Job Satisfaction as a Unified Mechanism for Agent Behaviour on a Labour Market with Referral Hiring

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Abstract—Existing agent-based labour-market models include a very simplistic mechanism of choosing vacancies. This paper proposes to use job satisfaction as a unified mechanism for deciding on both starting to work on a particular job and quitting the current job. An enhanced job satisfaction mechanism consisting of monetary, social, content, and career components is proposed. As an illustrative context, a labour-market model with referral hiring and informal job search through own social networks is presented.

I. INTRODUCTION

The importance of social networks on the labour market was repeatedly shown both empirically and theoretically. Social networks affect the actions of both firms and individuals at different stages of the employment process.

Firms frequently use the social networks of their employees in the process of referral hiring. Research shows that in different countries, 30 to 50 per cent of companies hire by employee referral [1], [2], but it is far more common in small and medium firms, while large firms tend to rely on formal hiring practices [2], [3]. Different theoretical explanations of the rationale behind using referral hiring were proposed, and all of them are connected to reducing the costs of hiring [4]. Firstly, the referrals of existing employees, which are a trusted source of information for their employer, help reduce the problem of bilateral asymmetric information and the associated costs. Secondly, asking employees for job candidates they would recommend is a much less costly way of finding workforce than going through formal channels.

For individuals, social networks are even more important. Studies show that between 30 and 50 per cent of individuals found their new jobs through friends and relatives [5], [6], and individuals with access to larger social networks use informal job search channels more often [7]. Moreover, social support from co-workers and managers, along with other factors, is an important component of job satisfaction [8]–[12]. The Job Demands-Resources model [13] notes that social support acts as a buffer against high job demands, thus, preventing job strain; it also improves employees' motivation and productivity. Low job satisfaction is a strong indicator of a decision to quit [14].

Job satisfaction (JS) is a multi-faceted construct. A significant body of research exists studying the factors important for JS. There is general agreement that, besides social support, an important role is played by intrinsic job attributes, financial rewards, career growth, job security, and working conditions [15]–[18]. Referral hiring and job search through social networks were modelled both mathematically [19]–[21] and through simulations [22]–[25]. A common deficiency of these models is simplistic modelling of the choice among available vacancies, where the unemployed either take any vacancy or choose the best vacancy only based on the proposed wage.

In [26], a mechanism for including JS in agent-based simulations was proposed for more comprehensive modelling of individual dynamics on the labour market. There, JS was used both to choose the most appealing vacancy and to decide about on-the-job search. JS depended on relative wage and social network component.

In this paper, I take the idea of [26] further and propose to include other important facets of job satisfaction: job content and career opportunities. This mechanism is then integrated into a labour-market model with referral hiring and job search through social networks. I then study how introducing the JS mechanism changes the dynamics on the labour market.

The paper is structured as follows. The following section describes the job satisfaction mechanism in detail. Section III sets up the labour-market model. Then Sect. IV discusses how parameters should be set up, taking into account existing empirical data. Results are discussed in Sect. V. The last section concludes.

II. JOB SATISFACTION MECHANISM

As in [26], I divide JS in two components: expected JS, s_{ijf}^e , and actual (or current, as called in [26]) JS, s_{ijf}^a . Both are defined for agent *i* relative to job *j* at firm *f*. In other words, I introduce the dependence of JS on the firm, whereby there is certain correlation in JS for jobs inside a firm. This reflects the perception that some companies are *in general* better employers than others.

As in real life, JS is modelled as a multi-faceted concept. It consisted of wages and social support (mainly from coworkers) in [26]. This does cover compensation and support facets, but does not take into account job content and career opportunities. Including these latter facets introduces substantial difficulties. The former two facets can be modelled objectively (with their relative importance depending on some agent-specific weight), in the sense that the agent can be absolutely sure about the wage it will receive and the number of friends (approximating social support) it will have on a concrete job. In contrast, job content and career opportunities are vague concepts, more related to perceptions rather than to hard data. Nowadays, nearly every job advertisement speaks about an "interesting" job with "ample" career opportunities, which individuals have to interpret in the context of their existing knowledge about the firm and the job under consideration.

To make the matters simple, I assume that there are two types of jobs. The first type has ample career opportunities and high variety (which approximates content), while the second has limited career opportunities and low variety. The former jobs can be represented (and will be calibrated) by non-manual jobs (International Standard Classification of Occupations (ISCO) major groups 1 (managers) through 5 (service workers)), while the latter by manual jobs (ISCO major groups 6 (skilled agricultural and fishery workers) through 9 (elementary occupations)).

While agents perceive, e.g., manual jobs as having limited career opportunities, the perception of career opportunities for a given vacancy for such job depends also on the firm that posted it. Again, I assume that the only characteristic of the firm important for the perception of both career opportunities and variety at a given vacancy is the size of the firm.¹

Thus, the perception of job content and career opportunities depend on the type of job (manual vs. non-manual) and firm size.

Hence, expected JS is a function of:²

- Monetary compensation defined as the ratio of the expected wage of agent *i* on job *j* in firm *f* to its reservation wage, w_{ijf}/w_i^r
- Social support defined as the ratio of the number of friends of agent *i* in firm *f* (which I will refer to as "local friends") to the total number of its friends (i.e., the share of its friends working in firm *f*), n_i^f/n_i
- Job variety defined as a function of the type of job and firm size, $v\{T(j), S(f)\}$
- Career opportunities defined as a function of the type of job and firm size, $c\{T(j), S(f)\}$

The functional form of expected JS is as follows:

$$s_{ijf}^{e} = \Lambda \left\{ 6 \left[\frac{w_{ijf}}{w_{i}^{r}} - 1 \right] \right\} + \left[2\Lambda \left\{ \frac{6n_{i}^{f}}{n_{i}} \right\} - 1 \right] + v\{T(j), S(f)\} + c\{T(j), S(f)\},$$
(1)

where $\Lambda\{\cdot\}$ is the logistic function, whose range is [0, 1]. The logistic function makes JS increase with monetary compensation and social support, but the return to these factors in terms of JS is decreasing (any next dollar or local friend increases JS less). Importantly, it also bounds the range of JS. The factor of 6 appears because $\Lambda(6) \approx 1$ and $\Lambda(-6) \approx 0$. Thus, the first summand approaches zero when $w_{ijf} \ll w_i^r$ and one when $w_{ijf} = 2w_i^r$. The second summand is zero when the agent has no local friends $(n_i^f = 0)$ and approaches one when it has all friends working with firm f. Functions $v[\cdot]$ and $c[\cdot]$ also have the range of [0, 1]; they will be defined in Sec. IV. Thus, s_{ijf}^e can take values in [0, 4].

 $^{\rm I} {\rm Industry}$ might be an additional important factor, but in the current paper it is ignored.

Algorithm 1 Monthly Actions on the Labour Market

· ·
if start of year then
New population added
Persons aged over \bar{a} retire
end if
Non-start-up firms with zero workforce die
if start of year then
Firms select annual workforce change
Firms select wage change factor
end if
Update labour-market experience of persons
Create new firms
Firms update wages for expiring contracts
Firms change workforce and/or publish vacancies
Persons update current job satisfaction and consider starting
on-the-job search
Persons update reservation wage and apply to vacancies
Firms send acknowledgements to selected persons
Persons reply to the best acknowledgement, quit current job
if needed, and start working
Firms update failed vacancies

Actual JS represents the dynamics in the facets of expected JS (mainly, wage and social support) and all other factors gauged by a normally distributed random disturbance ξ :³

$$\Delta s^a_{ijf}(t) = \Delta s^e_{ijf}(t) + \xi \,. \tag{2}$$

By construction, the expected JS is always in [0, 4]. The value of the actual JS is reset at the closest boundary of this interval if Eq. (2) gives out-of-boundary values.

III. MODEL SPECIFICATION

There are two types of agents: persons and firms. The model includes only the labour market; in particular, the education market is ignored. The degree of match between the person and the job is controlled through job requirements published in vacancies, see the job search mechanism below.

Timing is discrete with one period representing one month. Most actions on the labour market are done on a monthly basis. The only exceptions are changes in population (inflow of new school or university graduates) and in wages (standard assumption about wage stickiness), which happen annually (every 12 periods). Time-dependent variables are written as f(t) if they change monthly or as $f(\tau)$ if they change annually.

Every year, N new persons come to the model and N are retired after living in the model for \bar{a} years ("retirement age").

The overall view on monthly the labour-market actions of persons and firms related to job search are summarised in Algorithm 1. The following subsections describe its steps in detail.

²In this paper, I use parentheses and braces in the definition of functions and square brackets to group expressions. E.g., f(x+y) and $f\{x+y\}$ should be read as "function f of x+y," while f[x+y] should be read as "f multiplied by x+y."

³Delta (Δ) is used here as standard difference operator for time-dependent functions, i.e., $\Delta f(t) \equiv f(t) - f(t-1)$.

A. Job Search

There is a unique vacancy list in the market, which everyone is able to access (e.g., a country-wide job search website). Firms post vacancies on this list and persons may browse it to find new jobs, which is called formal job search. Alternatively, persons can choose to search for jobs informally, using their friends that are employed. Implicitly, I assume that all employees in a given firm are informed about all its vacancies.

A vacancy is a quadruple (f, T, x, w), where

- f is the firm hosting the vacancy
- T is the type of job (manual or non-manual)
- x ∈ Z, 0 ≤ x ≤ x̄ is the minimum required working experience measured in years; x̄ is the sufficient experience, which is common for all vacancies
- $w \in \mathbb{Z}, w \leq w_m$ is the proposed wage rate at the required experience $x; w_m$ is the minimum wage, which is common for all vacancies

Between the minimum required experience and the sufficient experience, wage changes linearly with experience x_i :

$$w(x_i) = \begin{cases} w[1+q(T)[x_i-x]], & \text{if } x \le x_i \le \bar{x} \\ w[1+q(T)[\bar{x}-x]], & \text{if } x_i > \bar{x}, \end{cases}$$
(3)

where q(T) is a constant specific for each job type.

Every person *i* knows its actual experience x_i and reservation wage w_i^r and, for each vacancy, is able to find out the wage it will be paid. The person decides probabilistically on formal vs. informal search. In both cases, the person creates a list of matching vacancies (i.e., set $\{v|x(v) \leq x_i \land w(v, x_i) \geq w_i^r\}$).⁴ As information processing capabilities of agents are limited, they consider only not more than K matching vacancies—randomly in case of formal search. It then sorts this list by descending expected JS and sends application to top k vacancies. Both k and K are the same for all persons.

Small (less than 25 employees) and medium-sized (25–499 employees) firms employ the referral hiring mechanism when choosing candidates to employ. If in the list of applications for the vacancy, there are candidates having friends employed in the firm, the firm chooses randomly from these candidates; otherwise, it chooses randomly from all candidates. Large (500+ employees) firms do not look on the existing social ties of candidates with their employees and choose randomly from all applicants.

Successful candidates receive acknowledgements. If a person receives acknowledgements from several applications, it chooses the job with the highest expected JS. It then starts working immediately on that job.

The vacancy may fail to attract applications if it has low expected JS. For a given person, the firm can increase the expected JS of the vacancy only by increasing the proposed wage, as other components—social support, job variety, and career opportunity—are fixed. At the same time, the firm cannot decrease the required experience to attract additional candidates, as it needs qualified employees. The firm then looks at the average wage for experience x and type of job T on the market. If it is above the wage proposed by the firm, it sets the new wage at market average. If the firm's proposal, w, was already higher than market average, the new proposal is set at $\nu w, \nu > 1$. If the firm still fails to hire anyone for this vacancy in the next month, it cancels the vacancy.

Reservation wage for a working person is equal to its current wage. For a person with no working experience, it is given by the minimum wage. For an unemployed, it decreases with the length of unemployment measured in months, starting from the last wage, but is bounded from below by the minimum wage. The decreases occurs with constant elasticity φ , which is the same for all persons. Thus, the longer the person is unemployed, the lower wage it is ready to accept.

If for an employed person, its current JS falls below the minimum level, which is the same for all persons⁵, it starts onthe-job search. In contrast with the unemployed, who consider all matching vacancies, the employed consider only those matching vacancies with the expected JS being higher than their current JS. If accepted for a vacancy, such person quits the current job and immediately starts working on the new position.

B. Dynamics Inside Firms

In the first month of the calendar year, firms plan changes in workforce and wages. Then, every month in that year, they implement these decisions.

If firms decide to change workforce by δ per cent this year, they implement it by changing workforce every month by $\delta/12$ per cent (rounded up or down as required). If the firm decides to expand this year, it publishes the according amount of new vacancies every month throughout the year and also publishes all vacancies substituting the employees who left after on-thejob search.

Each vacancy for a new position is created with the required experience x uniformly chosen from $[0, \bar{x}]$, where \bar{x} denotes sufficient experience, and with probabilistically chosen type of job (manual vs. non-manual). The corresponding proposed wage w is set to the average wage of the firm's employees with that experience and job type. If no such persons are currently employed in the firm, it makes interpolation from the average wage it pays employees with the experience nearest to x and same job type. For companies having no employees of this job type, they take average current wages at experience x and the selected type of job in the economy.⁶

⁴See below on the additional restrictions on the vacancies in this list for persons engaged in on-the-job search.

⁵Individuals start thinking about quitting the job when they feel that their job is "unsatisfactory." What different individuals mean by this is reflected by the combinations of the values of JS facets, but all these combinations lead to JS falling below certain boundary. Using a relative, rather than absolute, measure of JS, it seems realistic to assume that this boundary is the same for everyone.

⁶If there are no such persons in the economy, average wages are interpolated from employees of the same job type with nearest experience.

Firms also publish vacancies to substitute employees who just quit the firm either after reaching the retirement age or due to low JS (contracted workforce is not substituted). In this case, the experience is set below that of the worker who quit (but still keeping it in $[0, \bar{x}]$):

$$x = \max(\min(x', \bar{x}) - 2, 0),$$
 (4)

where x' is the experience of the worker who quit, and the type of job is left the same. The wage is set as described above.

If the firm decides to contract this year, its behaviour is slightly different. Every month, the firm has to lay off a certain number of employees. Before actually laying off agents, it looks on how many employees left the company in the previous month and first tries to implement the change in workforce by not publishing substituting vacancies. For instance, if the firm has to contract by 5 employees but 3 employees left it in the previous month, the firm does not publish these 3 substituting vacancies and lays off only 2 employees. All lay-offs are made randomly.

Every firm changes wages once a year, in accordance with standard economic results on the stickiness of wages. Wages are changed for all jobs in the firm by the same factor. That factor is chosen from the set $\{w_d, 1, w_u\}$, where $w_d < 1$ and $w_u > 1$ with the corresponding probabilities $\{\pi_u, 1 - \pi_u - \pi_d, \pi_d\}$. For a given employee, the wage is changed in the month it was hired on the current job (if it occurred in month 3 last year, it is changed in month 3 this year, although the decision to change wages was made in the beginning of this year). In other words, I assume yearly contracts with fixed wages.

C. The Birth and Death of Firms

A new firm can be born when a person probabilistically decides to create one. This probabilistic event occurs monthly, for both employed and unemployed persons. The mechanism of vacancy publication for new firms is the same as for any other firms. The only difference is that if a start-up is given Δt_s periods to find first employees. It allows new firms to search for workforce for more than one period, as otherwise, any new firm not having found at least one employee in the first month of its life would die (see the following paragraph). In other words, new firms are allowed to exist for their first Δt_s periods with zero workforce.

Otherwise, firms disappear when they are left with no workforce. Their owners become unemployed and start searching for a new job. When a firm's owner is removed from the simulation, the firm continues to exist without an owner: no other person is assigned as a new owner.

I assume that such entrepreneurs are not subject to onthe-job search or quitting their companies, which makes the definition of their wages and, more broadly, JS unnecessary.

Initially, the simulation is filled with ${\cal M}$ firms with no workforce.

D. Dynamics of Social Networks

Some of the persons that enter the model in the same period are interconnected, forming an *initial social network* of, e.g., secondary school or university friends⁷. They also have friendship ties with those persons already in the labour market (irrespective of whether they are employed or not), forming a *mature social network*. These two sets of connections form the social network with which the person enters the model.

This initial social network is generated using the Duplication model [27, Ch. 4] parametrised to build a scale-free social network, having many low-degree vertices and a few high-degree vertices.⁸ Empirical research indicates that such networks approximate the real-world social networks quite well [28]–[30]. Both networks are built separately with the same parameter $\rho \in (0, 1)$.

When person *i*, having a social network of n_i friends, first comes to a new job, it tries to make new friendship ties with $\lceil n_i/10 \rceil$ persons working in that firm; each tie is created with probability 1/2, as the other party can refuse the proposed friendship. The principle of homophily says that people make friendship ties from those close to them by some characteristics [31]. In accordance with it, persons make friends only with those working in the same job type as theirs.

As the person cannot have an indefinite number of friends, it substitutes the existing friends with these new friends. So if on the first working day, the person makes k new connections, it breaks connections with k its existing friends, firstly removing those with the longest period of unemployment.

IV. PARAMETRISATION

European Social Survey (ESS) Round 5 [32] has individuallevel data on the perceptions of the employed in 24 European countries⁹ in 2010–11 about their jobs. I use pooled data from these countries for setting parameter values. Tables I and II show the details. Note that, as assumed in this paper, the perceptions of both career opportunities and variety in work are better in non-manual occupations than in manual occupations. Functions $v[\cdot]$ and $c[\cdot]$ are defined according to this table. There are, thus, three categories of firm size, S(f): small (under 25 employees), medium (25 to 499 employees), and large (at least 500 employees).

Wage dynamics is set based on estimates available in the literature, see Table III. The average effect on wages from labour-market experience is around 2.5%. Estimates based on US data show that it is around 1.5 times larger for the tertiary-educated than for the secondary-educated. Assuming that the

⁷Friends in the broad sense, meaning both close friends and acquaintances ⁸In short, the Duplication model proceeds in two-step iterations. At the first step, a new vertex is added to the graph and connected randomly with an existing vertex. At the second step, the algorithm goes over each neighbour of the existing vertex and connects it to the new vertex with probability ρ . Thus, ρ is the probability of an agent creating a connection with a friend of its new friend. It was shown [27, 78] that the model generates scale-free networks with the exponent β that is a solution to the equation $1 + \rho = \rho\beta + \rho^{\beta-1}$.

⁹Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Lithuania, the Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the UK.

Miguel, Amblard, Barceló & Madella (eds.) Advances in Computational Social Science and Social Simulation Barcelona: Autònoma University of Barcelona, 2014, DDD repository http://ddd.uab.cat/record/125597

TABLE I
SHARE OF EMPLOYED INDIVIDUALS BELIEVING THAT THE OPPORTUNITIES FOR ADVANCEMENT ARE GOOD

		Firm Size (# employees)													
		< 25 25-499				500+									
Extent of Agreeing (Fully disagree 15 Fully agree)	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Non-manual occupations Manual occupations	11% 17%	27% 30%	29% 27%	27% 22%	6% 4%	9% 17%	27% 33%	29% 25%	30% 21%	5% 3%	9% 15%	23% 33%	27% 24%	33% 24%	7% 4%

Source: calculated from European Social Survey Round 5 pooled data from 24 European countries (see Footnote 9).

 TABLE II

 Share of Employed Individuals Believing that Variety in Work Is Good

		Firm Size (# employees)										
		<	25		25–499			500+				
Extent of Agreeing (Fully disagree 14 Fully agree)	1	2	3	4	1	2	3	4	1	2	3	4
Non-manual occupations Manual occupations	7% 17%	26% 31%	34% 28%	34% 24%	5% 17%	20% 31%	35% 30%	40% 23%	4% 18%	18% 27%	34% 30%	45% 25%

Source: calculated from European Social Survey Round 5 pooled data from 24 European countries (see Footnote 9).

 TABLE III

 EMPIRICAL DATA ON WAGE RETURNS ON YEAR OF EXPERIENCE

Author	Country	Sex	Education Level						
		~ ~ ~ ~	Secondary	Tertiary	Total				
[33]	Italy	Men Women			2.9% 1.1%				
[34]	UK	Men			2.2%				
[35]	UK	All			7.4%				
[36]	9 countries	All			1.06%-3.67%				
[37]	USA	Men Women	1.8% 1.9%	2.5% 3.2%					
[38]	USA	Men Women	3.1% 3.7%	5.8% 8.2%					

Estimates correcting for unobserved heterogeneity were taken where available. Where cumulative effect of experience over several years was given, it was converted into annual effect assuming that the effect from every additional year of experience is the same (e.g., a 20% cumulative effect over 10 years would be converted into a 2% annual effect). From [36], data were taken only on countries with positive relationship between wage and experience; the nine countries are Austria, Belgium, Germany, Greece, Ireland, Italy, Portugal, Spain, and the UK.

former work at non-manual jobs and the latter at manual jobs¹⁰, I set the wage-experience coefficient at 3.0% for nonmanual jobs and at 2.0% for manual jobs. The relationship between wage and experience is non-linear: returns are diminishing at higher experience levels and after 20–30 [36] years, the wage-experience curve flattens¹¹. Here, I assume that wage changes linearly with experience (recall Eq. (3)) and wage stops depending on experience starting with 20 years of experience, which I call "sufficient" experience level.

¹⁰In other words, I assume there is no over- or under-education and the education levels of all workers perfectly matches job demands.

¹¹In some countries, wages start dropping afterwards.

The distribution of annual workforce change is set in accordance with Amadeus data for European companies in 2010–2013, see Table III. Note that extreme changes (larger than 50 per cent in absolute terms) were filtered out from the sample and are also not allowed in the simulation. In around 70 per cent of cases, firms will change workforce by ± 10 per cent.

According to the job-search theory [39], reservation wage falls with unemployment spell duration. Empirical studies used constant-elasticity models for quantifying this effect, but came to substantially different elasticities, ranging from -10% [40] to -80% [41]. I set the elasticity at -20%, which means that for every 10 per cent increase in unemployment spell, reservation wage falls 2 per cent.

The probability of becoming entrepreneur is set based on the share of self-employed in Europe (ESS Round 5 data), which is¹² 13%, and Proposition A.1.

The Duplication model parameter ρ is set so that the model generates a scale-free network with exponent $\beta \approx 2.61$, which is inside the range [2, 3] typical for social networks [27]. The number of direct connections in initial and mature networks are set so that the average number of friends would be not more than 100–120, the maximum number of Facebook friends with which an individual interacted at least once [30, Fig. 15].

V. RESULTS

The model was implemented in Repast Simphony. At this moment, only preliminary results are available.

The initial number of firms is a major factor affecting the overall employment in all further periods. With M = 10, unemployment exceeded 95 per cent for the length of simulation, while with M = 50, there was nearly full employment on

¹²Share of self-employed from the employed in paid work, in education, unemployed and inactive. Not taking into account the disabled, retired, in military service or doing housework.

 TABLE IV

 Distribution of Annual Workforce Percentage Change

% Change	[-50, -41]	[-40, -31]	[-30, -21]	[-20, -11]	[-10, -1]	[0,9]	[10, 19]	[20, 29]	[30, 39]	[40,50]
% in Sample	0.7	1.0	2.4	7.0	25.3	45.2	10.4	4.4	2.1	1.5

Data from Amadeus, accumulated over 2010–2013. The sample contains active firms operating in EU-28, Norway and Switzerland. Only firms with annual change in workforce in the interval of [-50%, +50%] were selected. The distributions in each individual year in the 2010–2013 interval are very similar to that given in the table.

TABLE V Parameter Values

Parameter Name	Notation	Value
General		
Annual inflow of new persons	N	100
Retirement age, years	ā	30
Length of simulation, years		100
Initial number of firms	M	50
Job Satisfaction		20
Current job satisfaction disturbance		
mean	$\mu(\xi)$	0
std.dev.	$\sigma(\xi)$	0.1
Critical job satisfaction for on-the-job search	0(5)	20%
Workforce Dynamics		2070
Prob. of manual vacancy		0.30
Wage multiplier when updating vacancy	ν	1.05
Wage-experience multiplier	q	1100
manual jobs	4	2%
non-manual jobs		3%
Sufficient experience, years	\bar{x}	20
Job Search	w	20
# of simultaneous applications	k	5
Max # of vacancies considered	ĸ	50
Prob. of formal job search	11	0.3
Unempl. length elasticity of reservation wage	φ	-20%
Wage Specification	Ψ	2070
Minimum wage	w_m	100
Wage dynamics	ω_m	100
Prob. of increasing wage	π_{u}	0.6
Factor of wage increase	w_u	1.05
Prob. of decreasing wage	π_d	0.1
Factor of wage decrease	w_d	0.95
Entrepreneurship	ω_a	0.95
Prob. of becoming entrepreneur		0.95%
How long considered start-up, periods	Δt_s	6
Social Networks	<u> </u>	0
Duplication model parameter	ρ	0.45
Number of direct connections	P	0.15
initial social network		30
mature social network		10
matare boond network		10

the labour market. Further sensitivity analysis will reveal the dependence of unemployment on the initial number of firms.

Next I compare the model with full JS and the model with JS consisting only of the wage component. In other words, the latter model resembles typical economic models, where all decisions are based on proposed wages.

Both models lead to the creation of large firms (less than 5 per cent of all firms) an medium firms (20 to 30 per cent of all firms), see Fig. 1. Over time, the proportion of medium firms increases at the expense of small firms in the model with full JS, but drops in the model where decisions depend on wages only. Further analysis is needed to check for model stability.

The share of employees on manual jobs from all employed

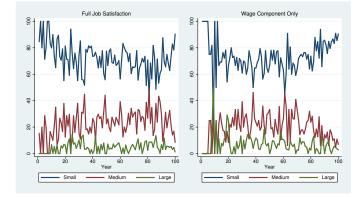


Fig. 1. Share of Firms of Different Size

Note: The size category of the firm (small, medium or large) is defined as in Sect. IV.

is nearly twice higher in the model with full JS than in the model with wage component (23 per cent vs. 13 per cent on average in the last period of the run). By construction, wages grow faster for non-manual jobs. Clearly, in the model with full JS, this is dampened by other factors, but when only wage is important, agents are still more inclined to choose non-manual jobs.

In the update to this version of the paper, I will add the results on the existence of social clustering in firms in both models, as well as comparing the base model with a model where persons use only formal search.

VI. CONCLUSIONS

APPENDIX

Proposition A.1. Let P be the observed share of entrepreneurs in the population and p be the probability of becoming entrepreneur at any time moment in the model (constant over time). Assume that once the person becomes an entrepreneur, it cannot revert its status at any later time and that all age groups are equally represented in the model population. Let \bar{a} be the maximum age of a person in the population (measured in years). Then the relationship between p and P is as follows:

$$P = 1 + \frac{1 - (1 - p)^{\bar{a}}}{\bar{a}\ln(1 - p)}.$$
(5)

Proof: Consider a random person. After living *a* periods

in the model, the probability of being entrepreneur is

$$\pi(a) = \sum_{k=0}^{a} (1-p)^{k-1}p \tag{6}$$

$$=\frac{p[1-(1-p)^k]}{1-(1-p)}$$
(7)

$$= 1 - (1 - p)^k \,. \tag{8}$$

To translate it to the whole population, first divide the interval of age, $[0, \bar{a}]$, into subintervals of length Δa . As the function $\pi(a)$ is smooth, for small enough Δa we can assume that $\pi(\cdot)$ is constant in any point inside such subinterval. Then the probability of a random person in the population to be entrepreneur is given by the sum over age subintervals of the products of the probability of falling into a particular age subinterval and the probability of being entrepreneur inside this interval. By assumption, the former probability is constant and given by $\bar{a}/\Delta a$. Then the probability of observing entrepreneur is

$$\pi = \sum_{k=0}^{\bar{a}/\Delta a - 1} \pi(k\Delta a) \frac{\Delta a}{\bar{a}}$$
(9)

$$=\sum_{k=0}^{\bar{a}/\Delta a-1} \left(1 - (1-p)^{k\Delta a}\right) \frac{\Delta a}{\bar{a}}$$
(10)

$$=\frac{\bar{a}}{\Delta a}\frac{\Delta a}{\bar{a}}-\frac{1-\left((1-p)^{\Delta a}\right)^{\frac{\bar{a}}{\Delta a}}}{1-(1-p)^{\Delta a}}\frac{\Delta a}{\bar{a}}$$
(11)

$$= 1 - \frac{1 - (1 - p)^{\bar{a}}}{1 - (1 - p)^{\Delta a}} \frac{\Delta a}{\bar{a}}.$$
 (12)

Finally, take this expression to the limit of Δa (note the use of l'Hôpital's rule):

$$\lim_{\Delta a \to 0} \pi = 1 - \lim_{\Delta a \to 0} \frac{1 - (1 - p)^{\bar{a}}}{1 - (1 - p)^{\Delta a}} \frac{\Delta a}{\bar{a}}$$
(13)

$$= 1 - \lim_{\Delta a \to 0} \frac{1 - (1 - p)^{\bar{a}}}{-\bar{a}(1 - p)^{\Delta a} \ln (1 - p)}$$
(14)

$$= 1 + \frac{1 - (1 - p)^{\bar{a}}}{\bar{a}\ln(1 - p)} \,. \tag{15}$$

This should be equal to P.

REFERENCES

- T. F. Bewley, Why Wages Don't Fall During a Recession. Cambridge, MA: Harvard University Press, 1999.
- [2] M. Hazans, "Labor market integration of ethnic minorities in Latvia," in *Ethnic diversity in European labor markets: Challenges and solutions*, M. Kahanec and K. F. Zimmerman, Eds. Cheltenham, UK: Edward Elgar, 2011, pp. 163–197.
- [3] A. Kuddo, "Employment services and active labor market programs in Eastern European and Central Asian countries," The World Bank, SP Discussion Paper 0918, 2009.
- [4] M. Granovetter, "The impact of social structure on economic outcomes," *Journal of Economic Perspectives*, vol. 19, no. 1, pp. 33–50, 2005.
- [5] A. Franzen and D. Hangartner, "Social networks and labour market outcomes: The non-monetary benefits of social capital," *European Sociological Review*, vol. 22, no. 4, pp. 353–368, 2006.
- [6] J. D. Montgomery, "Social networks and labor-market outcomes: Toward an economic analysis," *American Economic Review*, vol. 81, no. 5, pp. 1408–1418, 1991.

- [7] M. Caliendo, R. Schmidl, and A. Uhlendorff, "Social networks, job search methods and reservation wages: evidence for Germany," *International Journal of Manpower*, vol. 32, no. 7, pp. 796–824, 2011.
- [8] J. A. Alexander, R. Lichtenstein, H. J. Oh, and E. Ullman, "A causal model of voluntary turnover among nursing personnel in long-term psychiatric settings," *Research in Nursing & Health*, vol. 21, no. 5, pp. 415–427, 1998.
- [9] P. Brought and R. Frame, "Predicting police job satisfaction and turnover intentions: The role of social support and police organisational variables," *New Zealand Journal of Psychology*, vol. 33, no. 1, pp. 8–16, 2004.
- [10] C. G. Cortese, L. Colombo, and C. Ghislieri, "Determinants of nurses' job satisfaction: the role of work-family conflict, job demand, emotional charge and social support," *Journal of Nursing Management*, vol. 18, no. 1, pp. 35–43, 2010.
- [11] L. J. Ducharme and J. K. Martin, "Unrewarding work, coworker support, and job satisfaction: A test of the buffering hypothesis," *Work and Occupations*, vol. 27, no. 2, pp. 223–243, 2000.
- [12] S. Roxburgh, "Exploring the work and family relationship: Gender differences in the influence of parenthood and social support on job satisfaction," *Journal of Family Issues*, vol. 20, no. 6, pp. 771–788, 1999.
- [13] A. B. Bakker and E. Demerouti, "The job demands-resources model: state of the art," *Journal of Managerial Psychology*, vol. 22, no. 3, pp. 309–328, 2007.
- [14] J. Parry, "Intention to leave the profession: antecedents and role in nurse turnover," *Journal of Advanced Nursing*, vol. 64, no. 2, pp. 157–167, 2008.
- [15] A. L. Kalleberg, "Work values and job rewards: A theory of job satisfaction," *American Sociological Review*, vol. 42, no. 1, pp. 124– 143, 1977.
- [16] H. Lu, K. L. Barriball, X. Zhang, and A. E. While, "Job satisfaction among hospital nurses revisited: A systematic review," *International Journal of Nursing Studies*, vol. 49, no. 8, pp. 1017–1038, 2012.
- [17] A. Skalli, I. Theodossiou, and E. Vasileiou, "Jobs as lancaster goods: Facets of job satisfaction and overall job satisfaction," *The Journal of Socio-Economics*, vol. 37, no. 5, pp. 1906–1920, 2008.
- [18] A. Tarvid, "Job satisfaction determinants of tertiary-educated employees in European countries," Athens Institute for Education and Research, ATINER's Conference Paper Series No. ECO2012-0257, 2012.
- [19] Y. Bramoullé and G. Saint-Paul, "Social networks and labor market transitions," *Labour Economics*, vol. 17, no. 1, pp. 188–195, 2010.
- [20] A. Calvó-Armengol and M. O. Jackson, "The effects of social networks on employment and inequality," *American Economic Review*, vol. 94, no. 3, pp. 426–454, 2004.
- [21] B. V. Krauth, "A dynamic model of job networking and social influences on employment," *Journal of Economic Dynamics and Control*, vol. 28, no. 6, pp. 1185–1204, 2004.
- [22] M. Abdou and N. Gilbert, "Modelling the emergence and dynamics of social and workplace segregation," *Mind & Society*, vol. 8, no. 2, pp. 173–191, 2009.
- [23] S. Gemkow and M. Neugart, "Referral hiring, endogenous social networks, and inequality: an agent-based analysis," *Journal of Evolutionary Economics*, vol. 21, no. 4, pp. 703–719, 2011.
- [24] T. Tassier and F. Menczer, "Emerging small-world referral networks in evolutionary labor markets," *Evolutionary Computation, IEEE Transactions on*, vol. 5, no. 5, pp. 482–492, 2001.
- [25] —, "Social network structure, segregation, and equality in a labor market with referral hiring," *Journal of Economic Behavior & Organization*, vol. 66, no. 3–4, pp. 514–528, 2008.
- [26] A. Tarvid, "Job satisfaction modelling in agent-based simulations," in *The 23rd European Modeling & Simulation Symposium*, A. Bruzzone, M. A. Piera, F. Longo, P. Elfrey, M. Affenzeller, and O. Balc, Eds. Rende: DIPTEM Università di Genova, 2011, pp. 158–165.
- [27] F. Chung and L. Lu, Complex Graphs and Networks (Regional Conference Series in Mathematics, No. 107). Providence, RI, USA: American Mathematical Society, 2006.
- [28] R. Kumar, J. Novak, and A. Tomkins, "Structure and evolution of online social networks," in *Link Mining: Models, Algorithms, and Applications*, P. S. Yu, J. Han, and C. Faloutsos, Eds. Springer New York, 2010, pp. 337–357.
- [29] H. Kwak, C. Lee, H. Park, and S. Moon, "What is Twitter, a social network or a news media?" in *Proceedings of the 19th international*

conference on World wide web, ser. WWW '10. New York, NY, USA: ACM, 2010, pp. 591-600.

- [30] C. Wilson, B. Boe, A. Sala, K. P. Puttaswamy, and B. Y. Zhao, "User interactions in social networks and their implications," in *Proceedings of the 4th ACM European conference on Computer systems*, ser. EuroSys '09. New York, NY, USA: ACM, 2009, pp. 205–218.
- [31] M. McPherson, L. Smith-Lovin, and J. M. Cook, "Birds of a feather: Homophily in social networks," *Annual Review of Sociology*, vol. 27, pp. 415–444, 2001.
- [32] Norwegian Social Science Data Services, "European social survey round 5 data. Data file edition 3.0." 2010.
- [33] M. Battisti, "Individual wage growth: The role of industry experience," Ifo Institute for Economic Research at the University of Munich, Ifo Working Paper 152, 2013.
- [34] N. Williams, "Seniority, experience, and wages in the UK," *Labour Economics*, vol. 16, no. 3, pp. 272–283, 2009.
 [35] M. Myck and G. Paull, "The role of employment experience in explain-
- [35] M. Myck and G. Paull, "The role of employment experience in explaining the gender wage gap," Institute for Fiscal Studies, IFS Working Paper 01/18, 2001.
- [36] I. G. Mainar and V. M. M. Gómez, "Returns to education and to experience within the EU: Are there differences between wage earners and the self-employed?" Universidad de Zaragoza, Working Paper 2004-08, 2004.
- [37] H. Connolly and P. Gottschalk, "Differences in wage growth by education level: Do less-educated workers gain less from work experience?" IZA, IZA Discussion Paper 2331, 2006.
- [38] L. Munasinghe, T. Reif, and A. Henriques, "Gender gap in wage returns to job tenure and experience," *Labour Economics*, vol. 15, no. 6, pp. 1296–1316, 2008.
- [39] G. J. Stigler, "Information in the labor market," Journal of Political Economy, vol. 70, no. 5, pp. 94–105, 1962.
- [40] J. T. Addison, M. Centeno, and P. Portugal, "Reservation wages, search duration, and accepted wages in Europe," IZA, IZA Discussion Paper 1252, 2004.
- [41] S. Brown and K. Taylor, "Reservation wages, expected wages and unemployment," *Economics Letters*, vol. 119, no. 3, pp. 276–279, 2013.