JOB SATISFACTION MODELLING IN AGENT-BASED SIMULATIONS

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ABSTRACT
Theoretical labour market models that incorporate social networks have largely focused on the steady-state of the system, ignoring their short- and medium-term dynamic effects. In many agent-based models of job search, the unemployed were either static, taking any vacancy proposed to them, or chose among vacancies based on either proposed wage or whether there were any of their friends employed in the firm. Thus, job satisfaction, an important multi-faceted concept in the labour market literature, has been overlooked. We propose a way to measure job satisfaction and illustrate how it can be incorporated in an agent-based model of the labour market. We use a simulation to study the dynamics of this model.

Keywords: job satisfaction, agent based modelling, labour market, social network

1. INTRODUCTION

Empirical studies show that social networks are important in the labour market. Bewley (1999) reports that 96 out of 161 (or 60 per cent) US businesses interviewed use personal contact networks to find job candidates, where in most cases, this meant employee referrals. Based on a survey of 6066 employers in Latvia, Hazans (2011) found that networking is the most popular recruitment method used by enterprises (depending on language used in enterprises, 30% to 50% of them hire by referral), but the intensity of systematic use of social networks decreases with firm size. Latvia is not an exception—indeed, Kuddo (2009) notes that in all Eastern European countries, a usual way of finding and hiring for vacancies is through informal channels (relatives, friends, acquaintances), especially in the small and medium enterprise sector. Employees also use their social networks in the process of job search. Montgomery (1991) cites several studies reporting that around 50 per cent of employees in the US found their jobs through friends and relatives. In Estonia, using Estonian Labour Force Survey data, we find that every year during 2001-2009, 30 per cent of respondents reported asking relatives and friends as their most important step taken to find a job (30% mentioned watching job ads, 15%—directly contacting employers, and 15% found it most helpful to seek through the state employment office).

Granovetter (2005) mentions two reasons why social networks are so much used in the hiring process. Firstly, they help mitigate the problem of bilateral asymmetric information, when both prospective employers and employees do not know the other side's quality. In these settings, they search for more information about one another from personal sources they can trust. Secondly, the cost of searching for a new employee in existing social networks, which are maintained mainly for non-economic reasons, is far lower than using the formal channels. One could argue that existing employees may inflate the real qualifications of the friend they recommend, but this would contradict their long-term interest in the company. Therefore, using referral hiring is a theoretically clean way of reducing costs.

At this point, we would like to stress that we do not touch upon normative theories of human resource management concerning whether appointing one's friend to a position inside the company is a right way of doing management. Rather, we adhere to the literature on labour economics and observe what actually happens in real-world labour markets.

Realizing the importance of social networking for labour markets, researchers started investigating the interplay between social networks and the economic situation of workers and firms. Several theoretical results (see, e.g., Bramoullé and Saint-Paul 2010, Calvó-Armengol and Jackson 2007, Krauth 2004) have been obtained for the steady-state of Markov processes describing employment and social network dynamics. To analyse dynamic non-equilibrium short- and medium-term effects, agent-based models were built. However, there still are restrictive assumptions under many of them.

In some models, the unemployed were static—they were simply taking any vacancy the labour market proposed them. Abdou and Gilbert (2009) focus on the level of homophily driving the probability of both changing the social network and changing the employment status in a particular firm. They assume, however, that only social networking and homophily are the main determinants of labour status. Gemkow and Neugart (2011) use the experience-weighted attraction algorithm to guide agents in their network formation decisions. Nevertheless, by assuming that workers apply to all available vacancies, they do not model choice between them. The probability of being employed in their model depends only on whether an applicant has friends in the firm hosting the vacancy. Tassier and Menczer (2008) assume that agents learn about open vacancies after a formal search and based on information from their friends. Nevertheless, all vacancies are identical.

Other models introduced heterogeneous vacancies. For instance, Tassier and Menczer (2001) present an evolutionary model where vacancies differ by the associated wage rate, and the person chooses the vacancy with the highest proposed wage. However, the social network plays only a role of informing its member on the vacancies available.

In reality, individuals' decisions on which vacancy to choose or whether to leave the current job depend on a combination of monetary and social rewards, rather than on each of these in isolation. In particular, it is quite well-known that job satisfaction (JS) is an important predictor of the decision to quit (Acker 2004, Manger and Eikeland 1990, Parry 2008). Carless and Arnup (2011) found that JS increases statistically significantly after a job change, which means that workers take into account expected job satisfaction when choosing among several job proposals.

Kalleberg (1977, p. 126) defines JS as "an overall affective orientation on the part of individuals toward work roles which they are presently occupying" and views it as the result of an interplay between the values workers attach to job characteristics and the extent to which these values are satisfied. He proposes six dimensions of values: intrinsic (associated with the task itself), convenience, financial, relationships with co-workers (satisfaction of social needs), career, and resource adequacy. While he did not find that relationships with co-workers significantly affect JS, this does not mean that co-workers are irrelevant to it. Indeed, in his definition of resources he extensively mentions help, authority, information, supervision, and competency of co-workers, and these resources are found to significantly influence JS. Harris, Winskowski, and Engdahl (2007) arrive at a similar conclusion with a more recent dataset. Empirically, the level of social support from co-workers was found to be significant in many occupations (Alexander, Lichtenstein, Oh, and Ullman 1998; Brough and Frame 2004; Cortese, Colombo, and Ghislieri 2010; Ducharme and Martin 2000; Roxburgh 1999). This importance of the social support resource may come from it being a buffer against high job demands to prevent job strain and because it affects motivation and productivity, according to the Job Demands-Resources model (Bakker and Demerouti 2007).

This paper proposes a way to incorporate JS in an agent-based model of labour market, explicitly making several factors affect individuals' decision-making. The paper is structured as follows. Section 2 introduces our method of modelling JS. In Section 3, we put our JS model in the context of an artificial labour market. Section 4 provides the description of simulation setup that implements the labour market model and the analysis of its dynamics. The last section concludes.

2. MODELLING JOB SATISFACTION

To formally model job satisfaction (JS), we propose to separate it into two components: expected JS and current JS. The difference between the two is that the former can be measured for any job, as it depends only on the current situation in the firm hosting the job. The latter depends on the former but, in addition, incorporates a stochastic component tracking the experience of the person on the job.

In this paper, we assume that expected JS, s_j^e, is a function of the ratio of the wage of agent i to his reservation wage, w_{ij}/w_i^r, and the ratio of the number of friends he has in the firm hosting the job (also referred to as "the number of local friends") to the maximum number of friends he can have, $n_i^f/\overline{n_i}$. In other words, a person expects a certain level of monetary compensation and social support on the job. (Note that with the number of local friends we approximate a broad notion of social support rather than dividing it into support from management and from colleagues. More sophisticated frameworks should account for these two facets separately.) This is quite realistic, as normally, this is the only information individuals have before actually starting working in the firm. We also assume the following properties of expected JS:

- Its partial derivatives with respect to both parameters are decreasing functions of the absolute values of the respective parameters. Thus, any next friend working in the same firm would add less to job satisfaction. The same would go for any next dollar of wage change;
- Its range is bounded: $s_j^e \in [\underline{s}, \overline{s}]$. Firstly, the level of satisfaction cannot be arbitrarily large or arbitrarily low. Secondly, this requirement is consistent with empirical data from surveys, where satisfaction is normally measured on a Likert scale, which would help in validating the model;
- The same level of job satisfaction can be gained by different combinations of the relative wage and the number of friends.

On the contrary, when the person starts working, many other parameters start influencing his current JS—working conditions, job demands, role clarity, and other facets. As already noted above, we assume that these factors are pure noise captured by a random disturbance $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. The change in current JS in period t, therefore, is the sum of this random disturbance and the change in expected JS (due to changes in wage and the number of local friends):

$$s_{ijt}^c - s_{ij,t-1}^c = \left(s_{ijt}^e - s_{ij,t-1}^e\right) + \varepsilon_t \qquad (1)$$

Note that both s_{ijt}^c and s_{ijt}^e should remain in $[\underline{s}, \overline{s}]$.

3. SIMULATION CONTEXT

To illustrate how the proposed job satisfaction model could be used in a real simulation, we incorporate it in the following artificial labour market.

3.1. General Characteristics

The timing is discrete, one period representing one month, and 12 months constituting a year. Throughout the paper, we will use subscript t to refer to the monthly periods and τ to the yearly ones. Most actions in the labour market, such as changes in job satisfaction and in the workforce of a firm, are made on a monthly basis. Changes in the population and in wages are made once a year.

There are two types of agents in the economy: persons and firms. Initially, the economy is populated with N_0 persons. Each year $\tau \geq 1$, N_τ new persons are added to the population, with the number of new entrants growing at a fixed rate of g, $N_\tau = gN_{\tau-1}$. This can be regarded as an inflow of new secondary school graduates in the labour market. Persons are born with zero age and zero experience (including those in the initial population) and start seeking a job. They retire at the age of $\overline{a}$ years, at which moment they are removed from the simulation. Firms, on the contrary, are assumed to live forever, the number of firms being fixed at M.

3.2. Job Search

There is a unique vacancy list in the economy that is available to everyone for free. To find new labour, firms post vacancies on the vacancy list. Persons use the list to find new jobs.

A vacancy is a three-tuple (f, x, w), where

- f is the firm hosting the vacancy;
- $x \in \mathbb{Z}, 0 \leq x \leq \overline{x}$ is the required working experience measured in years, $\overline{x}$ being the sufficient experience, which is common for all vacancies;
- $w \in \mathbb{Z}, w \geq w_m$ is the proposed wage rate at the required experience x, w_m being the minimum wage, which is the same for the whole economy.

The proposed wage rate at experience $x_i \leq \overline{x}$ is

$$w_i = w + q(x_i - x), \tag{2}$$

where q is a constant equal for all vacancies. The proposed wage rate at experience $x_i > \overline{x}$ is given by the same equation with x_i taken equal to $\overline{x}$.

A person in search for a job browses through the vacancy list and creates a sub-list of vacancies that require a working experience not higher than his experience and, for his experience (q is known by everyone), propose a wage rate not lower than his reservation wage. He then sends applications to k vacancies from the sub-list with the highest expected job satisfaction, where k is constant for all persons.

A firm screens the applicant list for each of its vacancies and, if it finds its employees' friends, it randomly chooses among them; in the other case, it chooses randomly from all applicants. Successful candidates receive acknowledgements. If a person receives acknowledgements for several applications, he chooses the one with the highest expected job satisfaction. He then sends an acknowledgement in reply to the chosen vacancy and starts working immediately.

If the vacancy failed to attract a new employee, the hosting firm re-posts this vacancy in the next period, raising the proposed wage rate w by the factor of h, which is the same for all firms. Required experience does not change, because the firm needs qualified personnel for its vacancies. Instead, the firm realises that the reason of the failure of the vacancy is a lack of motivation, that is, expected job satisfaction, which the firm can improve only by raising the proposed wage rate. If the re-posted vacancy also fails, it is completely removed from the vacancy list.

For a working person, reservation wage is his current wage. For a person with no working experience, it is given by the minimum wage. For an unemployed, it is a decreasing function of his last wage and the length (in months) of the current unemployment period t_i^u,

$$w_i^r = \varphi^{t_i^u - 1} w_i,\ w_i^r \geq w_m \tag{3}$$

The parameter $\varphi, 0 < \varphi < 1$ is the same for all persons. Thus, the longer a person is unemployed, the lower wage rate he is ready to accept. Reservation wage, however, cannot fall below the minimum wage.

We also model on-the-job search. If current JS falls below the minimal level, which is the same for everyone, the person starts seeking job as if he was unemployed. However, in this case, he only considers the appropriate vacancies with expected JS not lower than his current JS. If he is selected to fill a vacancy, he quits his current job and then starts working on the new position (it could be hosted by the same firm where he worked before).

3.3. Firm Inside Dynamics

All firms start with no workforce. In the first month, each firm publishes N_0/M vacancies. Thus, at the beginning, all firms try to be of equal size.

Each month, firms randomly change the size of their workforce by δ_{ft} persons, which is distributed uniformly in $[-\underline{\delta}, \overline{\delta}]$. If $\delta_{ft} < 0$, the firm contracts its workforce by randomly firing $|\delta_{ft}|$ employees. If the change is positive, it publishes δ_{ft} vacancies.

Each vacancy for a new position is created with the required experience x uniformly chosen from $[0, \overline{x}]$. Given that value of x, the corresponding proposed wage w is set to the average wage currently received by the firm's employees having experience x. If no such persons are currently employed, the firm considers wages earned by the relevant employees who were working in the firm in the nearest month during the last year. If no such persons worked in the firm during the last year, it makes an interpolation from the point $(0, w_m)$ using Eq. (2).

A firm can also publish a vacancy that would substitute employee i who just quit the firm, either because of reaching the retirement age or due to a low job satisfaction (fired workers are not substituted). In this case, the vacancy is published with the required experience being two years smaller than that employee's experience, checking that the resulting experience is inside $[0, \overline{x}]$. The proposed wage corresponding to the required experience is then set so that an applicant with experience equal to that employee's experience had the same proposed wage as that employee, correcting it if it falls below the minimum wage. This is summarized by the following equations:

$$x = x_i - 2,\ 0 \le x \le \overline{x} \quad (4)$$

$$w = w_i - q(x_i - x),\ w \ge w_m \quad (5)$$

At the start of each year $\tau \ge 1$, each firm posts $\theta_{ft} N_\tau$ vacancies characterised by the tuple $(f, 0, w_m)$, where θ_{ft} is the firm's current labour market share. Thus, firms try to hire a share of fresh graduates that is consistent with their current labour market share, providing these graduates with vacancies with the lowest experience requirements, but also proposing them the minimum wage. While we do not explicitly model production and selling, by placing a cap on the share of graduates that can be hired, we are preventing the situation when a small firm hires an arbitrarily large number of new workers, for which it may not have enough resources.

For a firm's employee, wage can change only once a year—thus, we model stickiness of wages. Wages change as in the trinomial option pricing model, i.e., by a factor taken from $\{w_u, 1, w_d\}$, where $w_u > 1$ and $w_d < 1$ with the corresponding probabilities $\{p_w^u, p_w^n, p_w^d\}, p_w^u + p_w^n + p_w^d = 1$; all these parameters are fixed for all firms. In the beginning of the year, firms choose one of these factors and throughout the year, they change wages of all workers with expiring yearly contracts by this factor.

3.4. Social Network Dynamics

According to Granovetter (2005, p. 34), "people have cognitive, emotional, spatial and temporal limits on how many social ties they can sustain." Thus, maintaining a particular number of friends has an inherent cost for a person. We do not model such costs explicitly. Rather, we assume that each person has a maximal number of friends, $\overline{n_i}$, which depends on the importance of friends in his life, $\lambda_i \in [0,1]$, which, in turn, is generated by $logN(\mu_\lambda, \sigma_\lambda^2)$. Lognormal distribution was chosen because it approximates the degree distribution in networks of friends quite well (see, e.g., Toivonen et al 2009). The functional form of $\overline{n_i}(\lambda_i)$ can then be chosen so that maximal number of friends is distributed log-normally, too.

The person starts his life with a random number of friends from his generation that does not exceed the maximal number of friends he is ready to make. These can be regarded as his school-friends. Coming to a new workplace, he tries to make new $\Delta n_i = \lceil \overline{n_i}/10 \rceil$ friends working in the firm hosting this workplace. He succeeds in creating a friendship tie with a random firm's employee with probability $1/2$, as the employee can refuse the proposed friendship. If, due to additional ties created in the workplace, the number of friends exceeds the allowable ceiling, the person removes these extra friends. He first removes currently unemployed friends, starting with those with the longest period of unemployment. If this is not sufficient, he randomly removes friends who do not work with him in one firm. Finally, after there are no more such friends, he randomly removes his colleagues from his friendship circle.

4. SIMULATION RESULTS

4.1. Simulation Setup

We implemented a simulation of the model described in the two previous sections in Repast Simphony. Expected JS was represented as a sum of two logistic functions, which correspond to the three desirable properties stated in Section 2:

$$s_{ijt}^e = (1 - \lambda_i) P\left(6\left[\frac{w_i}{w_i^r} - 1\right]\right) + 2\lambda_i \left[P\left(\frac{6n_i^f}{\overline{n_i}}\right) - \frac{1}{2}\right] \quad (6)$$

In this formula, $P(\cdot)$ is the logistic function. In the definition of both summands, we took into account that $P(6) \approx 1$ and $P(-6) \approx 0$. Thus, when $w_i \ll w_i^r$, the first summand approaches zero, while it approaches one when $w_i = 2w_i^r$. The second summand is zero when the person has no local friends and approaches one when he has all his possible friends working with him. We also take into account the importance of friends, λ_i, so that the more important friends are for a person, the higher is the weight of the second summand. Since $\lambda_i \in [0,1]$, it follows that $s_{ijt}^e \in [0,1]$.

The maximum number of friends is determined according to the following linear relationship:

$$\overline{n_i} = \lceil 100\lambda_i \rceil \quad (7)$$

As $0 < \lambda_i \le 1$, Eq. (7) guarantees that maximum number of friends is distributed log-normally in the interval $[1,100]$.

Table 1 reports the values of the simulation's parameters. Annual population growth rate was taken approximately equal to the one characterising the situation in Europe in the last decade, as reported by Eurostat. Critical job satisfaction level is the level at which the person starts on-the-job search. Parameters of the friend importance distribution, μ_λ and σ_λ, were chosen so that the median importance is 0.07, leading to the median maximum number of friends equal to seven. The standard deviation of job satisfaction noise, σ_ε, is not reported in Table 1, since we will compare model dynamics depending on the values of this parameter.

4.2. Analysis

As the retirement age was set to 20 years and initially, everyone is of age zero, the size of the population grows rapidly until year $\tau = 20$, at which time the persons born in the first periods start retiring and the labour force size grows much less rapidly. Thus, we analyse only the last 20 years of the simulation, when the artificial labour market should have already stabilised.

Table 1: Simulation Parameter Values

	Parameter	Value
—	Simulation length (in months)	480
M	Number of firms	20
N_0	Initial population size	200
g	Annual population growth rate	1.005
$\overline{a}$	Retirement age (in years)	20
w_m	Minimum wage	100
h	Wage change factor for failed vacancy	1.1
w_u	Wage increase factor	1.05
p_w^u	Probability of wage increase	0.6
w_d	Wage decrease factor	0.95
p_w^d	Probability of wage decrease	0.1
μ_λ	Mean of friend importance	-2
σ_λ	Std. dev. of friend importance	0.8
$\underline{\delta}, \overline{\delta}$	Workforce change boundary	5
φ	Reservation wage modifying factor	0.9
$\overline{x}$	Sufficient experience (in years)	10
k	Number of simultaneous applications	5
q	Wage-experience multiplier	1.1
—	Critical job satisfaction level (%)	20

We compare four setups of the model, which differ, firstly, on the values of current JS noise: medium ($\sigma_\varepsilon = 0.1$) vs. low ($\sigma_\varepsilon = 0.05$), and secondly, on whether JS incorporates the local friend component (the second summand in Eq. (6)) or it consists of the wage component only. In models where friends are irrelevant to JS, persons still make friends and firms continue to hire by referral. Persons simply do not take the number of local friends into account when choosing among vacancies or considering starting on-the-job search.

Figure 1 compares the distribution of friend importance (which is identical to the distribution of the maximum number of friends) with the actual number of friends in the last period of the model. We can observe that the friend distribution is more peaked and has a thinner tail than the friend importance distribution.

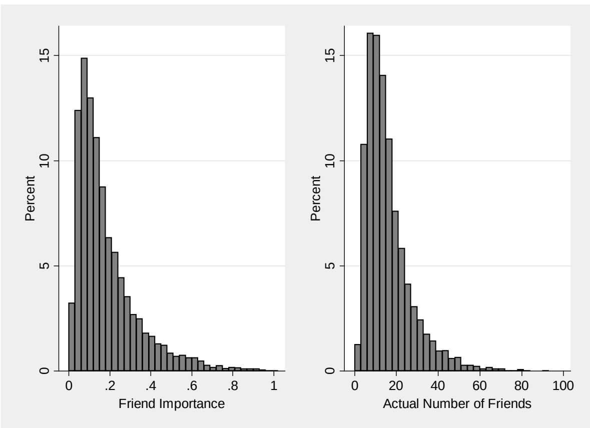

Figure 1: Distributions of friend importance and actual number of friends for the last period of the simulation.

This means that persons with a high maximum number of friends generally fail to make that many friendship ties, which should lead to their second component of expected JS being less than that of persons with lower friend importance—other things equal, the former are less happy than the latter because they do not meet their needs for social interaction. Consequently, we expect persons with higher friend importance to change jobs more frequently. Logistic regressions of leaving the job because of a low current JS (see Table 2) confirm this: in all four models, the largest effects in absolute terms are from friend importance and squared experience, and friend importance effects are positive. Note that the effect of friend importance on the probability of quitting the job increases if JS is based solely on the wage component.

Table 2: Marginal Effects after Logit Regression of Leaving the Job

Model	Med noise	Med noise, wage only	Low noise	Low noise, wage only
Friend imp.	.010***	.013***	.007***	.012***
# local friends	.000***	-.001***	.000**	-.001***
Wage	.000***	.000***	.000***	.000***
Age	.001***	.000***	.001***	.000*
$\text{Age}^2/100$	.004***	.002***	.003***	.002***
Experience	-.003***	-.004***	-.003***	-.004***
$\text{Exper.}^2/100$	-.009***	-.004***	-.008***	-.002**
Pseudo-R^2	.0848	.1232	.0806	.1210

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

The table shows median values for marginal effects and median pseudo-R^2s for runs of each model. Standard errors allow for intra-group correlations, where a group is defined as all observations belonging to one person.

To see whether friend importance systematically differs by the labour status of a person, we ran Kolmogorov-Smirnov two-sample tests on the runs of each of the four setups. The tests show that in the models where JS contained information on friends, the unemployed generally have a lower friend importance than the employed. For the two models where JS is based solely on wages, however, the situation is reversed.

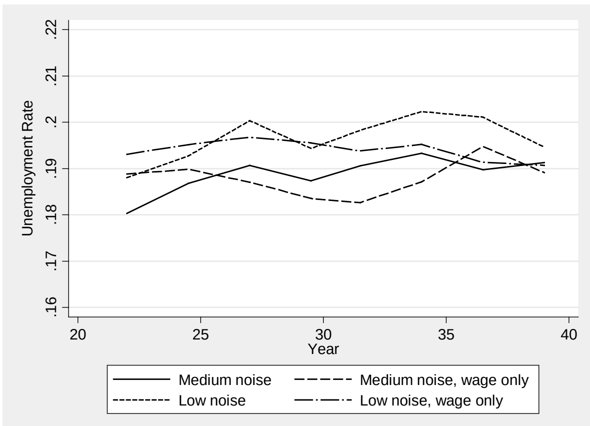

Figure 2: Median annual unemployment rates for the runs of the four setups.

Annual unemployment rates, however, do not differ much between the groups with differing JS functions—in all four cases shown in Figure 2, median unemployment rates are in the narrow interval $(0.18,0.20)$.

To check whether the difference in friend importance between the employed and the unemployed is significant in real terms, we compare the average of this characteristic for the two groups in each of the four model setups (see Table 3). The table shows that the differences between the groups are minor.

Table 3: Mean Friend Importance by Labour Status

Model	Friend Importance	
	Employed	Unemployed
Medium noise	0.18	0.17
Medium noise, wage only	0.18	0.19
Low noise	0.18	0.17
Low noise, wage only	0.18	0.19

Our final check for the link between friend importance and unemployment concerns the length of the longest period of unemployment experienced by the person. Results (see Table 4) show that, firstly, higher friend importance tends to reduce time to find the job, and secondly, that this reduction is much larger when JS is based on wages only. Note also that for wage-only JS models, regression fit is considerably lower than for the other two models. Another result is that the lower is JS noise, the more pronounced is the friend importance effect.

Table 4: Regression of the length of the longest period of unemployment experienced by the person

Model	Med noise	Med noise, wage only	Low noise	Low noise, wage only
Friend imp.	-1.356*	-3.691***	-1.448**	-4.082***
Age	4.025***	2.821***	4.338***	3.061***
Age^2/100	.826***	-5.098***	-1.792***	-5.474***
Experience	-5.214***	-3.173***	-5.914***	-3.296***
Exper.^{2}/100	5.527***	8.374***	8.166***	8.759***
Constant	21.117***	17.846***	21.570***	18.004***
R^2	.2887	.1870	.2736	.196

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

The table shows median values for regression coefficients and median R^2s for runs of each model.

Next, we check how the situation with person's friends relates to his own situation in the labour market. We find that the correlation coefficient between a person's wage and his friends' average wage is positive and quite high in all four model specifications (see Table 5), meaning that there is a certain degree of income homophily among persons. The coefficient is generally higher when friends are taken into account in JS. The coefficient value increases slightly with JS noise variance; moreover, for a lower noise, the difference in the correlation coefficient between JS specifications becomes larger.

Table 5: Correlation coefficient between person's wage and his friends' average wage

Model	Med noise	Med noise, wage only	Low noise	Low noise, wage only
Corr. coeff.	0.819***	0.816***	0.809***	0.780***

*** $p < 0.01$

Finally, we analyse situation within firms. We divide them into three groups by the average number of employees in the last month of each of the last 20 years of the simulation (see Table 6). While all firms were of the same size initially, several large (>500 employees) and medium-sized (50-500 employees) firms have evolved in the artificial economy. Note that with a lower JS noise, more large and medium firms evolve in the standard JS function setup. That can be explained by current JS changing less and, thus, decisions to quit taken less often—as a result, persons work longer at the same jobs, and firms can better accumulate workforce.

Large firms have a higher average friend importance than medium and small firms in the models where JS incorporates friends, while the situation is reversed when JS depends on wage only, and the magnitude of JS noise does not affect the results. The same holds for average total number of friends of firms' employees. Average number of local friends, on the contrary, is always greater, the larger the company, which was also expected. Note, however, that once friends become a component of current JS, the number of local friends in large and medium-sized companies increases 1.5 to 2 times, at the expense of a minor decrease of this characteristic for small companies. In other words, friendship networks are more clustered within companies than in models where JS depends only on wages.

Table 6: Firm-Level Statistics

Model	Firm Size	Number of Firms	Average Friend Importance	Avg. Number of Friends	Avg. No. of Local Friends
Medium noise	Large [a]	2	.18	15.47	10.27
	Medium [b]	2	.15	12.93	3.76
	Small [c]	16	.15	12.03	1.68
Medium noise, wage only	Large [a]	2	.17	14.38	6.10
	Medium [b]	4	.22	18.93	2.62
	Small [c]	14	.22	18.50	1.82
Low noise	Large [a]	3	.19	15.84	10.75
	Medium [b]	3	.15	12.83	4.42
	Small [c]	14	.15	11.93	1.67
Low noise, wage only	Large [a]	2	.17	14.28	5.67
	Medium [b]	4	.21	17.99	2.60
	Small [c]	14	.21	18.26	1.80

[a] Number of employees > 500.

[b] Number of employees in [50,500].

[c] Number of employees < 50.

The table shows average results for runs of each model.

5. CONCLUSION

In the present paper, we proposed a way to model job satisfaction and to incorporate it into an agent-based model of labour market. In our model, job satisfaction depends on two components: monetary benefits and social support, which were found to be empirically important factors; the influence of other factors is gauged by a random disturbance term. We created an artificial labour market simulation with heavy usage of social networking—during referral hiring, in choosing among vacancies, and in considering whether to start on-the-job search. The two latter choices are actually made based on job satisfaction.

We found that friend importance is an important determinant of the probability to quit the job and of the length of the longest unemployment period; both effects increase in absolute terms when job satisfaction does not depend on social support.

We also found evidence of social clustering. Firstly, labour market dynamics resulted in the emergence of a small number of large and medium-sized firms. Secondly, there is a substantial positive correlation between friends' wages, indicating income homophily of social groups. While, naturally, the average number of a person's friends working in the same firm increases with firm size, this number is nearly two times higher when job satisfaction depends both on wages and on social support than when it depends on wages only.

The model presented here has several limitations. Firstly, it does not distinguish among several components of social support, modelling it as a single factor. Moreover, it assumes that job satisfaction determinants other than monetary compensation and social support are pure noise, while they might be firm/job-specific and show serial correlation. Secondly, it portrays the behaviour of small and large firms analogically, while in a large firm, overall social support may be less important than social support in the department where the person works—thus, it may be useful to model the effects of social ties between workers of the same department and of different departments differently. In addition, empirical findings show that large firms rely on referral hiring to a lower extent than the small ones. Thirdly, it needs to be verified whether the same results hold when the production-consumption decisions are incorporated in the model. Further research should aim to overcome these limitations.

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