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Abstract

Job-Market signaling is ranked high among the explanations why individuals engage voluntarily in OSS projects. If true, signaling implies the existence of a wage premium for OSS engagement. However, due to a lack of data this issue has not been tested previously. Based on a novel data set comprising detailed demographic and wage information for some 7,000 German IT employees, this paper fills this gap. In the empirical analysis, however, we find no support for the signaling hypothesis, a result that is robust to different measures of OSS involvement and different model specifications.

Keywords: open source software, signaling, wage differentials.
JEL classification: J31, J24, D01

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1 Introduction

During the past years, the emergence of Open Source Software (OSS) and the associated development model have been the subject of extensive research in economics (cf. Rossi 2006 for a review). Although one might consider the study of the OSS phenomenon interesting in its own right, it is primarily the uncomfortable questions that the presence of OSS poses to mainstream economics that have attracted the attention of researchers. A central issue here is the question of what drives OSS programmers to donate valuable software code free of charge, and the important implications of this beyond the narrow field of OSS (see e.g., Lerner and Tirole 2002, Johnson 2002, Myatt and Wallace 2002, Bessen 2006, Bitzer et al. 2007).

A cursory overview of the OSS literature reveals that although voluntary OSS programmers donate software free of charge, they are by no means unrewarded. The rewards depend on the particular motives involved. Individuals may be user-programmers, they may be driven by the urge to donate a gift to the community, they may simply enjoy programming, or they may benefit from the learning associated with programming OSS (see Rossi, 2006, for a recent survey). Perhaps the most elegant explanation is the signaling hypothesis advocated by Lerner and Tirole (2002). They argue that programmers engage in voluntary OSS programming in order to disclose their unobservable ability to employers: a situation of classic Spence-type (1973, 1974) job-market signaling.

Viewed from this perspective, the presence of OSS is a unique natural experiment that allows us to investigate different motivational drivers that may be at work in an economy. Accordingly, the investigation of different motives and reward channels within OSS has been an area of lively empirical research (see, e.g., Hars and Ou 2002, Hertel et al. 2003, Krishnamurthy 2002, Lakhani and Wolf 2005, and Wu et al. 2007).

The lack of comprehensive data to date has prevented adequate empirical investigation of the wage premium predicted by the job-market signaling hypothesis. The data available to earlier studies covers only OSS and free software contributors; thus information on the counterfactual, i.e., wages of programmers who do not contribute to OSS, is missing; see, e.g., Orman (2008). Accordingly, previous data is ill-suited to estimate the wage premium for voluntarily OSS engagement. Moreover, even if data is available, an observed wage premium would be driven by both a potential signaling effect and a potential direct effect from the signal-carrying activity – say, learning effects from voluntary OSS programming that increase an individual's human capital. Accordingly, simple estimates of a wage premium from OSS activity would risk overstating the role of signaling.[1]

The present paper closes both of these gaps. First, we use a novel data set containing information on OSS contributors and non-contributors alike. To obtain the necessary information we augmented a longstanding general wage survey among German IT staff in the years 2006 and 2007 with a subset of questions concerning OSS activities. In addition, the survey features rich detail

[1] In the literature on the returns to education the related issue of signaling versus human capital effects of education has received a great deal of attention, see the survey of Weiss (1995) or Chevalier et al. (2004) for a recent empirical investigation based on UK data.

on individual characteristics such as job functions, educational background, etc. Out of the total of 7,115 programmers surveyed, 1,226 are active in OSS activity.

Of these active OSS contributors, approximately 60% think that their voluntary engagement benefits their career. Thus, their motive statement suggests signaling, and is in line with results of the aforementioned motivation studies based on active OSS contributors alone. Yet, whether the envisaged benefit actually materializes as a wage premium on the paycheck is an entirely different question.

Second, within our dataset we are able to construct various measures of the extent and nature of an individual's OSS involvement. We estimate variants of a Mincer wage equation to identify OSS wage premiums and to quantify the extent to which these can be explained by signaling. The signaling hypothesis assumes that the productivity of individuals is unobservable, and furthermore, that only productive individuals would invest in sending the signal. From an econometric point of view, the signal-carrying variable must thus be correlated with the error term. Hence, if signaling is indeed taking place, the coefficient of the potentially signal-carrying variable must suffer from endogeneity bias. By using instruments, we are able to quantify this bias and can therefore distinguish between direct effects (say learning) and signaling effects of voluntary OSS engagement on wages.

To summarize our main results, we find no evidence of a positive wage premium for OSS engagement. Thus neither the signaling hypothesis, nor the claim of learning effects is supported by the data. These results are robust to all our OSS indicator variables and different model specifications.

The next section provides a brief background for our empirical investigation. Section 3 presents the data and econometric method. Section 4 presents the results, and Section 5 concludes.

2 Organization of Thought

To guide our empirical investigation, we briefly illustrate some central mechanisms of signaling situations. The basic setup features workers with private unverifiable information about their individual productivity, which is heterogeneous across agents. On the labor market, firms make wage offers with the aim of hiring the most productive workers. An observable activity – say obtaining a university degree, the cost of which depends on the student's productivity – can then serve as a signal separating higher-productivity from lower-productivity individuals. However, depending on the cost and profit structures, heterogeneity distribution, and assumptions about the market structures, the system may equally well result in a pooling equilibrium, where no separation occurs.

We can mold these general principles into a simple stylized description of the software programming industry, in line with the arguments of Lerner and Tirole (2002). In doing so, it is instructive to account for key features of OSS contributions: the possibility of several simultaneously observable signal-bearing activities (e.g., education and OSS provision), private and unobservable pay-offs from such activities (e.g., user-programmer benefits, fun), and verification costs, where firms may have to expend effort in evaluating a signal (e.g., the cost of judging an individual's programming abilities based on his or her OSS code).

Avoiding unnecessary structure, these ideas can be consolidated into the following simple setup.[2] A population of software programmers features n individuals, i, that are each identified by a unique programming cost $c_i \geq 0$, i.e., reflecting his or her programming skills/productivity. These individuals may engage in various signal-carrying activities, j, such as obtaining university degrees or programming OSS. While in general the cost of displaying various signals will depend on and increase with an agent's programming costs, c_i, additional private benefits, b_i, may, however, enter and distort signals. If there exist user-programmer benefits, play values (homo ludens payoff, Bitzer et al. 2007), or gift benefits, then the private value of the verifiable activity j, net of any potential wage premium for individual i becomes $S_{ij}(c, b)$. The various payoffs are private knowledge, while the underlying distributions and dependencies are common knowledge. For our purposes, it is not necessary to make any assumptions about these underlying distributions or dependencies, e.g., c and b may or may not be correlated.

A simple labor market is given by competitive hiring from a number of identical software firms, each of which is assumed to employ $m < n$ computer programmers. Although individual programmers' cost and benefit realizations are private knowledge, employers (firms) know the distributions, and at a cost

[2]The setup presented here largely reflects the consensus ideas concerning signaling laid out by Michael Spence in his Nobel Prize Lecture, Spence (2002).

d_j can verify whether an individual displays a certain signal.[3] The production process is such that a firms revenue, R, depends, inter alia, on the average programming ability of its employees. Representing the sum of m individual programming costs by σ, we can postulate $\frac{\partial R}{\partial \sigma} < 0$. Thus hiring the average individual at wage w would imply $\sigma = \frac{1}{m}\sum_{i=1}^{m} c_i = \bar{c}$ and profits $\Pi = R(\sigma) - mw$. Finally, zero profits in equilibrium and the participation constraint of individuals complete the setup.

Within the above structure, a number of observations can be stated. First, in any pooling equilibrium, where firms pay the pooling wage w^P we have:

Result 1. *In a **pooling equilibrium**, the pooling wage is $w^P = \frac{1}{m}R(\bar{c})$, and individuals will display a given signal if $S_{ij}(c, b) > 0$, i.e., if their private benefits (e.g., play value) exceed their respective signal-displaying costs.*

Secondly, separation may occur along a given signal. In such a situation, it is the case that:

Result 2. *In a **separating equilibrium**, where $k < n$ individuals display a signal, l, the high-wage offer is $w^H = \frac{n}{mk}R(\frac{1}{k}\sum_{i=1}^{k} c_i - d_l)$, while the low-wage offer is $w^L = \frac{n}{m(n-k)}R(\frac{1}{n-k}\sum_{i=k}^{n} c_i)$, and individuals will display signal l if $S_{il}(c, b) > w^L - w^H$, i.e., the wage premium plus private benefits exceed the respective signal-displaying costs. At the same time, all other signals j will be displayed if $S_{ij}(c, b) > 0; j \neq l$.*

[3] The cost d_j would, in the case of OSS, for example, capture the effort required to actually obtain and evaluate a programmer's OSS code. In the case of a university degree, however, d_j may be zero.

Of course, we cannot determine here whether equilibria exist, whether separation or pooling takes place, which signal-bearing activities are observed, what size k is, or which signals are working, resulting in separation. Answers to these questions require more structure and will in general depend on the functions, R, S, the distribution of programming costs, c_i and private benefits, b_i, the size of the verification costs, d_j, and the various dependencies or independencies of these functions and distributions (see Spence 2002). However, the general results from above provide us with a series of implications, several of which can be applied to the data for empirical investigation.

Implication 1. *In a separating equilibrium, operating signals will be associated with a wage premium.*

Implication 1 contains the classic signaling hypothesis as evoked by Lerner and Tirole (2002) and leads to the straightforward empirical prediction at the center of our analysis.

In one respect, however, OSS signaling in the programmer labor market differs from classic job-market signaling. In contrast to an educational signal, which may last a lifetime, the OSS contribution is a recorded observation of programming skills for a given technology and programming challenge. Thus, in view of the rapid developments in the software industry, with short knowledge life-cycles, it is unlikely for old OSS signals to command a present-day wage premium. Accordingly, we expect to find the strongest wage premium effect for contemporaneous OSS contributions.

Implication 2. *With noise from private payoffs, b_i, signal-bearing activities* *may be observed but may not work. Thus signals may also appear in a pooling equilibrium. This is because, with unobserved private payoffs that may be very high, even individuals with low productivity can display the signal.*

Thus, by Implication 1 and 2, the observation of a potentially signal-bearing activity itself does not guarantee a situation in which the signal works. On the contrary, not only may these private benefits render a separation unstable, the observed signal-bearing – but malfunctioning – activity may only be explained by referring to the private benefits.

Moreover, in a situation depicted in Implication 2, the observed signal-bearing activity will not be associated with a wage premium. However, although this is generally the case for a pooling situation, separating equilibria may feature malfunctioning signals alongside the functional signal:

Implication 3. *In a separating equilibrium with the properly working signal l, an additional signal-bearing activity j may be observed. If $S_{ij}(c,b)$ and $S_{il}(c,b)$ are positively correlated, both activities may be associated with a wage premium.*

The above implications already sum up to an empirically relevant scenario where multiple signals may be observed and can be measured and compared to individual earnings. It also immediately becomes clear that this investigation strategy requires observation of individuals who do and individuals who do not display the particular signals. Any analysis based on observations of only those who do display a given signal will fail to test for the above mechanisms. Furthermore, the above illustrates that private benefits may in principle blur the situation substantially, rendering only some of all possible signals functional, or pushing the system into the pooling equilibrium. Finally, the wage premium may be inverted: for example, with dependent b and c distributions, positive mapping would disclose those displaying a signal driven by b as unproductive (high c).

In line with the effects from private benefits b, the role of direct effects from a signaling activity – such as learning effects – can be considered. It is a common simplification in models of signaling and screening that the observable activity has no effect on the underlying unobservable characteristics of individuals; e.g., it is assumed that education has no effect on the human capital and hence productivity of an individual. Obviously, these simplifications, though useful from a modeling perspective, do not hold when taking the theory to the data. This is particularly important in the extensive literature on returns to education, where signaling effects and direct human capital effects of education need to be disentangled in order to assess the true value of education; see, e.g. Weiss (1995) or Chevalier et al.(2004). The same issue occurs in the context of voluntary OSS involvement: where individuals benefit from their OSS activity in terms of training and learning (see the studies of Hars and Ou 2002, or Wu et al. 2007), this corresponds to a reduction in c_i as a result of OSS activity. Following the extension of signaling with direct productivity (human capital) effects provided in Spence (2002), we can state:

Implication 4. *In the presence of direct effects from the signal-carrying activity (learning effects), pooling equilibria may dominate some but not all previously viable separating equilibria, and investment into the signal-carrying* *activity may be observed even though no separation occurs.*

Next, we briefly illustrate further implications that are less suitable for empirical investigation.

Implication 5. *Ceteris paribus, more individuals will display a working signal, j, in a separating equilibrium, compared to the number of individuals displaying j in a pooling equilibrium.*

Implication 6. *An increase in the verification cost d_j makes activity j less likely to be a proper working signal.*

Verification costs will differ by the nature of the signal in question. While verifying university degrees is relatively cheap, assessing an applicant's programmed code might be relatively more cumbersome.

And finally, combining Implications 2 and 6:

Implication 7. *There exists a trade-off between verification costs, d_j, and noise from $S_{i,j}$, such that a signal associated with more noise may still work if it features lower verification costs.*

Finally, and outside the scope of the above simple framework, our empirical investigation may – and most likely is – confronted with out-of-equilibrium situations. For example, in disequilibrium, individuals may expend effort on signal-bearing activities with a view to higher wages, although no actual wage premium ultimately materializes. Whether or not such situations qualify as signaling cannot easily be resolved.

3 Data and Estimation Technique

Our data were collected in collaboration with the German computer magazine "*C't Magazin für Computer Technik*", by expanding their annual Internet-based IT wage survey for the years 2006 and 2007 to include a subsection of questions on whether the respondent contributes to OSS projects in his or her spare time. Our data are unique compared to data used in earlier empirical studies (e.g., Hars and Ou 2002, Hertel et al. 2003, Krishnamurthy 2002, Lakhani and Wolf 2005, and Wu et al. 2007) in that we assemble information on annual wages and numerous demographic and workplace-related characteristics both for individuals who do contribute as well as for those who do not contribute to OSS projects.

We restrict our sample to prime-age (18-65) men and women in full-time employment. In addition to gross annual wages, we measure all additional labor income such as premiums and bonus pay. To reduce the noisiness of the data, we recode a number of wage observations that appear to correspond to monthly instead of yearly labor income, and exclude remaining observations with implausibly low gross wages (below 1,000 euros).[4] To insure comparability across years, labor income for 2006 and 2007 is transformed into constant prices applying the national consumer price index. Annual labor income is then transformed into monthly labor income utilizing information on the number of work months per individual.

Pooled over the years 2006 and 2007, our sample contains a cross-section

[4] We also estimate all specifications with the pure unaltered data. Our key findings do not change.

of 7,115 individuals. Out of our sample, 1,226 individuals engage in voluntary OSS contributions, of whom 259 declare a role as a project leader. Most intriguing – and in line with the results of motive studies conducted among OSS contributors alone (Hars and Ou 2002, Hertel et al. 2003, Krishnamurthy 2002, Lakhani and Wolf 2005, and Wu et al. 2007) – 753 of the active OSS programmers in our sample state that they think their voluntary OSS activities benefit their career. Descriptive statistics by OSS contributor status are reported in Table 1.

To identify a potential OSS wage premium, we estimate variants of the following Mincer wage equation (see Mincer 1974):

$$\ln W_i = \alpha + \beta OSS_i + \theta DEMOG_i + \delta WORK_i + \epsilon_i \tag{1}$$

where OSS denotes OSS contributor status measured in various ways, $DEMOG$ a set of demographic controls such as age, gender, educational attainment, and work experience, and $WORK$ a number of workplace-related characteristics such as industry, occupational field, and firm size. We assume orthogonality of the error term ϵ with respect to our control variables except OSS. To accommodate heteroscedasticity, standard errors are bootstrapped.

According to Implication 1 in Section 2, OSS contributions should generate a positive wage premium if they work as a signal and if a separating equilibrium is feasible.

In the empirical application one has to be cautious, however, when interpreting the outcome of a simple regression model.

First of all, we have an identification problem similar to the one prevalent in the returns to schooling literature as surveyed in Weiss (1995). There is the theoretical possibility that OSS contributions have a direct positive or negative wage effect that may not be due to signaling, i.e., that may not be due to a selection of unobservable more productive workers into OSS activities. One possibility for a direct positive wage effect of OSS engagement arises through learning. Thus, individuals may become more productive through their OSS activity, yielding a wage premium. However, this effect has to be distinguished from a signaling effect, which refers to a selection of already more productive individuals into OSS activities; see Implication 4.

Accordingly, if OSS contributions indeed work as a signal for unobserved productivity, then by definition the residual must be correlated with the OSS indicator variable, i.e., OSS must be endogenous.[5]

However, endogeneity does not necessarily stem from unobserved heterogeneity. It can also arise from simultaneity between wages and OSS contributions. Thus, even if OSS contributions are found to be correlated with the error term, this is not sufficient to establish the relevance of signalling.

Our empirical strategy is therefore twofold. In a first step we estimate a simple OLS model deriving a composite OSS coefficient that consists of the direct wage effect of OSS contributions as well as an endogeneity bias

[5]Only if the OSS indicator variable is perfectly collinear with unobserved heterogeneity, this correlation should be zero. This is, however, unlikely as OSS is a binary variable and unobserved productivity arguably is continuous.

component due to unobserved heterogeneity or simultaneity. Subsequently, in a second step we instrument for OSS and quantify the endogeneity bias component.

To test the robustness of our results with respect to distorted income measures, we estimate two alternative models. First, we apply some top- and bottom-coding at the first and 99th percentile to monthly labor income. Second, we employ median regression, which is considerably more robust to outlying observations than the ordinary least squares estimator. Our main findings are reported in the following section.

4 Results and Discussion

Table 2 presents the results from the first step of our main empirical specification, in which the indicator variable *OSS* captures all individuals who report contributing to OSS projects during their spare time, irrespective of how much effort they actually invest.

Column 1 of Table 2 shows the results of a simple OLS model, while Columns 2 and 3 show the results of outlier-robust top/bottom-coding and absolute difference model estimations.

Overall, the models have a very good fit and the coefficients are generally in line with what one would expect from standard wage regressions in the literature (see, e.g., Brown and Medoff 1989, Schmidt and Zimmerman 1991).

Furthermore, the coefficients of the simple OLS and the two outlier-robust regressions are fairly similar. When focusing on the simple OLS model (Table 2, Column 1), our demographic and human-capital-related control variables age, tenure, and IT work experience affect wages in a non-linear way, with a peak at about 45 and at 19 and 23 years, respectively. Our results further indicate that in our sample, males, ceteris paribus, earn approximately 7 percent more than females.[6] In addition, we find a considerable correlation between education and wages. Respondents with a university, polytechnical, or advanced vocational degree earn about 21, 14, and 4 percent more, respectively, than respondents without any formal degree. Interestingly, respondents with a basic vocational degree are found to earn about 5 percent less, while individuals who have at least some university experience but no formal degree are found to earn 4 percent more than respondents with no degree at all. We also find statistically significant positive wage effects of around 7 percent for those living in an urban area.

Furthermore, with respect to workplace-related control variables, we find that respondents with supervisory responsibilities ceteris paribus earn about 9 percent more, while respondents who work partly abroad have a wage premium of about 9 percent. At the same time, wages consistently increase with firm size. Respondents in small, medium, and large firms, ceteris paribus, earn 10, 18, and 28 percent more than respondents in very small firms with up to 10 employees.

Regarding the OSS coefficient that is of highest interest in the context of the present study, none of the model specifications in Table 2 are suggestive

[6] $(exp(0.0633) - 1) * 100 = 6.5$

of any positive wage premium for voluntary OSS contributions. All OSS coefficients are very small, never exceed their respective standard errors, and in the two outlier robust estimations, even take on a negative sign.

In a second step, we now instrument for the OSS indicator variable to assess the scope of the endogeneity bias. What is required is a set of variables that has sufficient explanatory power for OSS contributions while being orthogonal to the error term in the wage regression.

Our data contains two variables that constitute ideal candidates for this task. Respondents give information on whether they are knowledgable in the Linux and/or Macintosh operating system. Arguably, Linux and Macintosh users share a certain opposition against the market leader, the MS Windows operating system, and also today perhaps moreso in the case of Linux rely more heavily on user community support. Such preferences and attitudes may be associated with a higher propensity to contribute to OSS projects on various platforms that challenge commercial software products. As the large F-Statistic for our excluded instruments (*linux* and *mac*) reported in Table 3 indicates, we indeed find strong support for this view. Knowledge of the Linux and/or Macintosh operating system is found to be a very strong predictor for voluntary OSS contributions. Furthermore, as the Hansen-J statistic in Table 3 shows, we cannot reject orthogonality of our excluded instruments within reasonable confidence bounds. Thus, the excluded instrumental variables are valid and we can carry out a Durbin-Wu-Hausman test to test for systematic differences between a consistent GMM model and a potentially inconsistent but efficient OLS model, i.e., to quantify the endogeneity bias component in the coefficients estimated in Table 2.[7]

As the test statistic in Table 3 indicates, however, we cannot reject the H_0 that differences in the parameters between the two models are not systematic. Accordingly, our OSS indicator variable can indeed be considered exogenous, i.e., the aforementioned endogeneity bias component is in fact zero. Thus, there is no evidence either for simultaneity or for unobserved heterogeneity bias. Summarizing, we find the direct wage premium of OSS contributions to be zero, and have no evidence supporting the idea that voluntary OSS contributions work as a signal for unobserved productivity.

However, according to Implication 3 in Section 2, several signals can be correlated and thereby associated with a positive wage premium. In our empirical analysis, this raises the issue of multicolinearity between the potential signals OSS and educational attainment. However, as reported in Table 1, it is obvious that there is no strong correlation between educational attainment and OSS contributions. Nevertheless, we re-estimate our baseline specifications without controlling for educational attainment to identify any potential collinearity issues. As is apparent in Columns 4-6 of Table 2, the coefficients on the OSS indicator variable remain very small and again never exceed their standard errors, while exogeneity cannot be rejected within reasonable confidence bounds (see Table 3). Thus, there is no evidence for multicollinearity between educational attainment and OSS contributions, and Implication 3 in

[7]All GMM regressions and associated tests are carried out using Stata's *ivreg2* module. Baum et al. (2003) give a detailed description of the computations and instrument validity tests.

Section 2 is not relevant.

We further search for evidence supporting the signaling hypothesis by differentiating between different OSS indicators. First of all, we condition the OSS indicator to take the value one only if respondents actually invest at least three ($OSS3$) or ten ($OSS10$) hours per week, respectively. Second, we generate an indicator variable exclusively for OSS project leaders ($OSSPL$). Third, we estimate a model with actual hours per week invested in OSS projects as a regressor ($OSS-Hours$, $OSS-Hours^2$). Table 4 shows the composite coefficient estimates from this exercise, reflecting the direct effect off OSS engagement as well as any potential endogeneity bias. Again, all OSS-related coefficients are very small, never exceed their respective standard errors, and even take on a negative sign. When testing for endogeneity bias, we again cannot reject the exogeneity assumption; hence, unobserved productivity is not correlated with OSS involvement.[8]

Thus, if voluntary OSS contributions indeed yield wage premiums, their relevance must be heterogeneous across the sample. To test for this, we estimate several specifications interacting our OSS indicator variables with education, age, and firm size. To save space, we only report results for our basic OSS indicator variable and for OSS project leaders in Table 5. However, none of the interacted estimations generated a positive, statistically significant coefficient on the OSS indicator variables.

As a final exercise, we considerably reduced sample heterogeneity by fo-

[8]We do not attempt to instrument the continuous variables $OSS-Hours$, $OSS-Hours^2$ with our binary instrumental variables.

cusing on the subgroup of software developers as opposed to the remaining IT personnel in employment fields such as network administration, consulting, and web design, yielding a reduced sample size of 2,548 observations. Arguably, the signaling effect of OSS contributions should be strongest among professional software developers. Table 6 shows the respective coefficient estimates for our basic OSS indicator.

Although we find no evidence for a significant general OSS wage premium (see Column 1, Table 6), when interacting the OSS indicator with educational attainment we find a sizable positive statistically significant wage premium of OSS contributions for respondents with no formal degree. Accordingly, in the subsample of software developers, voluntary OSS contributions raise wages for unskilled workers by 16 percent. Furthermore, as the test statistics reported at the bottom of Table 6 show, we cannot reject the H_0 of exogeneity of OSS within reasonable confidence bounds. Accordingly, the estimated OSS wage premium for unskilled workers can be fully accounted for by direct productivity-increasing effects (i.e., learning) and is not attributable to signaling.

Thus, our results lend some support to the idea that voluntary OSS engagement can make software developers without any formal degree more productive. It is, however, important to bear in mind that these findings only apply to a small subgroup of our sample: in total, our data only contain 17 unskilled OSS contributors.

Summarizing our results, we do not find any evidence for a selection of unobservably more productive workers into OSS activity in any specification. Hence, our empirical analysis does not lend any support to the signaling hypothesis outlined in Implication 1 in Section 2. The situation we observe is rather that described in Implication 2 of Section 2. Accordingly, voluntary OSS engagement is merely the result of higher private benefits, b, of contributors, and thus cannot carry a signal of higher productivity.

Even if there is some positive selection of higher productivity types into OSS contributions, the noise introduced by the aforementioned private benefits, b, requires firms to monitor the quality of OSS contributions. Thus, our results are also consistent with a situation in which positive selection in principle takes place, but in which monitoring costs, d, are too high, rendering OSS contributions unusable for signaling purposes.

In our theoretical reasoning, we did not make any assumptions about the distribution of unobserved productivity. If, conditional on all demographic and educational observables, unobserved productivity is sufficiently evenly distributed, then even with low monitoring costs, d, there would be no need for firms to use OSS contributions as an additional signal.

Finally, in our theoretical reasoning, we considered different equilibria. If, however, we are in a situation out of equilibrium, then a separating equilibrium (Result 2 in Section 2) with an associated positive wage premium for contemporaneous voluntary OSS contributions may still materialize in the future.

5 Conclusion

The economics literature argues that job-market signaling can explain why individuals acquire costly signals. This fundamental rationale is believed to apply to the case of volunteer contributors to OSS. The present paper has investigated this prospect with a novel data set based on a survey of some 7,000 German IT employees. The present approach differs from previous studies insofar as our data comprises demographics and wage information both for individuals who do and for those who do not contribute to OSS.

Our approach enables us to test for a wage premium associated with signaling and to differentiate it from direct wage effects, e.g., via learning. Concerning the signaling hypothesis, we do not find any evidence for a selection of unobservably more productive workers into OSS activities in any of our multiple specifications. Hence, our empirical analysis does not lend any support to the signaling hypothesis.

This highlights the importance of private payoffs such as play value or monitoring costs associated with OSS, which render a separating equilibrium in which voluntary OSS contributions signal higher productivity unfeasible. Accordingly, the implications of our results go beyond the narrow study of OSS, and relate to fundamental issues of work incentives.

Tables

Table 1: Descriptive Statistics

	OSS-contribution				
	No		Yes		
	Mean	Std-Deviation	Mean	Std-Deviation	Mean Comparison Test H_0: Means identical
	4284.31	(2273.58)	4422.04	(7564.49)	
Age (in years)	33.38	(6.78)	32.19	(6.32)	***
Tenure (in years)	6.30	(4.70)	6.42	(4.86)	
IT-Work Experience (in years)	8.52	(5.84)	8.23	(5.55)	
Gender	0.98	(0.14)	1.00	(0.05)	***
EDU: University	0.26	(0.44)	0.25	(0.43)	
EDU: Polytechnical	0.22	(0.42)	0.21	(0.41)	
EDU: Advanced Vocational	0.11	(0.32)	0.11	(0.31)	
EDU: Vocational	0.25	(0.44)	0.26	(0.44)	
EDU: Uni without Degree	0.09	(0.29)	0.13	(0.33)	***
EDU: No Degree	0.06	(0.24)	0.05	(0.23)	
Supervisor	0.27	(0.44)	0.33	(0.47)	***
Urban Area	0.58	(0.49)	0.57	(0.49)	
Firm Size: $1-10$	0.08	(0.27)	0.10	(0.30)	***
Firm Size: $11-100$	0.28	(0.45)	0.33	(0.47)	***
Firm Size: $100-1000$	0.27	(0.44)	0.26	(0.44)	
Firm Size: >1000	0.37	(0.48)	0.31	(0.46)	***
Foreign Work Experience	0.17	(0.38)	0.21	(0.41)	***
Observations	5889		1226		

Remarks: Dependent variable is $\log W$. *,**,*** indicate H_0 of Mean Comparison Test rejected with 10%, 5%, 1% error probability

Table 2: Basic Regression

	Simple OLS	OLS with Top/Bottom Coding	Median Regression Model	Simple OLS	OLS with Top/Bottom Coding	Median Regression Model
OSS	-0.0011	-0.0055	-0.0042	-0.0003	-0.0046	-0.0019
	[0.0097]	[0.0078]	[0.0104]	[0.0092]	[0.0078]	[0.0086]
Age	0.0453	0.0437	0.0420	0.0701	0.0686	0.0705
	[0.0073]***	[0.0057]***	[0.0061]***	[0.0074]***	[0.0053]***	[0.0060]***
Age^2	-0.0005	-0.0005	-0.0005	-0.0008	-0.0008	-0.0008
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Tenure	0.0113	0.0114	0.0107	0.0077	0.0077	0.0030
	[0.0031]***	[0.0028]***	[0.0032]***	[0.0030]**	[0.0026]***	[0.0035]
$Tenure^2$	-0.0003	-0.0003	-0.0003	-0.0002	-0.0002	-0.0001
	[0.0001]**	[0.0001]**	[0.0002]***	[0.0001]	[0.0001]	[0.0002]
IT Work Experience	0.033	0.0324	0.0295	0.0239	0.0234	0.0222
	[0.0029]***	[0.0026]***	[0.0035]***	[0.0029]***	[0.0026]***	[0.0037]***
IT Work Experience^2	-0.0007	-0.0007	-0.0005	-0.0005	-0.0005	-0.0004
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Gender	0.0633	0.0641	0.0603	0.0695	0.0704	0.0723
	[0.0230]***	[0.0222]***	[0.0285]***	[0.0255]***	[0.0236]***	[0.0222]***
EDU:University	0.1891	0.1837	0.1945			
	[0.0185]***	[0.0148]***	[0.0172]***			
EDU:Polytechnical	0.1298	0.1275	0.1450			
	[0.0187]***	[0.0157]***	[0.0155]***			
EDU:Advanced Vocational	0.0411	0.0366	0.0642			
	[0.0223]*	[0.0177]**	[0.0187]***			
EDU:Vocational	-0.0474	-0.0516	-0.0328			
	[0.0181]***	[0.0143]***	[0.0159]***			
EDU:Uni No Degree	0.0394	0.0383	0.0561			
	[0.0206]*	[0.0173]**	[0.0182]***			
Supervisor	0.0891	0.0867	0.0786	0.095	0.0926	0.0894
	[0.0075]***	[0.0080]***	[0.0080]***	[0.0079]***	[0.0079]***	[0.0089]***
Urban Area	0.0633	0.0631	0.0642	0.0685	0.0682	0.0722
	[0.0094]***	[0.0071]***	[0.0078]***	[0.0101]***	[0.0070]***	[0.0079]***
Firm Size:> 1000	0.2451	0.2418	0.2339	0.2645	0.261	0.2543
	[0.0168]***	[0.0162]***	[0.0158]***	[0.0171]***	[0.0174]***	[0.0201]***
Firm Size:$100 - 1000$	0.162	0.1602	0.1466	0.1708	0.1689	0.1570
	[0.0198]***	[0.0147]***	[0.0175]***	[0.0202]***	[0.0158]***	[0.0197]***
Firm Size:$11 - 100$	0.0918	0.0923	0.0853	0.1034	0.1039	0.0958
	[0.0171]***	[0.0155]***	[0.0151]***	[0.0180]***	[0.0165]***	[0.0187]***
Foreign Work Experience	0.0842	0.084	0.0786	0.0942	0.094	0.0856
	[0.0085]***	[0.0084]***	[0.0085]***	[0.0077]***	[0.0090]***	[0.0084]***
Year 2007	-0.0298	-0.0274	-0.0155	-0.0315	-0.0291	-0.0209
	[0.0066]***	[0.0063]***	[0.0076]***	[0.0070]***	[0.0063]***	[0.0081]***
Constant	6.4807	6.5154	6.5178	6.1186	6.1467	6.1398
	[0.1293]***	[0.1125]***	[0.1323]***	[0.1306]***	[0.0996]***	[0.1160]***
Observations	7115	7115	7115	7115	7115	7115
adj. R^2	0.52	0.56	0.38	0.49	0.52	0.35
Employment Field Dummies $Chi2$	540.14	589.89	331.50	980.69	973.96	543.47
Federal State Dummies $Chi2$	428.16	990.95	530.20	402.68	845.06	620.76
Industry Dummies $Chi2$	343.70	177.88	234.48	358.15	166.14	244.81

Remarks: Dependent variable is $\log W$. Bootstrapped standard errors in brackets.*,**,*** indicate significance at 10%, 5%, 1% error probability. Default categories: EDU: No Degree; Firm Size:$1 - 10$

Table 3: Exogeneity Test for OSS

Excluded Instruments:	Knowledge in Linux OS, Mac OS	
	With Edcucational Controls	Without Edcucational Controls
Predictive power for OSS ("first stage")	$F(2, 7053) = 135.72$ $p = 0.00$	$F(2, 7058) = 137.07$ $p = 0.00$
Kleibergen-Paap Underidentifikation LM Test	$Chi^2 = 260.263$ $p = 0.000$	$Chi^2 = 262.611$ $p = 0.000$
Hansen J statistic for orthogonality of instruments	$Chi^2 = 0.841$ $p = 0.359$	$Chi^2 = 0.788$ $p = 0.375$
Durbin-Wu-Hausman Exogeneity Test	$Chi^2 = 0.001$ $p = 0.977$	$Chi^2 = 1.016$ $p = 0.313$

Remarks: Based on GMM model to accomodate heteroskedasticity.

Table 4: Alternative OSS Measures

OSS3	-0.0098			
	[0.0111]			
OSS10		-0.0141		
		[0.0268]		
OSS-PL			-0.0067	
			[0.0224]	
OSS-Hours				-0.0044
				[0.0039]
OSS-Hours2				0.0002
				[0.0002]
Age	0.0436	0.0436	0.0437	0.0438
	[0.0065]***	[0.0057]***	[0.0065]***	[0.0051]***
Age^2	-0.0005	-0.0005	-0.0005	-0.0005
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Tenure	0.0114	0.0114	0.0114	0.0113
	[0.0028]***	[0.0028]***	[0.0029]***	[0.0032]***
$Tenure^2$	-0.0003	-0.0003	-0.0003	-0.0003
	[0.0001]***	[0.0001]**	[0.0001]**	[0.0001]**
IT Work Experience	0.0324	0.0324	0.0324	0.0325
	[0.0027]***	[0.0026]***	[0.0032]***	[0.0033]***
IT Work Experience^2	-0.0007	-0.0007	-0.0007	-0.0007
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Gender	0.0641	0.0636	0.0636	0.0646
	[0.0230]***	[0.0221]***	[0.0216]***	[0.0220]***
EDU: University	0.1836	0.1835	0.1837	0.1837
	[0.0180]***	[0.0148]***	[0.0150]***	[0.0168]***
EDU: Polytechnical	0.1274	0.1273	0.1275	0.1277
	[0.0183]***	[0.0157]***	[0.0143]***	[0.0161]***
EDU: Advanced Vocational	0.0367	0.0364	0.0365	0.037
	[0.0207]*	[0.0178]**	[0.0175]**	[0.0213]*
EDU: Vocational	-0.0515	-0.0517	-0.0516	-0.0517
	[0.0174]***	[0.0144]***	[0.0134]***	[0.0175]***
EDU: Uni No Degree	0.0384	0.0381	0.0381	0.0383
	[0.0198]*	[0.0173]**	[0.0161]**	[0.0196]*
Supervisor	0.0867	0.0866	0.0865	0.0868
	[0.0072]***	[0.0080]***	[0.0082]***	[0.0072]***
Urban Area	0.0632	0.0632	0.0632	0.0631
	[0.0083]***	[0.0071]***	[0.0072]***	[0.0070]***
Firm Size: > 1000	0.2417	0.2418	0.2418	0.2418
	[0.0159]***	[0.0163]***	[0.0152]***	[0.0137]***
Firm Size: $100 - 1000$	0.16	0.1601	0.1601	0.1605
	[0.0183]***	[0.0148]***	[0.0151]***	[0.0137]***
Firm Size: $11 - 100$	0.0922	0.0921	0.0922	0.0924
	[0.0160]***	[0.0157]***	[0.0144]***	[0.0144]***
Foreign Work Experience	0.0841	0.0838	0.0838	0.0839
	[0.0079]***	[0.0084]***	[0.0079]***	[0.0080]***
Year 2007	-0.0275	-0.0274	-0.0273	-0.0275
	[0.0060]***	[0.0063]***	[0.0067]***	[0.0073]***
Constant	6.5167	6.5155	6.5143	6.5138
	[0.1162]***	[0.1120]***	[0.1221]***	[0.1002]***
Observations	7115	7115	7115	7115
adj. R^2	0.56	0.56	0.56	0.56
Employment Field Dummies Chi^2	599.90	590.35	276.84	763.51
Federal State Dummies Chi^2	504.91	993.40	796.61	568.78
Industry Dummies Chi^2	346.50	176.83	329.76	249.26

Exogeneity Tests of	OSS3	OSS10	OSS-PL
Excluded Instruments:	Knowledge in Linux OS, Knowledge in Mac OS		
Predictive Power	$F(2, 7053) = 96.85$	$F(2, 7053) = 32.84$	$F(2, 7053) = 27.88$
("first stage")	$p = 0.00$	$p = 0.00$	$p = 0.00$
Kleibergen-Paap	$Chi^2 = 188.00$	$Chi^2 = 65.47$	$Chi^2 = 55.49$
Underidentifikation LM Test	$p = 0.00$	$p = 0.000$	$p = 0.000$
Hansen -J Statistic	$Chi^2 = 0.836$	$Chi^2 = 0.825$	$Chi^2 = 0.794$
for Orthogonality	$p = 0.3604$	$p = 0.3636$	$p = 0.3730$
Durbin-Wu-Hausman	$Chi^2 = 0.002$	$Chi^2 = 0.005$	$Chi^2 = 0.030$
Exogeneity Test	$p = 0.969$	$p = 0.942$	$p = 0.862$

Remarks: Dependent variable is $\log W$. Bootstrapped standard errors in brackets.*,**,*** indicate significance at 10%, 5%, 1% error probability. Default categories: EDU: No Degree; Firm Size:$1 - 10$

Table 5: Interactions

	Basic OSS			OSS Project Leader		
OSS	-0.1149			0.1375		
	[0.2727]			[0.6256]		
$OSS \times Age$	0.011			0.001		
	[0.0164]			[0.0394]		
$OSS \times Age^2$	-0.0002			-0.0002		
	[0.0002]			[0.0006]		
$OSS \times EDU : University$		-0.0017			0.0102	
		[0.0162]			[0.0298]	
$OSS \times EDU : Polytechnical$		-0.0134			-0.0489	
		[0.0211]			[0.0428]	
$OSS \times EDU : AdvancedVocational$		-0.029			-0.0649	
		[0.0270]			[0.0606]	
$OSS \times EDU : Vocational$		0.0001			-0.0084	
		[0.0148]			[0.0495]	
$OSS \times EDU : UniwithoutDegree$		0.0548			0.1348	
		[0.0353]			[0.1244]	
$OSS \times EDU : Non$		-0.0188			0.0226	
		[0.0280]			[0.0672]	
$OSS \times FirmSize :> 1000$			-0.0211			-0.0365
			[0.0158]			[0.0326]
$OSS \times FirmSize :<= 10$			0.0439			0.0524
			[0.0369]			[0.0730]
$OSS \times FirmSize : FirmSize : 100 - 1000$			0.0051			0.0096
			[0.0161]			[0.0253]
$OSS \times FirmSize : FirmSize : FirmSize : 11 - 100$			-0.0136			-0.0173
			[0.0150]			[0.0288]
Age	0.0436	0.0439	0.0438	0.0451	0.0437	0.0438
	[0.0071]***	[0.0057]***	[0.0064]***	[0.0053]***	[0.0069]***	[0.0060]***
Age^2	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Tenure	0.0111	0.0115	0.0113	0.0115	0.0115	0.0114
	[0.0027]***	[0.0028]***	[0.0029]***	[0.0032]***	[0.0030]***	[0.0030]***
$Tenure^2$	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003	-0.0003
	[0.0001]**	[0.0001]**	[0.0001]**	[0.0001]**	[0.0001]**	[0.0001]**
IT Work Experience	0.0323	0.0323	0.0324	0.0322	0.0323	0.0324
	[0.0027]***	[0.0026]***	[0.0032]***	[0.0033]***	[0.0026]***	[0.0024]***
IT Work Experience^2	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Gender	0.0633	0.0637	0.0631	0.0628	0.0636	0.0633
	[0.0228]***	[0.0224]***	[0.0213]***	[0.0219]***	[0.0284]**	[0.0247]**
EDU: Uni	0.1833	0.1928	0.1832	0.1839	0.1865	0.1836
	[0.0178]***	[0.0155]***	[0.0149]***	[0.0168]***	[0.0141]***	[0.0147]***
EDU: Polytechnical	0.1273	0.1385	0.127	0.1278	0.1326	0.1272
	[0.0183]***	[0.0174]***	[0.0142]***	[0.0160]***	[0.0151]***	[0.0145]***
EDU: Advanced Vocational	0.0368	0.0501	0.0362	0.0367	0.0414	0.0362
	[0.0207]*	[0.0196]**	[0.0175]**	[0.0211]*	[0.0180]**	[0.0158]**
EDU: Vocational	-0.0514	-0.0428	-0.0525	-0.0511	-0.0481	-0.0521
	[0.0173]***	[0.0159]***	[0.0135]***	[0.0175]***	[0.0137]***	[0.0143]***
EDU: Uni No Degree	0.0381	0.051	0.038	0.0382	0.0402	0.0376
	[0.0196]*	[0.0171]***	[0.0160]**	[0.0192]**	[0.0182]**	[0.0206]*
Supervisor	0.0866	0.0867	0.0867	0.0859	0.0867	0.0864
	[0.0072]***	[0.0080]***	[0.0082]***	[0.0073]***	[0.0084]***	[0.0065]***
Urban Area	0.0621	0.0631	0.063	0.0626	0.0633	0.0631
	[0.0082]***	[0.0071]***	[0.0073]***	[0.0072]***	[0.0087]***	[0.0080]***
Firm Size: > 1000	0.2423	0.2418	0.2546	0.2415	0.2415	0.246
	[0.0158]***	[0.0162]***	[0.0172]***	[0.0135]***	[0.0163]***	[0.0155]***
Firm Size: $100 - 1000$	0.1605	0.1603	0.1688	0.16	0.1601	0.163
	[0.0183]***	[0.0147]***	[0.0171]***	[0.0134]***	[0.0161]***	[0.0153]***
Firm Size: $11 - 100$	0.0921	0.0923	0.1044	0.0924	0.0923	0.0962
	[0.0160]***	[0.0155]***	[0.0169]***	[0.0145]***	[0.0156]***	[0.0167]***
Foreign Work Experience	0.0841	0.0841	0.0842	0.0847	0.0839	0.0838
	[0.0080]***	[0.0084]***	[0.0079]***	[0.0080]***	[0.0091]***	[0.0095]***
Year 2007	-0.0272	-0.0277	-0.0273	-0.0276	-0.0274	-0.0274
	[0.0061]***	[0.0063]***	[0.0067]***	[0.0073]***	[0.0063]***	[0.0071]***
Constant	6.5074	6.5034	6.5032	6.4858	6.5118	6.5093
	[0.1224]***	[0.1133]***	[0.1211]***	[0.1014]***	[0.1259]***	[0.1114]***
Observations	7115	7115	7115	7115	7115	7115
adj. R^2	0.56	0.56	0.56	0.56	0.56	0.56
Employment Field Dummies $Chi2$	606.96	601.70	275.89	756.39	739.95	858.38
Federal State Dummies $Chi2$	519.12	982.00	780.45	538.47	533.37	1231.11
Industry Dummies $Chi2$	356.18	177.32	334.42	252.58	270.81	464.80

Remarks: Dependent variable is log W. Bootstrapped standard errors in brackets.*,**,*** indicate significance at 10%, 5%, 1% error probability. Default categories: EDU: No Degree; Firm Size:$1 - 10$

Table 6: Regression for Programmer and Software Developer Subsample

OSS	0.0004 [0.0179]	
$OSS \times EDU: University$		-0.0203 [0.0221]
$OSS \times EDU: Polytechnical$		0.001 [0.0206]
$OSS \times EDU: Advanced\ Vocational$		0.0013 [0.0430]
$OSS \times EDU: Vocational$		-0.0366 [0.0317]
$OSS \times EDU: Uni\ without\ Degree$		-0.0219 [0.0391]
$OSS \times EDU: Non$		0.1492 [0.0591]**
Age	0.063 [0.0135]***	0.0626 [0.0106]***
Age^2	-0.0008 [0.0002]***	-0.0008 [0.0002]***
Tenure	0.0083 [0.0058]	0.0075 [0.0042]*
$Tenure^2$	-0.0002 [0.0002]	-0.0002 [0.0002]
IT Work Experience	0.0285 [0.0047]***	0.0296 [0.0045]***
IT Work Experience^2	-0.0004 [0.0002]**	-0.0004 [0.0002]**
Gender	0.0791 [0.0384]**	0.08 [0.0382]**
EDU: University	0.1744 [0.0367]***	0.2043 [0.0361]***
EDU: Polytechnical	0.1222 [0.0377]***	0.1535 [0.0384]***
EDU: Advanced Vocational	0.0336 [0.0405]	0.0622 [0.0391]
EDU: Vocational	-0.0853 [0.0396]**	-0.0416 [0.0381]
EDU: Uni No Degree	0.0654 [0.0426]	0.102 [0.0389]***
Supervisor	0.1039 [0.0138]***	0.0975 [0.0115]***
Urban Area	0.0729 [0.0121]***	0.0714 [0.0106]***
Firm Size: > 1000	0.2432 [0.0229]***	0.2309 [0.0202]***
Firm Size: $100 - 1000$	0.1613 [0.0229]***	0.1556 [0.0192]***
Firm Size: $11 - 100$	0.082 [0.0194]***	0.0803 [0.0177]***
Foreign Work Experience	0.0574 [0.0121]***	0.0585 [0.0128]***
Year 2007	-0.0334 [0.0104]***	-0.0311 [0.0090]***
Constant	6.2075 [0.2579]***	6.1833 [0.1975]***
Observations	2548	2548
$adj.R^2$	0.52	0.57
Federal State Dummies Chi^2	369.87	333.55
Industry Dummies Chi^2	62.74	72.84

Exogeneity Tests for OSS	
Excluded Instruments:	Knowledge Linux OS, Mac OS
Predictive power ("first stage")	$F(2, 2499) = 51.44$ $p = 0.00$
Kleibergen-Paap Underidentifikation LM Test	$Chi^2 = 98.51$ $p = 0.00$
Hansen J statistic for orthogonality of instruments	$Chi^2 = 0.29$ $p = 0.492$
Durbin-Wu-Hausman Exogeneity Test	$Chi^2 = 0.003$ $p = 0.954$

Remarks: Dependent variable is $\log W$. Bootstrapped standard errors in brackets. *,**,*** indicate significance at 10%, 5%, 1% error probability. Default categories: EDU: No Degree; Firm Size:$1 - 10$

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