Signaling through Open Source: How GitHub Contributions Influence Labor Outcomes

By Gabriel Solis and Seth Dowden*

This paper investigates how contributions to open-source projects on GitHub, influence labor market outcomes. Despite extensive research on the motivations for open-source contributions, there is limited work on how these contributions signal job market readiness and impact wages and productivity. Using GHTorrent and Glassdoor data, we analyze the signaling effect of open-source contributions on expected wages and employee productivity. Our findings reveal that individuals who directly contribute to a firm's open-source projects have significantly higher productivity levels upon employment. However, we find no significant evidence of a wage premium for signalers at both entry and senior levels. These results suggest that open-source contributions are effective productivity signals, but their impact on wage expectations remains unclear.

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Open-source represents a distinctive paradigm shift in the economic mode of production. The essence of this approach is rooted in sharing and collaboration, where source code is made available to the public under licenses that allow for modification, redistribution, and commercial utilization. This mode of production contrasts sharply with the traditional proprietary development process, where the intellectual property is closely guarded, and licenses are restrictive. Historically, strong IP rights were critical to fostering innovation because creators would have little incentive to innovate without exclusive rights to commercialize their inventions (Arrow, 1972). Open-source models, however, suggest an alternative path where innovation is spurred through collective effort and shared knowledge.

While conventional economic models posit that individuals and firms are motivated by self-interest and monetary gains, open-source contributors appear to voluntarily and altruistically contribute code, knowledge, and time without direct monetary compensation Lerner and Tirole (2002). Furthermore, traditional economic theory might predict a tragedy of the commons, in which individuals act in their own interest by actively benefiting from open-source software while choosing to not donate their time. Instead, the open source community actively benefits and functions from the contributions of others, contrasting the paradigms of public goods and the free-rider problem Sharma (2022).

While significant work has been done on individual motivations for contribution to open source software Von Krogh et al. (2012), relatively little attention has been paid to job market signaling as a motivating factor for open source contributions. The interaction of open-source contributions with labor market dynamics reveals unique signaling mechanisms. The public nature of these contributions reduces information asymmetry, enabling firms to gain near-perfect insights into a candidate's abilities. This transparency gives firms precise labor market signals related to open-source projects integral to their business models. Sending direct signals not only influence a targeted firm's hiring decision, but also to all firms that incorporate open-source into their production process.

This paper seeks to contribute to the literature on open-source contributions as a labor market signal by building upon existing theoretical and empirical work. Lee, Moisa and Weiß (2003) identified a signaling equilibrium where open-source contributors command wage premiums and demonstrate higher productivity. Recent empirical research by El-Komboz and Goldbeck (2024) revealed that individuals increase their open-source contributions in the months preceding job changes,

suggesting strategic use of open-source as a signaling tool. Our study aims to fill the remaining empirical gap by directly examining how signaling through open-source contributions impacts job productivity and expected wages. We utilize the GHTorrent dataset combining individual and firm-level GitHub contribution data with wage information from Glassdoor.

I. Background & Motivations

Economics of Open-Source

Our research is an extension to the body of literature that examines the dynamics of open source environments (Lerner and Tirole, 2002). One primary area is in the investigation of open innovation models and their effects on firm performance (Osterloh and Rota 2007; Lerner and Tirole 2005). In these models, open innovation contrasts traditional ones in that intellectual property (IP) rights are no longer exclusive. Instead, open innovation is collaborative where firms seek external input from individuals and competing firms (Hippel and Krogh, 2003).

Although there are comparative analyses between proprietary and open source technology platforms (see, for example, Conti et al. 2023; Economides and Katsamakas 2006; Anand et al. 2018), there has been little research done on the productive capacities of open source firms. Nagle (2019) measures productivity by looking at value-added from a 1% increase in open-source. While Nagle captures the dollar impact of open-source on firm productivity, we measure productivity by examining the number of direct contributions to open-source projects from those recently employed by the firm. This approach focuses on the output and engagement to open-source from individuals across time after being employed.

The second body of literature surrounds focuses on understanding the motivations driving open-source developers to contribute to open source projects. Krishnamurthy (2006) investigates both the intrinsic factors and external rewards that influence volunteer developers in the open-source community. Similarly, Alexander Hars (2002) identifies self-determination, learning, and reputation as the main reasons for contributions. Gerosa et al. (2021) expands on these motivations, highlighting ideology, altruism, fun, kinship, reputation, reciprocity, learning, own-use, career, and financial incentives as additional motivations. Although our study does not delve into individual motivations, these findings are crucial for comprehending why individuals engage in open-source contributions.

Labor Market Signaling

In the labor market, firms face uncertainty in hiring decisions due to asymmetric information and moral hazard. For example, individuals may misrepresent their abilities to secure higher wages, leading firms to seek credible signals of productivity. In the context of software development, open-source contributions on platforms like GitHub serve as a valuable signaling mechanism. Long (2009) and Marlow and Dabbish (2013) study the revealed preferences of hiring managers for open-source experiences. These contributions, alongside traditional signals such as education and work experience, help reduce information asymmetry between employers and job candidates. Indeed, open-source participation allows individuals to publicly demonstrate their technical proficiency and collaboration skills, providing employers with near-perfect information on individuals.

From an economic perspective, engaging in open-source projects represents an investment in human capital by the job seeker, incurring an opportunity cost in terms of time that could otherwise be spent on paid employment or leisure (Spence 1973; Holmstrom 1999). This costly signal differentiates candidates who contribute to open-source projects from those who do not, indicating a lower signaling cost and potentially higher productivity. Consequently, employers incorporate open-source contributions into their hiring criteria, enabling more accurate and efficient evaluation of candidates' suitability. This approach helps firms mitigate the risks associated with adverse selection and potentially reduces the likelihood of sub-optimal job matches in the labor market, leading to higher wages for highly skilled workers.

The Spence (1973) signaling model posits that individuals who have signaled receive higher compensation from firms that value signal, and in turn, firms receive higher productivity in the present competitive market. In open source where firms directly benefit from the contributions of signalers, Lee, Moisa and Weiß (2003) and Holmstrom (1999) found that an increase in the reputation of ability may initially have nonlinear returns to investments in signals. Based on the literature, we test the following two hypotheses:

> **Hypothesis 1**: *(Productivity) Employees who signaled have higher levels of contributions after employment compared to those who have not signaled*

Hypothesis 2: *(Income) Signaling through contributions increase expected wages*

II. Data

To study how signaling between contributors and firms affects labor market outcomes, we must examine the collaboration platforms used by open-source communities. Git and GitHub have become central to this ecosystem, redefining how collaborative projects are managed. The nature of working in public presents a unique opportunity for researchers to examine the signaling interactions and outcomes for both firms and individuals. GitHub's project count grew from 46,000 in 2008 to over 420 million by 2023[1]. This considerable growth has positioned GitHub as a leading repository for open-source development and an essential source for this study. However, it is important to acknowledge that it represents only a part of the broader open-source ecosystem.

We use two primary data sources to investigate the impact of open-source contributions on labor outcomes. The first is the GhTorrent dataset by Gousios (2013), which provides structured metadata on all contributions to GitHub between 2008 and 2021. This dataset includes detailed information on users, organizations, and projects, allowing for the analysis of complex interactions and relationships between contributors and firms. Due to the dataset's sheer size, computational limitations, and time constraints, we restrict our analysis to interactions with a stratified random sample of 100 firms by organization size.

The second source is Glassdoor, a leading job search platform, from which we extract 2024 wage data for entry and senior-level software engineer positions four our sampled firms. Figure 1 shows the distribution of wages for our sample between entry and senior-level software engineering positions. Additionally, we collect data on the characteristics of our sampled firms. Wage data and firm characteristics are merged back into the GhTorrent dataset, generating a panel dataset from 2008 to 2021 of all contributions made to the 100 firms with the complete contribution history of each contributor.

Using relational data in the dataset, we classify each contribution into three categories of signaling behavior. The first category is "personal contributions,"

[1] https://github.blog/2023-11-08-the-state-of-open-source-and-ai

which captures contributions made to one's own projects, including personal, educational, and showcase projects. The second category is "collaborative contributions," which captures an individual's contributions to collaborative open-source, community, and work projects. The third category is "direct contributions," which are contributions made to one of the 100 firms. Additionally, outcome characteristics for individual members of the firms are observed and classified into two categories: signalers and non-signalers. These three contribution categories generate a mutually exclusive partition of the dataset.

Table 1 provides an overview of our sample, comparing the three contribution categories as well as the characteristics of firms and individuals. In general, most contributions are collaborative with a mean of 524 total commits. Direct contributions are the smallest of the three types averaging 77 total commits per user. Our sampled organizations are evenly split between private and public with an average of 1281 members per organization. Table 2 summarizes entry and senior wage information between signalers and non-signalers. Overall, signalers have lower wages compared to non-signalers.

III. Methodology

Hypothesis 1 (Productivity)

To evaluate differences in productivity between signalers and non-signalers, we limit the dataset to all contributions made by employees of the 100 firms sampled. We employ a panel regression on $\text{Productivity}_{ijt}$, which captures the total number of contributions by employee i from firm j at time t since employment. The variable of interest is the dummy variable Direct Signaler_j, which indicates whether an employee made a direct contribution to the firm prior to employment.

$$\text{Model 2:} \quad Productivity_{ijt} = \beta_0 + \beta_1 \,\text{Direct Signaler}_j + \beta_2 \,\text{Personal}_{it} + \beta_3 \,\text{Collaborative}_{it} + \beta_4 \,\text{Members}_{jt} + \beta_5 \,\text{Followers}_{it} + \beta_6 \,\text{IsPublic}_j + \epsilon_{ijt}$$

We include the following variables: $Personal_{it}$ which captures contributions from individual i to personal projects at time t and $Collaborative_{it}$ which measures the number of contributions to a firm from individual i not directly signaled

to at time t. These covaraiates help to capture the effects of other types of contributions on the internal productivity of a firm. Lastly, we account for fixed effects with three independent variables: $Members_{it}$ which includes the total members at a firm in time t; $Followers_{it}$ which measures the number of followers each user has at time t; and $IsPublic_j$ which is a dummy for whether the firm is public.

Hypothesis 2 (Wages)

To investigate the influence of job market signaling through open-source contributions on individual expected earnings, we focus on hiring outcomes within firms. Our study targets candidates who have directly engaged with the firm's open-source projects. We explore not only direct contributions but also indirect signals such as Personal and Collaborative contributions. Our analysis considers one observation per employee, including variables such as the number of Direct, Collaborative, and Personal contributions. Additionally, we include the number of followers each candidate had at the time of hiring to account for their social capital. Firm characteristics like size and public or private status are also controlled for in our study. To address potential nonlinear effects of signaling, as suggested by Holmstrom (1999), we include a quadratic term for direct contributions to capture potential increasing initial returns to scale for signaling.

$$\begin{aligned}\text{Model 1:}\quad \text{Wage}_{ij} = \alpha_{ij} &+ \beta_1 \,\text{Direct}_{ij} + \beta_2 \,\text{Direct}_{ij}^2 + \beta_3 \,\text{Personal}_i \\ &+ \beta_4 \,\text{Collaborative}_i + \beta_5 \,\text{Members}_j + \beta_6 \,\text{Followers}_i + \epsilon_{ij}\end{aligned}$$

This equation reflects how wages (Wage_{ij}) by a combination of signals Direct_{ij} and Direct_{ij}^2, capture the effects of directly signaling to an employer on wage outcomes, while Personal_i and Collaborative_i show how personal projects and involvements collaborative open source project affect wages respectively. Members_j and Followers_i control for firm size and the social capital of individuals, measured by followers. Robust standard errors are clustered at the firm level to account for potential correlation within firms.

IV. Results

This section first presents the results for Hypothesis 1, comparing productivity levels between employees who have signaled and those who have not. We then conclude with Hypothesis 2, examining the influence of open-source signaling on expected wages. For both hypotheses, we discuss the limitations of our approach.

Hypothesis 1 (Productivity)

Table 3 illustrates that, on average, signalers contribute 21.36 times in the first month of employment, considerably higher than the 8.37 contributions made by non-signalers. This elevated productivity is sustained over 3, 6, and 12 months post their employment. Although average weekly productivity for signalers is statistically higher compared to non-signalers, as we approach 50 weeks, the average weekly productivity becomes statistically insignificant (see Figure 2). The convergence of average productivity among signalers and non-signalers can be explained by improved efficiency from new hires (e.g., job training programs or adjusting to workplace culture). This analysis reveals a strong positive relationship between open-source contributions as a signal of employee productivity.

Table 4 displays the results of our panel regression. The naive specifications without firm fixed effects, Model (1) and (2), shows a negative relationship between the impact of signaling and productivity. However, after adjusting for firm size and organizational structure, the coefficient of interest becomes positive, increasing to approximately 438 contributions over an employee's tenure. In fact, we find that publicly traded firms experience significantly lower productivity, with 2050 fewer contributions than their private counterparts. Additionally, we find increasing economies of scale, where marginally increasing the number of members in a firm correlates with a 0.81 unit increase in the firm's productivity.

Moreover, we find a positive and statistically significant correlation between employees' ongoing contributions to personal and collaborative open-source projects and their productivity at work. Specifically, each personal contribution correlates with a 0.59 unit increase in workplace contributions. In contrast, collaborative projects correlate with a smaller effect, yet significant, of 0.019 unit increase at a one percent significance level. These findings suggest that an employee's engagement in outside open-source projects can enhance their internal productivity for a firm, possibly due to the continuous development of skills and knowledge.

Discussion and Limitations

These results confirm and expand upon existing literature on signaling theory within labor markets. The pronounced initial productivity of signalers corroborates Spence 1973 model by demonstrating that open-source contributions are effective signals of capability. This observation is consistent with Long (2009) and Marlow and Dabbish (2013), who noted a preference among hiring managers for candidates with open-source experience. While the initial productivity difference between signalers and non-signalers suggests that employers may leverage these signals to identify high-productivity employees and reduce adverse selection, the eventual convergence in productivity levels highlights the potential for non-signalers to attain similar skills through on-the-job learning.

A further limitation of the data which may be a source of error is that we do not observe the date an individual leaves the firm. When we extend Figure 2 to more than 2-years, the trend becomes noisy. We deal with this by limiting our observations to 1-year, assuming that turnover during this period is relatively low. This assumption limits the scope of the number of years post an individual's employment to a firm. Nevertheless, we argue this assumption is practical since we might assume a lower turnover during the first year one is hired compared to periods post their first year of employment.

Hypothesis 2 (Wages)

Figure 1 presents the entry and senior salaries from the 100 sample firms, with the mean observed salaries of $\$127,767$ and $\$194,010$, respectively. The senior salary is observed to have a significantly higher standard deviation compared to the entry-level salaries. Table 2 compares the average wages of the signaling group with those of the non-signaling group for both entry and senior positions. The standard deviations for all groups are significantly higher than the differences between the signaling and non-signaling groups. We find no significant differences in income between signalers and non-signalers at both entry and senior levels.

Due to the heterogeneous motivations of individual contributors, the Direct_{ij} capture both the contributions of individuals who are making targeted contributions to signal to a specific firm but also employees of other firms who incorporate open-source into their production process, and employees of $Firm_j$ who are not a member of firms GitHub organization. To account for this and exclude the latter

group, we run a series of restricted regressions limiting the sample to those in the 25th, 50th, 75th, and 90th percentiles of direct contributions for both the entry and senior wages see Table 5 and Table 6 .

Tables 7 and 8 show the final specifications for the effect of open-source signaling on entry and senior wages, restricted to observations under the 50th percentile. Personal contributions are not statistically significant or consistent in direction across all specifications, likely due to the significant heterogeneity in the type and quality of personal and own contributions. While collaborative contributions are associated with a $0.49 increase in senior wages and are statistically significant at the 10 percent level, the magnitude of this effect is negligible. The negative coefficient of direct signals, with a positive quadratic term, implies that initial contributions to a firm are negative, but as you continue to contribute, the quadratic term dominates the negative level coefficient. In the final specification, for both entry (see Table 7 equation 4 and senior salaries Table 8, equation 4), individuals begin to observe positive returns to their direct signals after the third and fourth contributions, respectively.

Discussion and Limitations

These results align with the literature from Spence (1973) where individuals who signal more are offered a wage premium as the decrease in information asymmetry allows the firm to be reasonably confident in assessing their suitability for the role. Additionally, the positive quadratic term provides limited empirical evidence for Holmstrom (1999) concerning positive returns to scale for signaling.

Despite statistical significance and an alignment with the literature, we are hesitant to draw conclusions from the results. The model suffers from issues since wage data is aggregated at the firm level rather than at the individual level, preventing us from observing how individual firms react differently to signals. Additionally, due to the limited number of firms and aggregated data, exceptionally large firms such as Microsoft, with 5,394 employees, represent 46% of the observed 11,635 observations. Figure 4 presents a scatter plot of each individual's entry and senior salary at the firm where they are employed and the number of signals they made prior to employment. The data is very noisy and results in less confidence in the findings; Future work should aim to identify more accurate individual-level salary outcomes for employees, to more accurately estimate the true effects of signaling on labor market outcomes.

V. Conclusion

This study investigates the influence of open-source contributions on labor market outcomes, focusing on productivity and wage effects. Our analysis reveals that individuals who contribute directly to a firm's open-source projects exhibit an increase of 437 contributions over signalers' tenure compared to non-signalers. These results are consistent with Spence (1973) signaling theory and suggest that open-source contributions serve as credible signals of a candidate's capabilities, thus reducing information asymmetry for employers.

Our results also suggest the presence of a wage premium for these contributors. However, we are hesitant to draw definitive conclusions regarding the wage premium due to data limitations, such as aggregated wage data at the firm level and the substantial representation of large firms. These constraints prevent us from accurately observing individual-level wage outcomes and how different firms might respond to signaling.

While open-source contributions appear to be valuable productivity signals, their precise impact on wage expectations remains ambiguous. These findings indicate that while open-source participation enhances perceived employee productivity and potentially influences wages, more precise data is necessary to confirm these effects. Future research should aim to overcome these limitations to provide a clearer assessment of the signaling value of open-source contributions in the labor market.

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Appendix

Tables

Table 1—Summary Statistics for Filtered Commits

	Mean	Std Dev	Min	Max
Individual Characteristics:				
Direct Signaler	0.603	0.489	0	1
Direct Contribution	77.56	340.79	0	18,320
Personal Contribution	316.09	818.52	0	43,004
Collaborative Contribution	524.55	2,998.75	0	252,118
Followers	123.49	856.33	0	53,467
Organization Characteristics:				
Members	1,281.79	1,682.02	1	6,424
Entry Salary	148.54	38.40	57	207
Private Firm	0.503	0.50	0	1
Public Firm	0.487	0.50	0	1
Observations:				11,635

Table presents summary statistics on individual and organizational characteristics of members of firms at the point at which they joined the firm.

Table 2—Summary Statistics of Wages on Direct Signaling

	Mean	Median	SD	Min	Max
Signaler					
entry	147.7706	164	37.61892	57	207
senior	250.4936	298	88.06489	80	385
Non-Signaler					
entry	153.3277	164	33.92234	57	207
senior	260.8835	298	79.92052	80	385
Total					
entry	148.0629	164	37.45414	57	207
senior	251.0401	298	87.68606	80	385
Observations					100

Note: Entry and senior salaries are denoted in thousands of dollars.

Table 3—Average Productivity by Group

	Mean	Median	SD	Min	Max
Non-Signaler					
1 Month	8.37	3	15.00	1	204
3 Month	16.02	5	37.28	1	523
6 Month	25.26	6	65.21	1	970
12 Month	41.98	8	123.00	1	2,508
Signaler					
1 Month	21.36	8	37.80	1	501
3 Month	45.19	13	86.18	1	1,498
6 Month	71.62	20	143.21	1	2,954
12 Month	107.36	26	238.75	1	5,671
Total					
1 Month	19.51	7	35.80	1	501
3 Month	39.19	11	79.52	1	1,498
6 Month	59.70	14	129.38	1	2,954
12 Month	87.65	17	212.79	1	5,671
Observations					11,635

Table 4—Regression Results: Signaling and Contributions

	(1)	(2)	(3)
Signaler	-308.860***	-313.748***	437.624***
	(11.726)	(12.053)	(12.573)
Collaborative	0.020***	0.020***	0.019***
	(0.000)	(0.000)	(0.000)
Personal	0.608***	0.607***	0.590***
	(0.001)	(0.001)	(0.001)
Followers		0.069***	0.027***
		(0.004)	(0.004)
Members			0.818***
			(0.002)
Public Firm			-2050.649***
			(14.577)
Constant	487.115***	480.196***	-208.394***
	(9.130)	(9.497)	(12.907)
Observations	2,351,030	2,245,467	2,245,467
Adjusted R^2	0.371	0.371	0.434

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Data is limited to all contributions in the first year of employment. Panel regression includes time, individual, and organization fixed effects, with robust standard errors clusters at the firm level.

Table 5—Signaling on Senior Wage by Percentiles of cumulative Direct Contributions

	(25%)	(50%)	(75%)	(90%)	(Full)
Own	-2.50	-1.68	-3.05**	-2.86**	-3.19**
	(1.37)	(1.31)	(1.03)	(1.02)	(1.01)
Collaborative	0.70**	0.49*	0.59**	0.49*	0.53*
	(0.24)	(0.24)	(0.20)	(0.24)	(0.24)
Direct	-9203.28**	-2485.54***	-604.75***	-185.15***	-18.13***
	(3240.18)	(569.34)	(130.11)	(44.74)	(3.60)
Direct × Direct	1707.11	107.18**	5.88**	0.76***	0.00**
	(954.27)	(32.84)	(1.85)	(0.21)	(0.00)
Followers	9.57***	5.35**	5.85**	6.24***	6.26***
	(1.91)	(1.77)	(1.82)	(1.88)	(1.86)
Members	21.68***	21.65***	22.06***	21.90***	21.97***
	(0.50)	(0.45)	(0.41)	(0.40)	(0.38)
Constant	232138.06***	231457.96***	229543.21***	228125.94***	226584.60***
	(1626.61)	(1479.12)	(1331.67)	(1238.18)	(1103.51)
Observations	5497	7061	8596	9478	10071
Adjusted R^2	0.202	0.190	0.184	0.173	0.171

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Specification regression with Direct Contributions restricted by quantile %25: 5; %50: 23; %75: 96; %90: 305; Full: 18,320

TABLE 6—SIGNALING ON ENTRY WAGE BY PERCENTILES OF CUMULATIVE DIRECT CONTRIBUTIONS

	(25%)	(50%)	(75%)	(90%)	(Full)
Own	-0.33	0.01	-0.95	-0.89	-1.04*
	(0.67)	(0.65)	(0.56)	(0.55)	(0.53)
Collaborative	0.19	0.09	0.18	0.13	0.14
	(0.13)	(0.14)	(0.11)	(0.12)	(0.12)
Direct	-4604.59**	-1231.87***	-314.30***	-81.48***	-10.97***
	(1573.91)	(267.98)	(60.70)	(20.04)	(1.67)
Direct × Direct	830.31	53.66***	3.15***	0.31***	0.00***
	(466.76)	(15.34)	(0.86)	(0.09)	(0.00)
Followers	4.52***	2.57**	2.88**	3.06***	3.11***
	(0.95)	(0.87)	(0.90)	(0.93)	(0.93)
Members	7.44***	7.50***	7.76***	7.76***	7.85***
	(0.23)	(0.20)	(0.19)	(0.18)	(0.17)
Constant	143988.71***	143515.10***	142587.88***	141704.45***	140887.81***
	(771.81)	(704.77)	(643.10)	(598.44)	(534.12)
Observations	5497	7061	8596	9478	10071
Adjusted R^2	0.126	0.118	0.118	0.111	0.115

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Specification regression with Direct Contributions restricted by quantile %25: 5; %50: 23; %75: 96; %90: 305; Full: 18,320

Table 7—Regression Results: Effect of Signaling on Entry Wages

	(1)	(2)	(3)	(4)
Own	1.15	1.15	0.50	0.01
	(0.75)	(0.74)	(0.71)	(0.65)
Collaborative	-0.01	-0.01	0.04	0.09
	(0.19)	(0.19)	(0.16)	(0.14)
Direct	-513.30***	-2144.48***	-2303.47***	-1231.87***
	(77.37)	(240.90)	(265.73)	(267.98)
Direct^2.		95.01***	102.15***	53.66***
		(13.25)	(14.55)	(15.34)
Followers			2.15***	2.57**
			(0.61)	(0.87)
Members				7.50***
				(0.20)
Constant	152716.21***	154044.44***	154658.45***	143515.10***
	(489.55)	(512.27)	(559.94)	(704.77)
Observations	8152	8152	7118	7061
Adjusted R^2	0.006	0.013	0.016	0.118

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regression is restricted to direct contributions below the median level. Standard errors are clustered at the firm level. Data represent individual and organization characteristics at the time of employment for all observations.

TABLE 8—REGRESSION RESULTS: EFFECT OF SIGNALING ON SENIOR WAGES

	(1)	(2)	(3)	(4)
Own	1.032	1.029	-0.237	-1.683
	(1.574)	(1.567)	(1.516)	(1.309)
Collaborative	0.273	0.265	0.358	0.492*
	(0.370)	(0.368)	(0.313)	(0.242)
Direct	-1274.538***	-5122.728***	-5525.528***	-2485.536***
	(172.918)	(530.664)	(581.770)	(569.344)
Direct × Direct		224.155***	242.875***	107.185**
		(29.417)	(32.089)	(32.836)
Followers			4.130***	5.348**
			(1.090)	(1.773)
Members				21.651***
				(0.447)
Constant	259135.978***	262269.481***	263603.807***	231457.957***
	(1098.184)	(1157.605)	(1259.443)	(1479.124)
Observations	8152	8152	7118	7061
Adjusted R^2	0.007	0.014	0.017	0.190

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: OLS regression is restricted to direct contributions below the median level. Standard errors are clustered at the firm level. Data represent individual and organization characteristics at the time of employment for all observations.



Figure 1. Sample Wage Distribution

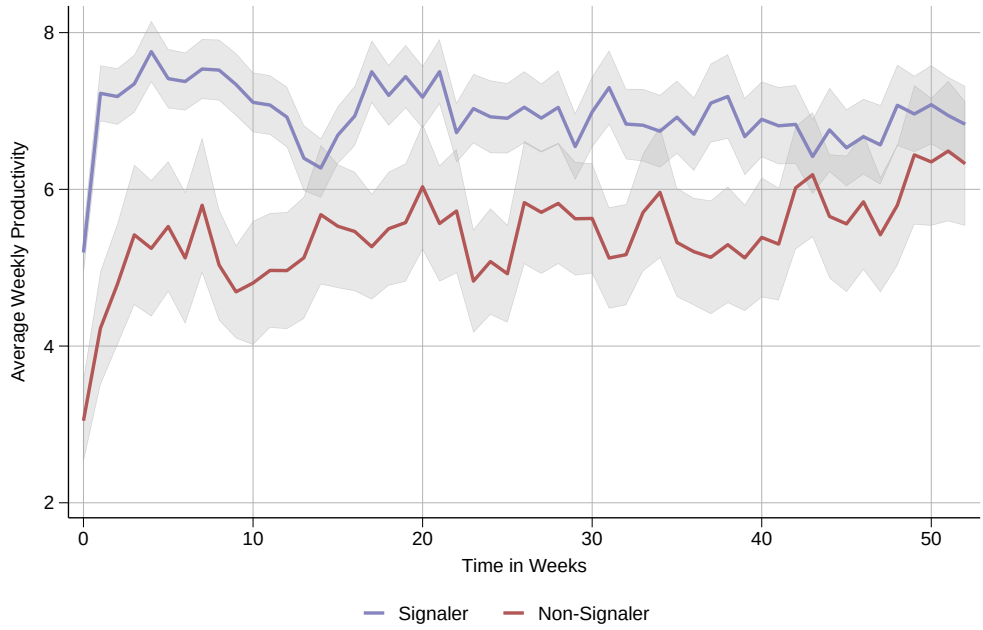


Figure 2. Average Weekly Contributions by Group

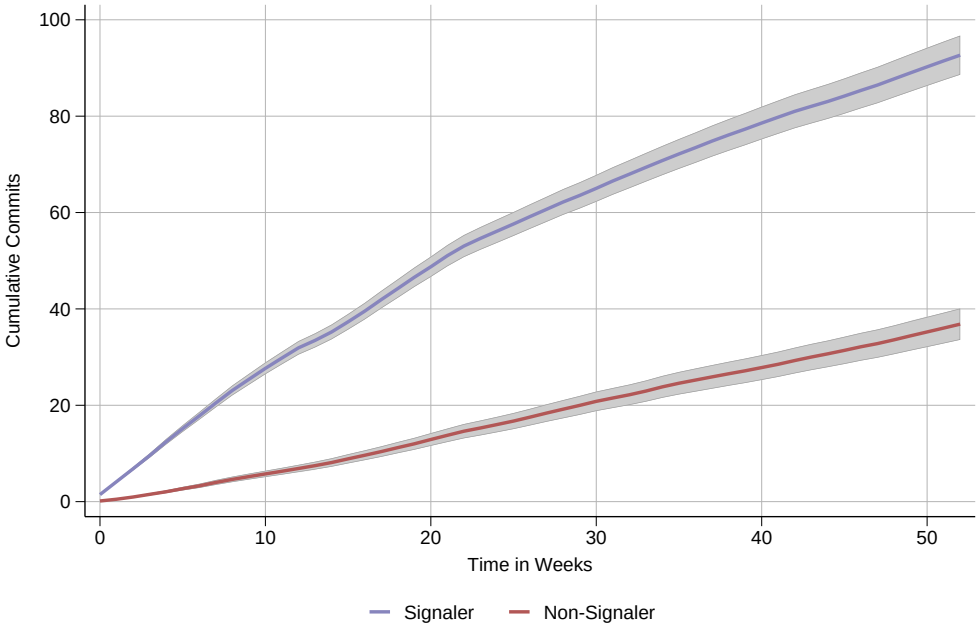


FIGURE 3. AVERAGE CUMULATIVE CONTRIBUTIONS BY GROUP

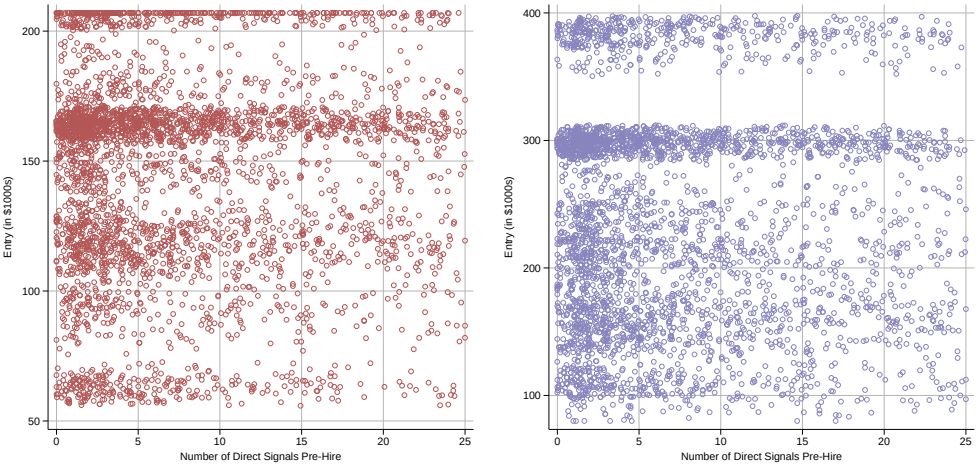


FIGURE 4. WAGE BY DIRECT SIGNALS