Are you planning to attend continuing vocational training over the next two years?”, and “Would you attend continuing training with the primary intention of adopting a new activity, of staying in touch with professional developments or would it serve another purpose?”.

to train, and to inform the employees in advance. This is unobservable to us and treated as an idiosyncratic shock. Then, individuals are going to show presence behaviour or overtime hours as a signal for high productivity or dedication. If management positively reacted to that, one would see a positive correlation of absence or presence behaviour or overtime hours within the recent year, and the probability to participate in planned further training.

However, it could be the case that individuals who have received further training in the past put up overtime hours or show presence behaviour as a consequence (reverse causality problem, see Figure A.2). In this case, the correlation between the main variables of interest may not be interpreted as causal or could be biased. A potential methodological remedy for this effect could be the use of natural experiments or the use of panel data to control for unobserved heterogeneity. Unfortunately, the data at hand, especially regarding information on presence behaviour, does not allow for this.

Therefore, an important point for the analysis is the timing of questions on further training. In the BIBB/BAuA Employment Survey, the items on further training are prospective, while the items on presence behaviour and overtime are retrospective (during the last year). Additionally, one can observe the training participation during the last two years. In effect, a timing structure evolves, that allows assessing the effect of recent overtime hours or presence behaviour on future continuous training probability, conditional on past training probability.

The stylized estimation equation for the different models reads as follows:

$$\begin{aligned} F^{-1}(\text{planned_training}_{\text{i2012}-2014}) &= \beta_1 + \beta_2 \text{presence}_{i2012} + \beta_3 \text{absence}_{i2012} \\ &+ \beta_4 \text{overtime}_{i2012} + \text{previous_training}_{i2011-2012} \\ &+ \mathbf{x_{i2012}}\boldsymbol{\delta}' + u_{i2012}. \end{aligned} \tag{1}$$

It represents the planned participation of individual i in continuous training courses in the next two years, i.e., in 2012 to 2014, explained by contemporary presence behaviour, absence behaviour, as well as overtime hours in the year 2012, past training activity in the past two years, i.e., in 2011 and 2012, a vector $\boldsymbol{X}$ that contains contemporary confounding factors, and an error term u. The model cannot make use of a panel dimension, but benefits from the fact that the questions resulting in the variables of interest are asked with different time perspectives, i.e., retrospective, contemporary, or predictive.

In this paper, both linear probability (OLS) and Probit models are used when analysing the probability to receive further training[14]. In the first case, F^{-1} is a

[14] Linear probability models are easier to interpret in certain conditions, such as for panel data or when using interaction terms, because no (average) marginal effects need to be calculated when analysing the effect size in addition to the significance of the coef-

simple linear function and in the second case, F^{-1} is the standard normal cumulative distribution function. Table 1 presents the Probit results for the variables of interest, while Table A.3 uses OLS. The size and significance of the average marginal effects from the Probit models vs. the OLS coefficients are very similar. The paper also presents results from Probit models in the analyses for different types of further training planned.

A further dependent variable in the paper is the number of different types of trainings planned. This variable is a nonnegative integer between zero (none) and seven (all types). The appropriate econometric models for this type of data are count data models such as the Poisson, (Zero-Inflated) Negative Binomial, or Hurdle models. These models account for the fact that nonnegative integers usually have small means due to an excess of zeros and that they are truncated at zero. The properties of the dependent variable suggest that there is overdispersion, such that the use of a Negative Binomial model is preferred over a Poisson model[15]. Furthermore, it is not known whether the zeros and the positive values emerge from different data-generating processes, i.e., if the decision of having one versus zero further training planned differs from the decision of having an additional training planned after the first[16]. In the paper, results from OLS models are presented, while count data models have been applied as a robustness check.

In a further analysis, one can also observe the reason why employees would attend further training. Here, one could argue that adopting a new activity would suggest that employees 'have to' receive further training, either because they got promoted or relocated. Otherwise, if employees attended further training with the main purpose of staying in touch with professional development, this would suggest high motivation on their side. Therefore, the latter variable serves as a proxy for employee motivation to attend continuous training, while the former variable can be seen as (at least somewhat) exogenous to the employee, which makes this type of training uncorrelated with their presence behaviour or their general motivation in a job. The hypotheses suggest that the effects should differ between the groups. One would expect a smaller or insignificant coefficient if further training is planned due to relocation and a larger or significant coefficient if further training is planned due to personal motivation.

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ficients. Probit models adequately model the binary nature of the dependent variables. This especially affects outside predictions of linear models, a problem which is, however, relatively small when using binary variables with centred means.

15 The mean is 1.56 and the standard deviation is 1.61. A formal test reveals that overdispersion is in place (Cameron/Trivedi 2010: 561). Alternatively, robust standard errors may be used with the Poisson estimator.

16 Simple regressions on both margins suggest that there are differences in the observable determinants. The Vuong test statistic of 130.67 (p=0.000) favours the Zero-Inflated Negative Binomial (ZINB) model.

4. Results

The empirical results are shown in three parts. First, the paper presents results for analysing determinants of future continuous training. These focus on the effects of the extensive and intensive margins as well as on potential nonlinear effects of absence behaviour, presence behaviour and overtime hours. Second, the results of an analysis examining the determinants of planned further training are shown, distinguished by different types of and different reasons for future further training. Third, several robustness checks are discussed.

All estimations use similar control variables, which will not be commented on in detail, since they just capture individual heterogeneity. The signs and magnitudes of the coefficients of the covariates are mostly in line with studies analysing the determinants of further training. Also, the regression diagnostics are presented. The estimations explain a significant part of the variance and F-tests reject the null hypothesis that all coefficients are jointly zero.

4.1 Determinants of Planned Further Training

The basic estimations explaining further training participation are presented in Table 1 for the variables of interest and in Table A.3 for all coefficients. The paper presents a total of seven specifications using similar control variables, but different alternative measures for the variables of interest to examine a potential nonlinear relationship for each variable. The specifications iterate the operationalisation of one specific variable of interest at a time, holding all others constant as indicator variables. The iterations use both the extensive and intensive margin of absence behaviour, presenteeism, or overtime. Additionally, possible non-linear effects have been tested by introducing a second-order polynomial, as well as by generating category dummy variables for the total numbers of absence days. Presence days or overtime hours are included[17], the paper presents the latter. The dependent variable is the probability to receive further training within the next two years.

First, the results for presence behaviour are shown, which is measured via incidence, times, and days. When employees have come to work ill at least once during the last year, they show a 1.9 percentage points higher likelihood (3.2 %)[18] of having a further training course planned within the next two years

[17] Second-order polynomials have been employed in OLS models due to the problematic computation of interaction effects in non-linear models. Eight equally-sized bins are generated for each variable of interest using the STATA command "xtile varname, n (8)". For each variable, the first four bins together form the zero days / hours category.

[18] The relative marginal effect is calculated in comparison to the mean of the respective variable, e.g., the mean of the dependent variable "Planned Training in next two Years" is 0.59, hence an increase by 0.0188 is a relative effect of 0.0188 / 0.59 = 0.0318.

compared to employees who did not. The effect is economically sizeable, for example it is about 25% larger than the effect of the gender dummy variable. Working ill more often, however, does not significantly influence this likelihood. In contrast to the results for absenteeism further below, the effect of days spent ill at work is also significant. For every eight days being ill at work during the last year, the likelihood of having further training planned in the next two years increases by one percentage point. This relationship, however, only holds if individuals who never come to work ill are included in the sample. The effect is halved and insignificant in a conditional sample. There is no evidence for a non-linear effect when looking at the second-order polynomial (results not shown here). The effect on the intensive margin, however, is driven by employees who work ill for at least seven days a year; these are 2.6 to 2.8 percentage points more likely to have a training course planned[19].

Next, the results for absence behaviour are discussed. Being absent for at least one day of the year (incidence) increases the likelihood of receiving further training during the next two years by 2.9 percentage points (5.7%). Calling in sick multiple times a year also significantly increases planned training participation; however, calling in sick for a higher total amount of days does not. This also holds for a sample conditional on at least one day absent. Using a second-order polynomial suggests a non-linear effect, but with a peak at 46 days of absence (results not shown here). Indeed, further analyses show that the likelihood for employees calling in sick for 1, 4, or 12 days to receive further training equally increases by up to 3.9 percentage points, but calling in sick longer or calling in sick between 4 to 7 days does not affect planned training participation. Therefore, one would not conclude that a non-linear effect exists. These results are surprising, as sickness absence is usually considered a bad signal for productivity.

For overtime, only the extensive margin is significantly correlated with having further training planned in the next two years. Compared to individuals without overtime hours, those who do at least one overtime hour per week have a 2.9 percentage-points higher likelihood of having further training planned in the next two years. The effect of overtime hours is insignificant in both the unconditional and the conditional sample. However, in contrast to above, a non-linear relationship is found for overtime hours. The results from a model with a second-order polynomial suggest a peak at 21 overtime hours a week (results not shown here). For the model with categorical variables, there is a positive effect of having between three and ten overtime hours a week. Overtime hours below and above this range do not significantly influence planned training participation compared to no overtime hours. The results suggest that there might be a peak in effort when working around 50 hours per week,

[19] The coefficients for the top two categories are, however, only marginally significant at the 10% level.

whereas employees going beyond that are not providing more effort, but report such high numbers for other reasons.

All these models include the indicator variables for the two other variables of interest, respectively. Their coefficients stay significant and do not change in size. This also holds for other control variables, as shown in Table A.3 in the Appendix. It is to note that there are no significant effects on the probability to receive further training within the next two years according to an indicator variable for female employees, once absence behaviour is controlled for in the models. Other results indicate negative correlations for age, bad health and higher tenure, and positive correlations for education, full-time workers, employees with higher wages and more demanding tasks, instructors and civil servants. These results are in line with the literature on the determinants of further training (see Section 2.1).

The findings support the existence of reciprocal behaviour of firms against individuals who signal productivity through overtime hours and presence behaviour. As discussed before, one can consider this behaviour as economically optimal for the employee if the costs of coming to work ill or putting up overtime hours are outweighed by the benefits of receiving further training. Similarly, the firm might profit from employees coming to work more often. It might consider training these employees as a reward or as a further incentive. However, this behaviour could also be contra-productive from a firm's perspective if the employees' health or productivity are affected, but the magnitude of the negative effect is small and mostly limited to the extensive margin. It seems to be effective for employees to signal motivation or productivity once in a while or to a small amount, but not all the time or excessively. Hence, negative effects for the firm due to inefficient productivity signalling for future continuous training might exist, but are not likely to yield huge losses.

Furthermore, employees who call in sick are also more likely to have a training course planned. In the traditional literature on absence behaviour, calling in sick is seen as a bad signal, i.e. as shirking behaviour (cf. Treble/Barmby, 2011). Therefore, one would not interpret these findings as support for the existence of reciprocal behaviour of firms. If one would like to do so, it must be assumed that firms regard employees who call in sick as responsible: instead of working ill, they stay home and try to recover in order to be more productive afterwards. The firm could reward these employees using further training measures. However, this is less common for employees with long sickness durations, where other reasons might come into play. That being said, it would be the case that a reciprocal interpretation of the positive relationship between sickness absence and further training is counter-intuitive and contradicts the established use of absence behaviour as a (negative) effort proxy. A different interpretation would indicate that employees with high absence rates are considered as low-performers. The firm would then send these individuals to further training courses to remedy this "defect".

Table 1

Determinants of Planned Further Training, Probit Results (Average Marginal Effects)

Dependent Variable	Planned Training in next two Years						
Presence Behaviour (Incidence)	0.0184** (0.0091)			0.0228** (0.0090)	0.0186** (0.0091)	0.0191** (0.0091)	0.0182** (0.0091)
Presence Behaviour (Days)		0.0013** (0.0006)					
Absence Behaviour (Incidence)	0.0306*** (0.0085)	0.0311*** (0.0085)	0.0302*** (0.0085)			0.0313*** (0.0085)	0.0309*** (0.0085)
Absence Behaviour (Days)				0.0004 (0.0004)			
Overtime (Incidence)	0.0296*** (0.0089)	0.0300*** (0.0089)	0.0296*** (0.0089)	0.0301*** (0.0089)	0.0295*** (0.0089)		
Overtime (Hours)						0.0009 (0.0010)	
Presenteeism Category (Reference: No Presence Behaviour)							
1 or 2 Days Sick at Work			0.0205 (0.0167)				
3 to 5 Days Sick at Work			0.0127 (0.0114)				
6 to 8 Days Sick at Work			0.0145 (0.0176)				
9 to 15 Days Sick at Work			0.0251* (0.0139)				
More than 15 Days Sick at Work			0.0275* (0.0153)				
Absenteeism Category (Reference: No Absence Behaviour)							
1 or 2 Days Calling in Sick					0.0383** (0.0157)		
3 to 5Days Calling in Sick					0.0343*** (0.0117)		

Table continued next page

Table 1 continued

Dependent Variable	Planned Training in next two Years						
6 to 8 Days Calling in Sick					0.0019 (0.0176)		
9 to 14 Days Calling in Sick					0.0390*** (0.0128)		
More than 14 Calling in Sick					0.0239* (0.0142)		
Overtime Category (Reference: No Overtime)							
0.2 to 1.5 Overtime Hours a Week							–0.0007 (0.0168)
1.6 to 3.0 Overtime Hours a Week							0.0171 (0.0134)
3.2 to 5.0 Overtime Hours a Week							0.0498*** (0.0127)
5.0 to 10.0 Overtime Hours a Week							0.0538*** (0.0133)
More than 10 Overtime Hours a Week							–0.0007 (0.0173)
Socio-Demographic and Work-Related Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy Variables for Firm Size Classes, Industry Classification and Occupational Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.6288*** (0.1114)	–0.6242*** (0.1113)	–0.6277*** (0.1115)	–0.6312*** (0.1115)	–0.6273*** (0.1114)	–0.6392*** (0.1114)	–0.6370*** (0.1114)
Number of Observations	12405	12405	12405	12405	12405	12405	12405
Chi^2-Statistic	79.59	79.84	74.02	79.22	74.19	78.97	74.16
Pseudo R^2	0.19	0.19	0.19	0.19	0.19	0.19	0.19

Note: Average Marginal Effects from a Probit Regression. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01. Other control variables are similar to Table A.3.

Source: Own calculations based on the BIBB/BAuA Employment Survey 2012.

In any case, having positive coefficients for both absence and presence behaviour suggests that different mechanisms are at play. It may be the case that different types of information asymmetries exist. Presence behaviour, where superiors can monitor whether the employee is severely ill, might be better observable to the firm than absence behaviour, where superiors usually cannot assess the existence of shirking[20].

4.2 Different Types of and Reasons for Further Training

After having presented the basic specifications, the paper now tries to shed some further light on the mechanisms of how absence and presence behaviour and overtime hours influence future training participation. To achieve this, it first presents the results from an empirical analysis on different types of planned further training participation, as shown in Table 2. The results resemble the ones from above, but they are only shown for the extensive margins of absence and presence behaviour and for the categorical dummy variables of overtime hours. In addition to the previous analysis, the empirical specification also controls for past training activity, such that the results may be interpreted in a more causal way. It captures the effects conditional on past training participation, which is a strong predictor of future training participation and may also influence absence and presence behaviour or overtime hours. The dependent variables are binary variables indicating the existence of planned further training in the next two years, differentiated by topic.

In the first row of Table 2, all types of training courses are considered, similarly to above, but using the past training incidence as an additional control variable. It can be seen that this has a strong explanatory power and that it also somewhat influences the variables of interest. The average marginal effects of absence behaviour and the overtime categories between 3 and 10 hours are reduced in size and the average marginal effect for presence behaviour loses its significance.

In the next rows only certain types of planned further training courses are considered. It can be seen that the effects of absence and presence behaviour and overtime hours differ between the types of planned training, but that there is almost always a non-negative relationship. Presence behaviour is positively correlated with the probability to receive further training in communication skills, in project management, and business training. Absence behaviour is positively linked to receiving further training in communication skills and professional training. Overtime hours are positively correlated with the probability to receive further training in foreign languages, communication skills, and in project management. It can be seen that especially further training types that can

20 Thanks to an anonymous referee for pointing this out.

Table 2

Determinants of Different Types of Planned Further Training

Dependent Variable	Type of Planned Training								
	All	ICT	Foreign Language	Communication Skills	Project Management	Health	Business	Professional	Other
Incidence of Presence Behaviour	0.0075	0.0012	–0.0049	0.0184**	0.0106	0.0070	0.0124*	0.0098	–0.0020
	(0.0084)	(0.0082)	(0.0064)	(0.0083)	(0.0074)	(0.0066)	(0.0074)	(0.0090)	(0.0076)
Incidence of Absence Behaviour	0.0204***	0.0090	0.0018	0.0131*	0.0015	0.0031	–0.0043	0.0300***	0.0108
	(0.0078)	(0.0076)	(0.0059)	(0.0078)	(0.0070)	(0.0061)	(0.0069)	(0.0083)	(0.0071)
Overtime Category (Reference: No Overtime)									
0.2 to 1.5 Overtime Hours a Week	–0.0129	–0.0244*	0.0054	0.0010	0.0067	0.0032	–0.0196	0.0077	0.0045
	(0.0151)	(0.0140)	(0.0110)	(0.0146)	(0.0133)	(0.0114)	(0.0127)	(0.0162)	(0.0137)
1.6 to 3.0 Overtime Hours a Week	–0.0027	0.0013	0.0127	0.0011	0.0144	0.0063	–0.0110	0.0071	0.0104
	(0.0119)	(0.0117)	(0.0090)	(0.0118)	(0.0107)	(0.0096)	(0.0105)	(0.0129)	(0.0111)
3.2 to 5.0 Overtime Hours a Week	0.0288**	0.0206*	0.0439***	0.0249**	0.0325***	0.0178*	0.0171	0.0220*	0.0124
	(0.0116)	(0.0115)	(0.0091)	(0.0116)	(0.0104)	(0.0094)	(0.0105)	(0.0126)	(0.0107)
5.0 to 10.0 Overtime Hours a Week	0.0341***	0.0006	0.0295***	0.0330***	0.0319***	0.0108	0.0092	0.0239*	0.0032
	(0.0125)	(0.0120)	(0.0094)	(0.0121)	(0.0109)	(0.0097)	(0.0108)	(0.0133)	(0.0112)
More than 10 Overtime Hours a Week	–0.0136	–0.0054	0.0342***	0.0242	–0.0105	–0.0051	–0.0181	–0.0115	–0.0041
	(0.0164)	(0.0152)	(0.0126)	(0.0155)	(0.0130)	(0.0120)	(0.0139)	(0.0169)	(0.0139)
Past Training Incidence Once	0.2265***	0.0814***	0.0216***	0.0957***	0.0616***	0.0348***	0.0772***	0.1566***	0.0739***
	(0.0132)	(0.0106)	(0.0082)	(0.0108)	(0.0098)	(0.0079)	(0.0096)	(0.0124)	(0.0097)
Past Training Incidence Multiple Times	0.4057***	0.1703***	0.0577***	0.2304***	0.1337***	0.1341***	0.1430***	0.3309***	0.1527***
	(0.0097)	(0.0081)	(0.0064)	(0.0083)	(0.0075)	(0.0068)	(0.0072)	(0.0094)	(0.0075)
Control Variables		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	12405	12385	12388	12374	12379	12402	12381	12366	12265
Chi^2-Statistic	3407.85	1156.17	912.66	1862.29	1953.20	1673.33	1307.07	2313.07	1031.38
Pseudo R^2	0.25	0.10	0.11	0.15	0.19	0.19	0.13	0.15	0.09

Note: Average Marginal Effects calculated in a Probit Regression. Robust standard errors in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Other control variables are similar to Table A.3.

Source: Own calculations based on the BIBB/BAuA Employment Survey 2012.

lead to better job perspectives in the future are used as a reward for past productivity signalling (e.g. project management, a type of course typically needed for employees in order to be promoted). Contrarily, the probability of participating in more basic or general courses such as ICT skills or trainings in health management does not react to absence behaviour, presence behaviour, or overtime hours.

Next, the information on different types of trainings is used to construct an indicator of how many different further trainings an individual has planned for the next two years. The results can be seen in Table 3 in column 1. Absence behaviour, presence behaviour and overtime hours are all significantly positively correlated with the number of different further trainings planned. The effects are sizeable: individuals who call in sick or come to work ill have 0.054 to 0.060 more trainings planned, which amounts to a relative effect of 3.4% to 3.8%. Employees who work between 3.2 and 5.0 overtime hours a week have 0.15 or 10% more training courses planned. These results imply that the effect of productivity signalling works also on the intensive margin: it does not only

Table 3

Determinants of Different Reasons for Planned Further Training

Dependent Variable	Number of Different Planned Trainings in next two Years				
	All	New Task	Keeping up	Other Reason	Entrant Sample
Incidence of Presence Behaviour	0.0543*	0.0138	0.0413	–0.0008	0.0217
	(0.0285)	(0.0161)	(0.0288)	(0.0134)	(0.1198)
Incidence of Absence Behaviour	0.0603**	0.0282*	0.0124	0.0196	0.2206**
	(0.0263)	(0.0148)	(0.0266)	(0.0125)	(0.1111)
Overtime Category (Reference: No Overtime)					
0.2 to 1.5 Overtime Hours a Week	–0.0307	–0.0031	–0.0322	0.0046	–0.1251
	(0.0512)	(0.0292)	(0.0495)	(0.0239)	(0.2560)
1.6 to 3.0 Overtime Hours a Week	0.0121	–0.0478**	0.0386	0.0212	0.1547
	(0.0408)	(0.0217)	(0.0407)	(0.0199)	(0.1676)
3.2 to 5.0 Overtime Hours a Week	0.1575***	0.0374	0.0875**	0.0327	0.1899
	(0.0407)	(0.0246)	(0.0412)	(0.0206)	(0.1593)
5.0 to 10.0 Overtime Hours a Week	0.1286***	–0.0097	0.0923**	0.0460**	–0.0752
	(0.0435)	(0.0248)	(0.0442)	(0.0233)	(0.1730)
More than 10 Overtime Hours a Week	0.0072	–0.0479	0.0454	0.0096	–0.1076
	(0.0557)	(0.0301)	(0.0587)	(0.0289)	(0.2138)
Past Training Incidence Once	0.5076***	0.0296	0.4436***	0.0344**	0.4060***
	(0.0393)	(0.0215)	(0.0372)	(0.0170)	(0.1556)
Past Training Incidence Multiple Times	1.1941***	0.0690***	1.0379***	0.0871***	0.6400***
	(0.0297)	(0.0158)	(0.0288)	(0.0137)	(0.1231)
Control Variables	Yes	Yes	Yes	Yes	Yes
Number of Observations	12405	12405	12405	12405	978
F-Statistic	109.88	30498	66.36	35490	42589
R^2	0.28	0.04	0.20	0.03	0.22

Note: Results from OLS regression. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01. Other control variables are similar to in Table A.3.

Source: Own calculations based on the BIBB/BAuA Employment Survey 2012.

affect the probability of receiving a further training course (versus not receiving a training course), but also the probability of receiving *more* continuous training. In addition, these significant effects hold when controlling for past training activity.

The next three specifications of Table 3 differentiate between the reason for planned further training: because of a new task (exogenous), to keep up (endogenous), or for other reasons. The results support the hypotheses and findings so far. First, there is always a non-positive relationship of recent absence and presence behaviour and planned further training. Second, for presence behaviour and overtime hours, the effects are larger for employees that plan training to keep up with business developments, i.e., highly motivated individuals. The respective coefficient is close to zero for individuals for whom training comes either through promotion or relocation (to a new task within the firm). Following this line of argumentation, training participation is to a certain degree exogenous for them.

Contrarily, there are larger and marginally significant effects of overtime hours and presence behaviour for employees that plan to participate in further training because they want to keep up with business developments. This reason seems highly endogenous: the respective employees are either highly motivated or they may fear a job loss if they do not keep up. Either way, one would expect a stronger effect, which can actually be observed in the respective column. Following the line of argumentation, among employees that do not 'need' continuous training (because they are not promoted or relocated), signalling high motivation or productivity does not pay off.

The last column of Table 3 analyses employees with less than two years of tenure. There, one can see larger, albeit insignificant, coefficients. These suggest that for workers that are new to the firm, signalling productivity might be more important than for employees who have stayed in the firm for a long time and for whom the firm has more information on their productivity and effort levels.

4.3 Robustness Checks and Discussion

During the analysis, a series of robustness checks has been performed. This captures methodological issues that may arise, measurement issues, and effect heterogeneity.

First, various microeconometric methods have been applied to all estimations. These include Probit or Logit vs. Linear Probability models for binary dependent variables as well as count data models for the discrete choice variables. Differences between OLS and Probit for the main results can be compared between Table 1 and Table A3. Differences between OLS and count data models are presented in Table 4. They show the average marginal effects for

the variables of interest for specification (1) of Table 3. As you can see, the results remain qualitatively the same[21]. This is especially true for the differences between simple OLS and the methodologically most appropriate ZINB model.

Table 4

Determinants of the Number of Different Planned Trainings, Count Data Models

Dependent Variable	Number of Different Planned Trainings in next two Years			
	OLS	**Poisson**	**NegBin**	**ZINegBin**
Incidence of Presence Behaviour	0.0543*	0.0454	0.0435	0.0534*
	(0.0285)	(0.0288)	(0.0305)	(0.0312)
Incidence of Absence Behaviour	0.0603**	0.0574**	0.0646**	0.0605**
	(0.0263)	(0.0269)	(0.0284)	(0.0290)
Overtime Category (Reference: No Overtime)				
0.2 to 1.5 Overtime Hours a Week	–0.0307	–0.0098	–0.0084	–0.0137
	(0.0512)	(0.0528)	(0.0547)	(0.0555)
1.6 to 3.0 Overtime Hours a Week	0.0121	0.0501	0.0489	0.0238
	(0.0408)	(0.0417)	(0.0436)	(0.0448)
3.2 to 5.0 Overtime Hours a Week	0.1575***	0.1861***	0.2011***	0.1655***
	(0.0407)	(0.0403)	(0.0430)	(0.0437)
5.0 to 10.0 Overtime Hours a Week	0.1286***	0.1339***	0.1504***	0.1306***
	(0.0435)	(0.0407)	(0.0434)	(0.0452)
More than 10 Overtime Hours a Week	0.0072	0.0198	0.0168	–0.0185
	(0.0557)	(0.0488)	(0.0517)	(0.0575)
Control Variables	Yes	Yes	Yes	Yes
Number of Observations	12405	12405	12405	12405

Note: Average Marginal Effects. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01. Other control variables are similar to in Table A.3. Source: Own calculations based on the BIBB / BAuA Employment Survey 2012.

Second, different measurements of both the dependent variables and the independent variables of interest have been tried out. For the latter, the paper has transparently shown results for margins of both overtime and presence behaviour. In addition, the sample was also restricted to individuals with at least one day of sickness absence per year. It could be the case that there are people who only *claim* to be ill at work. Furthermore, robustness checks have differentiated the overtime information by remuneration, i.e., whether overtime is paid, unpaid, or can be balanced with vacation (or a combination). Regarding the dependent variable, the item of the survey on future training has been differentiated into "no training planned", "one training planned" and "more than one training planned". The results stay qualitatively the same, but are far more complicated to interpret. Similarly, the results remain the same when looking at subsamples of different types of training courses, i.e., ignoring ICT, health, and

[21] This means that the results show similar significance levels and, if comparable, similar coefficient sizes.

other courses. It could be argued that these courses are different from the other types and should therefore not be counted.

Third, subsamples of the data have been analysed, e.g., looking only at men or only at women, only at permanent employees, dropping very sick people etc. Apart from small differences between genders, they all show similar results. In fact, it seems to be the case that both sexes use productivity signalling to receive further training, but that they focus on different types of signalling. For males, overtime hours and presence behaviour have larger and more significant effects, while the opposite is true for women: they receive further training more frequently if they are not present at work when ill more often.

5. Conclusion

This study has analysed whether productivity signalling by employees increases the likelihood for receiving further training in a firm. The allocation of continuous training in a firm might encourage employees to signal effort or productivity by putting up overtime hours or coming to work while being ill. While this might be a possible way to overcome information asymmetries between management and employees, it could also have negative consequences for the firm because employees are actually less productive. It could encourage employees to come to work while being ill or to work too long hours, which both is costly for the firm. In effect, the allocation of continuous training might go to individuals who use signals potentially harmful to them, their co-workers and the company.

The results provide evidence for a positive effect of overtime hours and presence behaviour on future training participation. However, they suggest that a modest use of both signals is optimal for employees. Working beyond 10 overtime hours per week or coming to work ill for many days does not pay off in terms of a higher training probability. Furthermore, the results suggest that signalling works only for certain types of training courses and that only certain types of employees use these signals. The results also show that, counter-intuitively, calling in sick also increases the likelihood of receiving further training. However, first robustness checks indicate that there are differences between male and female employees, i.e., this relationship only holds for females. Further research will be needed to investigate this topic.

The identification of potentially decreasing returns to scale from an increase in presence days is also a topic of further analysis. In a similar manner, it could be the case that reciprocal employees work ill more often, but for shorter durations, or that they work overtime only when it is actually demanded, but not always. Due to the fact that there is no further information on sickness durations and severity, nor on the reasons to work overtime hours, productivity estimates of both overtime and presence behaviour are missing. Further work on

the topic will also require controlling for individual heterogeneity, since selection on observables remains the sole identification strategy possible with the data at hand, a problem other studies on presenteeism share with the paper presented.

Furthermore, while positive correlations with the probability of receiving further training are observed, it remains unclear whether the signalling behaviour of employees changes their returns on training. It could be the case that overtime hours or presence behaviour increase on-the-job training of individuals to an extent that they do not need a formal further training anymore. They might still go to the training course, e.g. because they think they earned it. In this case, it could be argued that the training would go to the wrong person.

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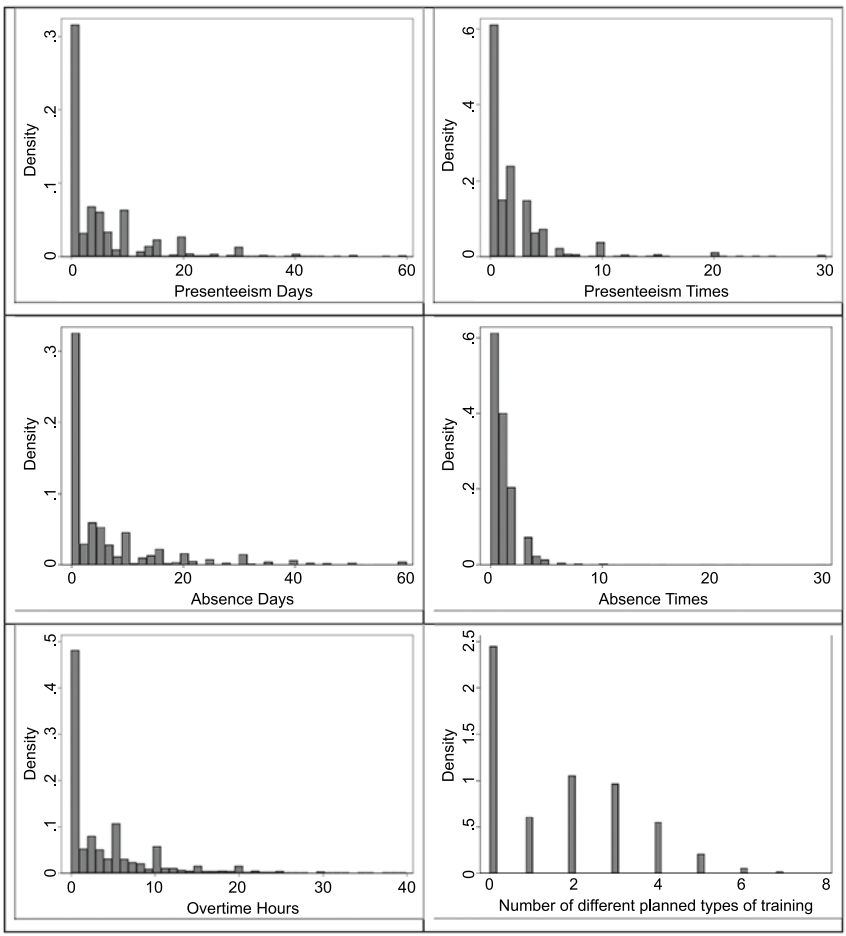
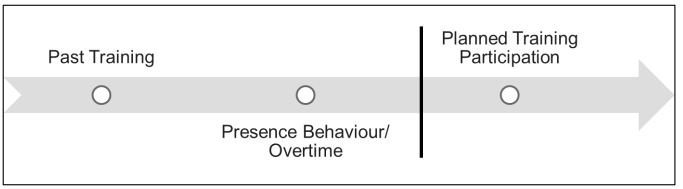
Appendix



Source: Own calculations based on the BIBB/BAuA Employment Survey 2012.

Figure A.1. Histograms of Presence Behaviour, Absence Behaviour, Overtime Hours, and Training



Source: Own representation. The vertical line depicts the point in time of the questionnaire.

Figure A.2. Timing of Events

Table A.1

Past and Future Training

	Planned Training									
Past Training	No		New Tasks		Keeping Up		Other Reason		Total	
None	3,358	26%	243	2%	946	7%	177	1%	4,724	37%
One	815	6%	148	1%	913	7%	117	1%	1,993	15%
Multiple	1,438	11%	549	4%	4,577	36%	468	4%	7,032	55%
Total	5,611	44%	940	7%	6,436	50%	762	6%	12,405	

Source: Own calculations based on the BIBB/BAuA Employment Survey 2012.

Table A.2

Overview of Variables Used

Variable	Obs.	Mean	Std. Dev.	Min	Max
Planned Further Training (Yes or no)	12,405	0.59	0.49	0	1
Type: ICT	12,405	0.22	0.41	0	1
Type: Foreign Language	12,405	0.11	0.32	0	1
Type: Communication Skills	12,405	0.26	0.44	0	1
Type: Project Management	12,405	0.20	0.40	0	1
Type: Health	12,405	0.14	0.35	0	1
Type: Business	12,405	0.18	0.38	0	1
Type: Professional	12,405	0.38	0.48	0	1
Type: Other	12,405	0.18	0.38	0	1
Number of Different Planned Trainings	12,405	1.56	1.61	0	7
Reason: New Task	12,405	0.19	0.8	0	7
Reason: Keeping Up	12,405	1.22	1.55	0	7
Reason: Other	12,405	0.14	0.66	0	7
Past Training (None, One, 2= more)	12,405	1.17	0.90	0	2

Present (Yes or no)	12,405	0.55	0.49	0	1
Present (Number of Times)	12,405	1.91	3.05	0	30
Present (Number of Workdays)	12,405	5.25	7.83	0	60
Absent (Yes or no)	12,405	0.54	0.49	0	1
Absent (Number of Times)	12,405	0.95	1.33	0	30
Absent (Number of Workdays)	12,405	6.17	10.21	0	60
Existence of Overtime	12,405	0.55	0.49	0	1
Overtime Hours	12,405	3.65	5.36	0	40
Female	12,405	0.52	0.50	0	1
Age	12,405	45.28	10.06	19	62
Age²	12,405	2151.55	876.06	361	3844
Tenure	12,405	15.65	11.06	1	49
Tenure²	12,405	366.73	443.72	1	2401
Hauptschulabschluss / Volkshochschulabschluss (Lower Secondary Education)	12,405	0.22	0.41	0	1
Qualifizierender / erweiterter Hauptschulabschluss (Lower Secondary Education and some Medium Secondary Education)	12,405	0.02	0.14	0	1
Realschulabschluss / Mittlere Reife (Medium Secondary Education)	12,405	0.41	0.49	0	1
Fachhochschulreife (Secondary Education and some Highschool)	12,405	0.05	0.21	0	1
Abitur / Hochschulreife / Fachabitur (Highschool Diploma)	12,405	0.30	0.46	0	1
Job Qualification. Reference: Non- Specific					
Apprenticeship	12,405	0.56	0.50	0	1
Foreman etc.	12,405	0.07	0.25	0	1
College	12,405	0.25	0.43	0	1
German Nationality	12,405	0.97	90.15	0	1
Health Subject. Reference: Excellent					
Very good	12,405	0.22	0.41	0	1
Good	12,405	0.55	0.50	0	1
Less than good	12,405	0.13	0.34	0	1
Bad	12,405	0.02	0.15	0	1
Number of Health Problems	12,405	5.25	4.57	0	25
Marital Status	12,405	0.88	0.67	0	2
Children (Yes or No)	12,405	0.65	0.47	0	1
Working Time	12,405	38.25	9.73	10	80
Imputed Log. Gross Monthly Wage	12,405	7.86	0.54	4.67	11.45

Table continued next page

Table 2 continued

Variable	Obs.	Mean	Std. Dev.	Min	Max
Temporary Contract (Yes or no)	12,405	0.08	0.27	0	1
Type of Job. Reference: Blue-Collar Worker					
White-Collar Worker	12,405	0.74	0.43	0	1
Civil Servant	12,405	0.08	0.28	0	1
Job Qualification Status. Reference: Simple Tasks					
Medium Tasks	12,405	0.25	0.43	0	1
Higher Tasks	12,405	0.46	0.49	0	1
Highest Tasks	12,405	0.22	0.41	0	1
Instructor (Yes or no)	12,405	0.69	0.46	0	1
Sector. Reference: Public Sector					
Manufacturing	12,405	0.22	0.41	0	1
Crafts	12,405	0.09	0.29	0	1
Trade	12,405	0.10	0.30	0	1
Services	12,405	0.19	0.39	0	1
Others	12,405	0.06	0.24	0	1
Firm Size Class. Reference: Up to 4 Employees					
5 to 19 Employees	12,405	0.18	0.39	0	1
20 to 99 Employees	12,405	0.28	0.45	0	1
100 to 249 Employees	12,405	0.15	0.36	0	1
250 to 999 Employees	12,405	0.18	0.39	0	1
More than 1000 Employees	12,405	0.17	0.38	0	1
1-Digit Occupational Group	12,405				

Source: Own calculations based on the BIBB/BAuA Employment Survey 2012.

Table A.3

Determinants of Planned Further Training, OLS Regression

Dependent Variable	**Planned Training in next two Years**						
Presence Behaviour (Incidence)	0.0184**			0.0228**	0.0186**	0.0191**	0.0182**
	(0.0091)			(0.0090)	(0.0091)	(0.0091)	(0.0091)
Presence Behaviour (Days)		0.0013**					
		(0.0006)					
Absence Behaviour (Incidence)	0.0306***	0.0311***	0.0302***			0.0313***	0.0309***
	(0.0085)	(0.0085)	(0.0085)			(0.0085)	(0.0085)
Absence Behaviour (Days)				0.0004			
				(0.0004)			
Overtime (Incidence)	0.0296***	0.0300***	0.0296***	0.0301***	0.0295***		
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)		
Overtime (Hours)						0.0009	
						(0.0010)	
Presenteeism Category (Reference: No Presence Behaviour)							
1 or 2 Days Sick at Work			0.0205				
			(0.0167)				
3 to 5 Days Sick at Work			0.0127				
			(0.0114)				
6 to 8 Days Sick at Work			0.0145				
			(0.0176)				
9 to 15 Days Sick at Work			0.0251*				
			(0.0139)				
More than 15 Days Sick at Work			0.0275*				
			(0.0153)				

Table continued next page

Table 3 continued

Dependent Variable	Planned Training in next two Years						
Absenteeism Category (Reference: No Absence Behaviour)							
1 or 2 Days Calling in Sick					0.0383** (0.0157)		
3 to 5Days Calling in Sick					0.0343*** (0.0117)		
6 to 8 Days Calling in Sick					0.0019 (0.0176)		
9 to 14 Days Calling in Sick					0.0390*** (0.0128)		
More than 14 Calling in Sick					0.0239* (0.0142)		
Overtime Category (Reference: No Overtime)							
0.2 to 1.5 Overtime Hours a Week							–0.0007 (0.0168)
1.6 to 3.0 Overtime Hours a Week							0.0171 (0.0134)
3.2 to 5.0 Overtime Hours a Week							0.0498*** (0.0127)
5.0 to 10.0 Overtime Hours a Week							0.0538*** (0.0133)
More than 10 Overtime Hours a Week							–0.0007 (0.0173)
Sex	–0.0147 (0.0100)	–0.0145 (0.0099)	–0.0147 (0.0100)	–0.0146 (0.0100)	–0.0146 (0.0100)	–0.0145 (0.0100)	–0.0142 (0.0100)
Age	0.0259*** (0.0034)	0.0259*** (0.0034)	0.0259*** (0.0034)	0.0257*** (0.0034)	0.0258*** (0.0034)	0.0262*** (0.0034)	0.0258*** (0.0034)

Age squared	–0.0004***	–0.0004***	–0.0004***	–0.0004***	–0.0004***	–0.0004***	–0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education. Reference: Basic Highschool							
Education: Realschule	0.0370***	0.0368***	0.0370***	0.0373***	0.0368***	0.0377***	0.0364***
	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)	(0.0115)
Education: At least Fachhochschulreife	0.0420***	0.0417***	0.0420***	0.0433***	0.0419***	0.0431***	0.0415***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)
Job Qualification. Reference: No Specific							
Apprenticeship	0.0938***	0.0944***	0.0941***	0.0936***	0.0937***	0.0942***	0.0932***
	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0150)	(0.0149)
Foreman etc.	0.1616***	0.1624***	0.1618***	0.1608***	0.1611***	0.1632***	0.1600***
	(0.0218)	(0.0218)	(0.0218)	(0.0218)	(0.0218)	(0.0218)	(0.0218)
College	0.1449***	0.1462***	0.1453***	0.1448***	0.1444***	0.1459***	0.1435***
	(0.0194)	(0.0194)	(0.0194)	(0.0194)	(0.0194)	(0.0194)	(0.0194)
German Citizen	0.0508*	0.0498*	0.0499*	0.0526*	0.0514*	0.0515*	0.0512*
	(0.0281)	(0.0281)	(0.0281)	(0.0282)	(0.0281)	(0.0281)	(0.0281)
Health Subject. Reference: Excellent							
Very good	0.0017	0.0026	0.0019	0.0041	0.0018	0.0018	0.0008
	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0160)
Good	–0.0172	–0.0155	–0.0170	–0.0133	–0.0170	–0.0176	–0.0183
	(0.0155)	(0.0155)	(0.0155)	(0.0155)	(0.0156)	(0.0155)	(0.0156)
Less than good	–0.0522**	–0.0537**	–0.0538**	–0.0475**	–0.0511**	–0.0537**	–0.0533**
	(0.0209)	(0.0210)	(0.0210)	(0.0210)	(0.0210)	(0.0209)	(0.0209)
Bad	–0.1325***	**–0.139**3***	–0.1352***	–0.1283***	–0.1308***	–0.1333***	–0.1303***
	(0.0424)	(0.0427)	(0.0425)	(0.0427)	(0.0426)	(0.0424)	(0.0423)
Number of Health Problems	0.0014	0.0013	0.0012	0.0017	0.0015	0.0016	0.0014
	(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Marital Status	–0.0127*	–0.0127*	–0.0128*	–0.0122	–0.0128*	–0.0125*	–0.0128*
	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)	(0.0074)

Table continued next page

Table 3 continued

Dependent Variable	Planned Training in next two Years						
Children	0.0137	0.0136	0.0135	0.0127	0.0136	0.0130	0.0134
	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)
Tenure in Years	–0.0048***	–0.0048***	–0.0048***	–0.0048***	–0.0048***	–0.0049***	–0.0047***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Tenure squared	0.0001*	0.0001*	0.0001*	0.0001*	0.0001*	0.0001*	0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Working Time	0.0018***	0.0018***	0.0018***	0.0017***	0.0018***	0.0020***	0.0020***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)
Log. Imputed Gross Monthly Wage	0.0382***	0.0385***	0.0384***	0.0405***	0.0381***	0.0384***	0.0388***
	(0.0123)	(0.0122)	(0.0122)	(0.0123)	(0.0123)	(0.0123)	(0.0123)
Temporary Contract	0.0269*	0.0270*	0.0270*	0.0259*	0.0267*	0.0258	0.0272*
	(0.0157)	(0.0157)	(0.0157)	(0.0157)	(0.0158)	(0.0157)	(0.0157)
Type of Job. Reference: Blue-Collar Worker							
White-Collar Worker	0.0246	0.0246	0.0246	0.0250	0.0244	0.0242	0.0247
	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)	(0.0171)
Civil Servant	0.0501**	0.0508**	0.0504**	0.0514**	0.0497**	0.0482**	0.0514**
	(0.0223)	(0.0223)	(0.0223)	(0.0223)	(0.0223)	(0.0223)	(0.0223)
Job Qualification Status. Reference: Simple Tasks							
Medium Tasks	0.0476**	0.0479**	0.0477**	0.0482**	0.0477**	0.0482**	0.0480**
	(0.0214)	(0.0214)	(0.0214)	(0.0214)	(0.0214)	(0.0214)	(0.0214)
Higher Tasks	0.1381***	0.1387***	0.1383***	0.1389***	0.1379***	0.1400***	0.1383***
	(0.0243)	(0.0243)	(0.0243)	(0.0244)	(0.0243)	(0.0243)	(0.0243)
Highest Tasks	0.1692***	0.1699***	0.1696***	0.1695***	0.1691***	0.1711***	0.1682***
	(0.0270)	(0.0270)	(0.0270)	(0.0271)	(0.0270)	(0.0271)	(0.0270)
Instructor (Yes or no)	0.0533***	0.0534***	0.0531***	0.0522***	0.0530***	0.0544***	0.0514***
	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)	(0.0092)

Dummy Variables for Firm Size Classes, Industry Classification and Occupational Group	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.6288*** (0.1114)	–0.6242*** (0.1113)	–0.6277*** (0.1115)	–0.6312*** (0.1115)	–0.6273*** (0.1114)	–0.6392*** (0.1114)	–0.6370*** (0.1114)
Number of Observations	12405	12405	12405	12405	12405	12405	12405
Chi^2-Statistic	79.59	79.84	74.02	79.22	74.19	78.97	74.16
Pseudo R^2	0.19	0.19	0.19	0.19	0.19	0.19	0.19

Note: Results from OLS regression. Robust standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01. Source: Own calculations based on the BIBB / BAuA Employment Survey 2012.