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Expectation Formation and Social Influence ☆

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Abstract

This article investigates the role of social influence for the expectation formation of economic agents. Using self-organizing Kohonen maps the repeated cross-section data set of the University of Michigan consumer survey is transformed into a pseudo panel allowing to monitor the expectation formation of cohorts with regard to business confidence over the whole available time span (January 1978 - June 2013). Subsequently the information theoretic concept of transfer entropy is used to reveal the role of social influence on the expectation formation as well as the underlying network structure. It is shown that social influence strongly depends on socio-demographic characteristics and also coincides with a high degree of connectivity. The social network estimated in this way follows a power-law and thus exhibits similar structure as networks observed in other contexts.

Keywords: social networks, expectations, household survey
JEL: D12, D83, D84, D85

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1. Introduction

1.1. Objectives

The Michigan consumer survey as most household surveys today is mostly based on qualitative questions with regard to the financial situation of the interviewed household or the general economic situation. The latter category of questions is of specific interest for researchers as it allows to make assertions of the formation of expectations, not least because the responses can be compared between households and correspond to measurable variables (inflation, employment, economic growth etc.). Standard topics investigated in this field of research comprehend the rationality and unbiasedness of expectations. The article at hand contributes to the literature addressing the latter question.

Using repeated cross-section data from the University of Michigan consumer survey this article investigates how consumers or agents form their expectation within their social environment. This means how and to what degree agents influence or are influenced by other agents in their expectation formation? Which groups of agents are the most influential and best connected, and on what factors does influence and connectedness depend? By applying neural network clustering techniques (*self-organizing Kohonen maps*) the cross-section data of the University of Michigan consumer survey is transformed into a pseudo panel. A non-parametric information-theoretic approach from Physics denoted as *"transfer entropy"* (Schreiber, 2000) is then used to measure the information flows between cells. The findings show that agents with higher education, higher income and to a certain degree higher age are more influential and better connected than others. It is further shown that so measured social network is scale free and thus follows a power law distribution.

Approaches to indirectly infer structures of social influence and networks via behavioural data as introduced in this article are new to economics. This is remarkable as social influence and in this context also imitation or conformity are often emphasized as important factors for decisions of economic agents and contributions to this topic can be traced back to early seminal works by e.g. Sherif (1936), Hyman (1942), Asch (1951), Jahoda (1959) or Merton (1968). This as Manski (2000) points out might be due to the fact that social interactions as object of investigation in economics are often reduced to the market. In consumer research on the other hand social influence is perceived as one of the "*... most pervasive determinants*

			income		age	
sex	education	n	mean	sd	mean	sd
male	no highschool	10901	22580	24011	52	19
	highschool	52257	41721	38367	44	17
	college	36872	70155	67400	45	15
female	no highschool	14895	15837	17341	56	19
	highschool	69487	34960	33776	46	18
	college	36324	62612	59527	44	15
	All	220736	45088	48698	46	17

Table 1: University of Michigan Consumer Survey: Descriptive Statistics

[...] of individual's behaviour..." (Burnkrant and Cousineau, 1975). As behaviour is strongly shaped by expectations it is believed that it is worthwhile to investigate and understand how information transfer ("*social influence*") within a society works and which factors determine this influence. For this purpose the University of Michigan consumer survey which is conducted since 1978 to capture the evolution of households perceptions and expectations with regard to the economy seems to be ideal. Technically the paper at hand was inspired by Ver Steeg and Galstyan (2012) who use information theory to expose structures of social influence and networks on the social media network Twitter.

In the following subsection the University of Michigan consumer survey as well as the data set used for the article at hand is described. Section 2 introduces *transfer entropy* the information theoretic measure used to estimate the information flows between different agents. Section 3 discusses the techniques applied to create a pseudo panel, to estimate information flows and basing on this network connections between agents. Section 4 presents and discusses the results.

1.2. The Data Set: University of Michigan Consumer Survey

The University of Michigan Michigan consumer survey is a household survey conducted by the Survey Research Center of the University of Michigan since 1966. Each month at least 500 representative households from the United States excluding Hawaii and Alaska are selected and surveyed about their respective financial situation, buying attitudes as well with regard to their perceptions/expectations regarding the general economic development in the short and long run. Next to this topically specific question the data set also contains various socio demographic variables such as education, sex, household size, region of residence, age, household income etc.. The data set also contains a variable with survey weights by the supplier of the data set. This will be further on useful when correcting for majority effects while estimating the degree of social influence.

The data set available at the time this article was written contained 215.629 observations between January 1978 and June 2013. A descriptive statistics of the data set used can be found in Table 1. Within the survey one question is specifically important for the article at hand:

How about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?

- *Better a year from now*
- *About the same*
- *Worse a year from now*

This question (we further on refer to this variable as $BEXP$) is used to measure the information transfer between agents or cells respectively. It was selected as it is very general. A question with regard to expectations about things like inflation for example would have not been suitable as inflation perceptions/expectations strongly depend on the individuals/households consumption behaviour.

2. Transfer Entropy

The information associated with outcome x with probability $p(x)$ of a random variable X is defined as:

$$I(x) = log_a \left(\frac{1}{p(x)} \right) = -log_a(p(x)) \tag{1}$$

The smaller the probability of the event the higher is the information content of the event itself. The unit of information depends on the choice of the logarithmic base a. If $a = 2$ the unit of $I(x)$ is *bits*, if $a = e$ the unit is *nats* and if $a = 10$ the unit is *hartley*. For the sake of clarity the base will be ignored for now. Basing on this the *Shannon-Entropy* $H(x)$ (Shannon, 1948) represents the information content of a message which in this context is a row of events of which the combined information corresponds to the sum of single informations multiplied with the respective event probabilities:

$$H(x) = \sum_x p(x)I(x) = -\sum_x p(x)log(p(x)) \tag{2}$$

For two systems the joint Shannon-Entropy might be written down as,

$$H_D(x,y) = -\sum_{x,y} p(x,y)log(p(x,y)) \tag{3}$$

if independence between x and y cannot be assumed or

$$H_I(x,y) = -\sum_{x,y} p(x,y)log(p(x)p(y)) \tag{4}$$

in the case of independence between x and y. Basing on (3) and (4) one can construct a measure for mutual information between the two systems x and y. I.e. the excess amount of information when wrongly assuming independence although the opposite is true:

$$\begin{aligned} M(x,y) &= H_I(x,y) - H_D(x,y) \\ &= -\sum_{x,y} p(x,y)log(p(x)p(y)) + \sum_{x,y} p(x,y)log(p(x,y)) \\ &= \sum_{x,y} p(x,y)[log(p(x,y)) - log(p(x)p(y))] \\ &= \sum_{x,y} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right) \end{aligned} \tag{5}$$

The *Mutual-Information* is a concept related to the *Kullback-Leibler distance* (also called *relative entropy*) (Kullback, 1959). The *Kullback-Leibler divergence* $K(x)$ corresponds to excess amount of information when wrongly assuming a probability distribution $q(x)$ in contrast to the true distribution $p(x)$ (Schreiber, 2000), i.e. it is a measure of distance between two different distributions.

$$K(x) = \sum_x p(x)\log\left(\frac{p(x)}{q(x)}\right) \tag{6}$$

The same measure can also be applied to conditional probabilities:

$$K(x|y) = \sum_x p(x,y)\log\left(\frac{p(x|y)}{q(x|y)}\right) \tag{7}$$

The problem with the *Mutual Information* measure (5) or the *Kullback-Entropy* (7) however is that it doesn't incorporate any directional dynamic between the two system. I.e. $M(x,y) = M(y,x)$ is symmetric. Reformulating $M(x,y)$ however hints how such a dynamic could be taken into account. It can be shown that $M(x,y) = H(x) - H(x|y)$ or alternatively due to symmetry $M(x,y) = H(x) - H(y|x)$. The Mutual-Information measure can thus be interpreted as a "*... reduction in the uncertainty of x due to the knowledge of y.*" (Cover and Thomas, 1991, p. 20), or the other way around. This points to the related concept of conditional entropy: $H(x|y) = -\sum p(x,y) log(p(x|y))$. One could thus ask if the history of one variable could contribute to its predictability. In this case one could assume that the random variable follows a k^{th} order Markov process and write it down in the form of a conditional entropy:

$$H(x_{t+1}|x_t) = -\sum_{x_{t+1}} p(x_{t+1}, x_t^k) \log(p(x_{t+1}|x_t^k)) \tag{8}$$

where $x_t^k = x_t, \ldots, x_{t-k+1}$. This concept can again be extended to two systems x and y:

$$H(x_{t+1}|x_t, y_t) = -\sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k, y_t^k)) \tag{9}$$

The idea of Schreiber (2000) is now to use the divergence from the Markov property $p(x_{t+1}|x_t) = p(x_{t+1}|x_t, y_t)$ as a proxy for the information flow between y and x.[1] This means one takes the difference between (9) and $H(x_{t+1}|x_t) = -\sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k))$.

$$\begin{aligned} H(x_{t+1}|x_t) - H(x_{t+1}|x_t, y_t) &= -\sum_{x_{t+1}; x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k)) \\ &+ \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \log(p(x_{t+1}|x_t^k, y_t^k)) \\ &= \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \left(\frac{p(x_{t+1}|x_t^k, y_t^k)}{p(x_{t+1}|x_t^k)} \right) \end{aligned} \tag{10}$$

Equation (10) is a again a kind of Kullback-Leibler entropy denoted by (Schreiber, 2000) as the transfer entropy $T_{y \to y}$ which now allows to measure

[1] The assumption of independence between x and y would have again resulted in a symmetric measure.

the flow of information from y to x. Because of its inherent asymmetry there are two relevant equations:

$$T_{y \to x} = \sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t^k, y_t^k) \left(\frac{p(x_{t+1}|x_t^k, y_t^k)}{p(x_{t+1}|x_t^k)} \right) \quad (11)$$

$$T_{x \to y} = \sum_{x_{y+1}, y_t, x_t} p(y_{t+1}, y_t^k, x_t^k) \left(\frac{p(y_{t+1}|y_t^k, x_t^k)}{p(y_{t+1}|y_t^k)} \right) \quad (12)$$

Equation (11) measure the flow of information from y to x while equation (12) measures the flow of information from x to y. In the case one uses a logarithm of base 10 as it is done in the remainder of this article e.g. $T_{x \to y}$ signifies the amount of digits system x adds to system y.

As Ver Steeg and Galstyan (2012) point out sparse data can lead to a systematic bias of the transfer entropy measures (11) and (12) derived above. Therefore along the example by Ver Steeg and Galstyan (2012) the empirical bias estimate by Panzeri and Treves (1996) is used to correct for this systematic error. The Panzeri-Treves bias estimate is calculated for the conditional entropies in (10) on which the transfer entropy is based and subsequently subtracted from the same respectively:

$$BIAS[H(R|S)] = \frac{-1}{2 \cdot N \cdot log(2)} \sum_{s \in dom(S)} (N_s - 1) \quad (13)$$

Here R and S are the response and the signal respectively. The variable N denotes the common sample size while N_s is the number of unique responses for a response $r \in dom(R)$.

3. Measuring Information Flows and Network structures with household surveys

To apply the transfer entropy measure introduced in the last section to e.g. a pair of two agents a time series of one factor variable has to be available for each of the two agents (in the context of this article this factor variable is going to be the question with regard to business conditions $BEXP$ outlined in section 1.2). The University of Michigan consumer survey however unfortunately exhibits a repeated cross section structure and is thus not directly usable for this purpose. Therefore a pseudo-panel structure has to be artificially established beforehand. This is done via neural network clustering as opposed to the traditional technique by Deaton (1985).

3.1. Construction of a pseudo panel

The panel-structure problem mentioned above is addressed by forming a synthetic or pseudo-panel. This technique was originally introduced by Deaton (1985) who uses variables which are not supposed to change over time like sex and birth cohort to group the survey population. The article at hand however applies a neural network clustering technique to construct the pseudo panel, originally suggested by Gardes et al. (1996). This approach has the following crucial advantages: First, it allows to include more comprehensive and precise socio-demographic information when building the pseudo panel and also permits to incorporate more comprehensive socio-demographic information. Second, the information content of continuous variables as for example income does not have to be artificially reduced by grouping them into different classes as this would be necessary if one used Deaton's approach. Such variables can here be used directly in the construction of the pseudo panel. Third, because of the inclusion of more and continuous socio-demographic variables a pseudo panel constructed by the neural network approach is better balanced. Fourth, it can be shown that the construction of cohorts via neural networks results in a lower within cohort and a higher between cohort variance than when using the technique by Deaton Cottrell and Gaubert (2007).

Following the example by Gardes et al. (1996) and Cottrell and Gaubert (2007) this article uses self-organizing Kohonen maps Kohonen (2001) to group the participants within the repeated cross sections into synthetic cohorts. For this reason variables like gender, age, years of school, region of residence, income and race were presented to the algorithm in all in all 1000 iterations to construct a 8×8 hexagonal Kohonen map resulting into 64 cells. For the construction of the Kohonen map the "kohonen" R-package was used (Wehrens and Buydens, 2007).

The ordinal business expectation variable $BEXP$ (see section 1.2) which is central within this article was averaged on a cohort level. Since the computation of the transfer entropy demands a discrete variable the cohort means were then transformed into an ordered variable with three categories. For this purpose a discretization approach was chosen which yields approximately similar frequencies for each category Meyer (2008). This is another remedy to keep the estimation bias of transfer entropies as low as possible. As will be seen in the end of the next section the estimates can be biased by sparse data, which in this context means that not all areas of the probability distributions are observable. Choosing a discretization algorithm which focuses on equal frequencies seems thus appropriate.

		outgoing mean	incoming mean	balance mean
income	(0,200000]	0.04683	0.05663	-0.00980
	(200000,400000]	0.28519	0.05821	0.22698
	(400000,600000]	0.47400	0.09344	0.38056
age	(20,40]	0.03549	0.05329	-0.01780
	(40,60]	0.08693	0.06237	0.02456
	(60,80]	0.03567	0.05380	-0.01812
education	(5,10]	0.07075	0.05124	0.01951
	(10,15]	0.03330	0.05738	-0.02408
	(15,20]	0.08258	0.05896	0.02362
	All	0.05723	0.05723	0.00000

Table 2: Transfer Entropies: split up by education and age

3.2. Calculating the Transfer Entropy for a Social Network

The transfer entropy measure for asymmetrical information transfer (see equations 11 and 12; a lag of one was used) is calculated for each pair of the 64 cohorts which were constructed along the technique outlined in the last subsection in both directions. This results into 4032 transfer entropy measures, two for every cohort. To avoid majority effects the active transfer entropy measures are corrected by means of the survey weights of the respective cohorts as well as the cohort size. This means the outgoing information transfer of cohorts with high survey/cohort weights has been revised downwards, while the outgoing information transfer of cohorts with small survey/cohort weights has been revised upwards. Additionally the balance of outgoing and incoming information transfer was computed.

4. Results

4.1. Summary

Table 2 and 3 present an overview of the results. In both tables three variables are displayed: the average outgoing information, the average incoming information as well as the balance of these two variables for the respective subgroups listed on the left. The higher the balance number the more influential the respective subgroup is.

Especially in Table 2 it is striking that the social influence of cohorts/individuals increases with education and income: While cohorts with a mean income below USD 20.000 are net receivers of information the other income groups are net senders of information. The degree of net sent information is

age	education	outgoing mean	incoming mean	balance mean
(20,40]	(5,10]	0.08525	0.05977	0.02548
	(10,15]	0.03363	0.05350	-0.01987
	(15,20]	0.03236	0.05192	-0.01956
(40,60]	(5,10]	0.09912	0.05226	0.04686
	(10,15]	0.03870	0.06389	-0.02519
	(15,20]	0.12494	0.06342	0.06152
(60,80]	(5,10]	0.04585	0.04833	-0.00249
	(10,15]	0.02044	0.05472	-0.03428
	(15,20]	0.04276	0.05724	-0.01448

Table 3: Transfer Entropies: by income, education and age

increasing in the average income. As far as education is concerned the most influential group is that with between fifteen and twenty years of schooling. The group with ten to fifteen years of schooling are net receivers of information (negative balance value) where the balance of received and sent information is negative and in absolute terms approximately corresponds to the positive balance value of the group with between fifteen and twenty years of schooling. The cohorts with the lowest education in contrast have a positive balance value. This as one will see later on might be explained by some kind of majority effect which persists in spite of the correction by survey and cohort weights outlined above. As far as age is concerned the most influential groups are those with an average between forty and sixty years.

This is also reflected in the more detailed Table 3: The most influential agents are between 40 and 60 years old and hold at least a college degree.

4.2. Identifying information transfer between social groups

The method outlined in section 3.2 supplies list of transfer entropies for each pair of cohorts which alone only permits to present rather superficial results as they were presented in the last section. To allow a better assessment on how information is transmitted within and between different social groups and to make this transmission of information better visible local regressions (locally weighted scatterplot smoothing) (Cleveland et al., 1992) are used to fit the estimated transfer entropy values to a polynomial surface of degree two determined by socio-demographic characteristics as education, income or age. The above described procedure allows to produce continuous heat-maps (also called elevation maps) as in the Figures 1, 2 and 3 which in this context capture the information transmission between social groups of

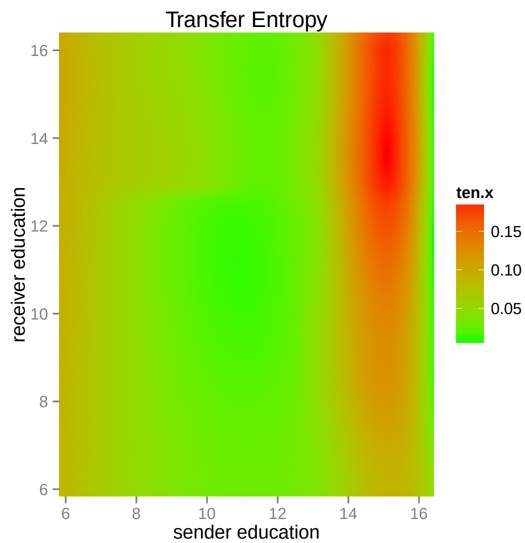

Figure 1: Information transfer between social group with different educational background (x-Axis: sender education; y-Axis: receiver education)

different educational background, different income and different age. The x-axis displays the years of schooling / income / age of the sending individual (cohort) and the y-axis the educational background / income / age of the receiving individual (cohort). Darker shades of red represent a high degree of information transmission. In region with a lighter green shade in contrast the information transmission from the x-axis to the y-axis is lower.

Figure 1 suggests that there is a high degree of information transfer from groups with high education to both groups with lower and higher education. This means that agents with high education are not only net senders of information as was already evident by the figures in Table 2 but are influential beyond their social class. It is however noteworthy that this influence is not equal on all social groups. The dark red shades in the upper right corner suggest some kind of peer effect: Agents with high education mainly interact with highly educated peers. The degree of information transmission is accordingly higher within this group.

Figure 2 supports the findings of the last section. Social influence here in the context of expectations with regard to the overall economic development is increasing with income. Two things are worthwhile to note: First, as far as high income groups are concerned there also seems to be a peer effect

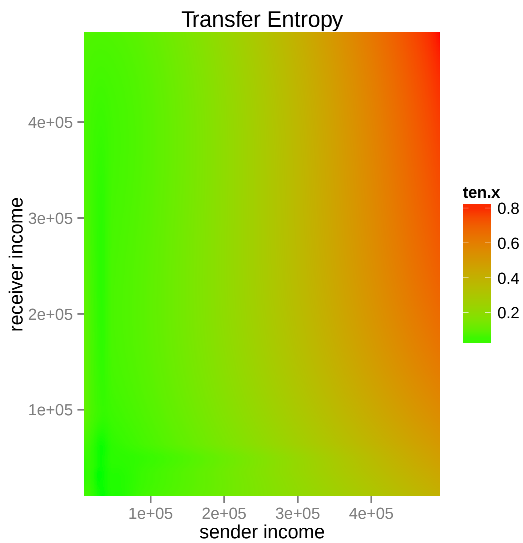

Figure 2: Information transfer between social groups with different income (x-Axis: sender income; y-Axis: receiver income)

mechanism at work as it is the case in the of education which was discussed above. Second, agents with low income are susceptible to adopt opinions from other social groups.

Figure 3 finally breaks down the transmission of information by the age of agents. As was already seen in the last section the most influential agents are between forty and sixty years old. The social influence of this group is however not only limited to peers but extends to all age groups.

4.3. Transfer Entropy and Social Networks

A striking feature of applying information theory to survey data as outlined in sections 2 and 3 is that it not only allows to measure information transmission between different social groups (some results were presented above) but also to take a closer look at the structure of social networks themselves.

To do so it is simply assumed that one cohort X has strong ties to another cohort Y if the transfer entropy T_{xy} surpasses as certain value. In this context we do so by only looking at highest decile of transfer entropies. Only then it is assumed that there is a close and stable connection between two agents/cohorts. The result is graphically displayed in Figure 4. It is

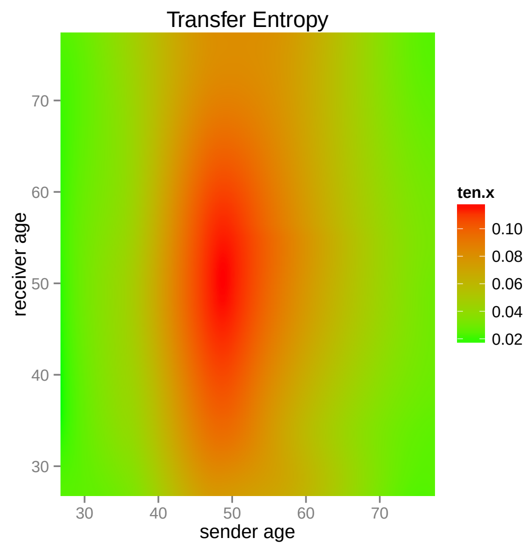

Figure 3: Information transfer between social groups with different age (x-Axis: sender age; y-Axis: receiver age)

striking that there seems to be a hierarchy between the different nodes (of which each represents a cohort; some cohorts dropped out due to the lack of strong connections). This means there are some nodes with a lot of connections while other only have few.

Calculating the degree distribution this means the cumulative frequencies or probabilities of nodes with a given degree (number of ties) we can investigate the structure of the network. E.g. the $P(d)$ is the fraction of nodes with a degree d. When k is the number of nodes and $P(k) = 1$ as well as $P(d \neq k) = 0$ then one speaks of a *regular network*. In reality networks however rather follow a *power-law*. This means the probability of nodes with higher degrees falls exponentially as the number of degrees increases. In this case such a network is denoted as a *scale-free network*: $P(d) = cd^{-\gamma}$. Here $c > 0$ is a scalar and γ is the exponent of the power law (Jackson, 2010, p. 31).

To test if the social network we established by measuring transfer entropies between each pair of cohorts within the Michigan consumer survey also follows a scale free distribution we can simply fit a power-law to the empirical

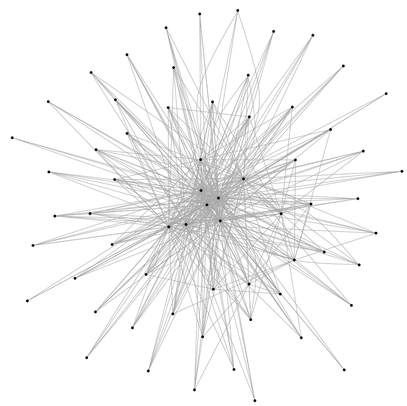

Figure 4: The social network as estimated by the University of Michigan consumer Survey

degree distribution.[2] The result is displayed in Figure 5.

The estimated value of γ corresponds to 2.277632. A Kolmogorov-Smirnov test with a test statistic of 0.0854612 (p-value: 0.8503368) suggests that the hypothesis that the original sample data from the network established by measuring transfer entropies between pairs of cohorts within the Michigan Consumer Survey could have been drawn from the fitted power-law distribution cannot be rejected. It follows that the estimated network follows a power-law distribution and thus represents a scale free networks.

The network estimated by the technique outlined above further exhibits a high degree of clustering: The cluster or transitivity coefficient (Wasserman and Faust, 1994) is at 0.2900302 reflecting a rather high probability that the neighbouring nodes of a node are connected.

4.4. Higher connectivity, more influence

With regard to the results presented in section 4.2 one might ask if the influence of certain agents on others is also reflected in their connectivity,

[2] This was done using the power.law.fit function implemented in the R package igraph (Newman, 2005; Clauset et al., 2009).

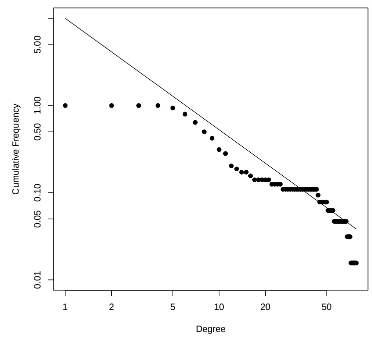

Figure 5: Cumulative degree distribution with power law fitted

namely in the degree of the most influential nodes. The transfer entropy alone only measures the information flow from one agent to another. This means the figures presented until now could have depended on a few very strong connections.

Displaying Figure 4 in the form of arcplots as done in Figure 6 has the advantage that one can order the nodes by certain characteristics which in turn allows to make assertions about how the characteristics influence the connectivity of the nodes. Figure 6 shows that the influence of agents indeed coincides with very high connectivity: This means the higher the education or the income of agents the better connected they are. The same is true for higher age. This might seem contradictory to the results discussed in section 4.2. One has to note however Figure 6 only displays the strongest 10% of connections and weaker connections were dropped. Therefore not the whole range of age classes (in example those weaker connected age classes beyond 60 years) are displayed in the plots.

To-do: 1)group level centrality measures; 2) group level clustering measures

4.5. Information transfer over time

Figure 7 displays the measured transfer entropies with respect to education, age and income as a function of time. In contrast to before here the width of the time bin k (outlined in section 2) which used to be one month for the results presented above is now varied between one and twelve months. This means while we before only paid attention to the contributions in terms of

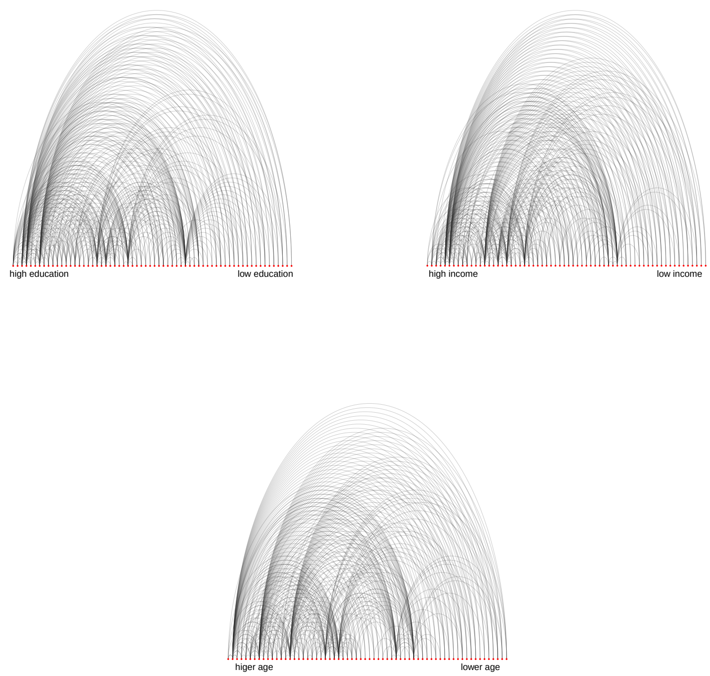

Figure 6: The Social Network in the form of ordered arcplots

predictability from y_t to x_{t+1} that is $H(x_{t+1}|x_t) - H(x_{t+1}|x_t, y_t)$ we now instead extend the signal length and look at $H(x_{t+1}|x_t^k) - H(x_{t+1}|x_t^k, y_t^k)$ where $x_t^k = x_t, \ldots, x_{t-k+1}$, $y_t^k = y_t, \ldots, y_{t-k+1}$ and $k \in 1, \ldots, 12$.

Extending the signal length into the past shows that the information transfer on average sharply increases until $k = 3$ and slowly decreases for higher bin widths. As already seen in Figures 1 to 3 influence increases with education as well as income. As far as age is concerned one observes a clear peak at age groups between forty and sixty years. The decline of the transfer entropies when extending the signal length beyond $k = 3$ is approximately equivalent over all groups.

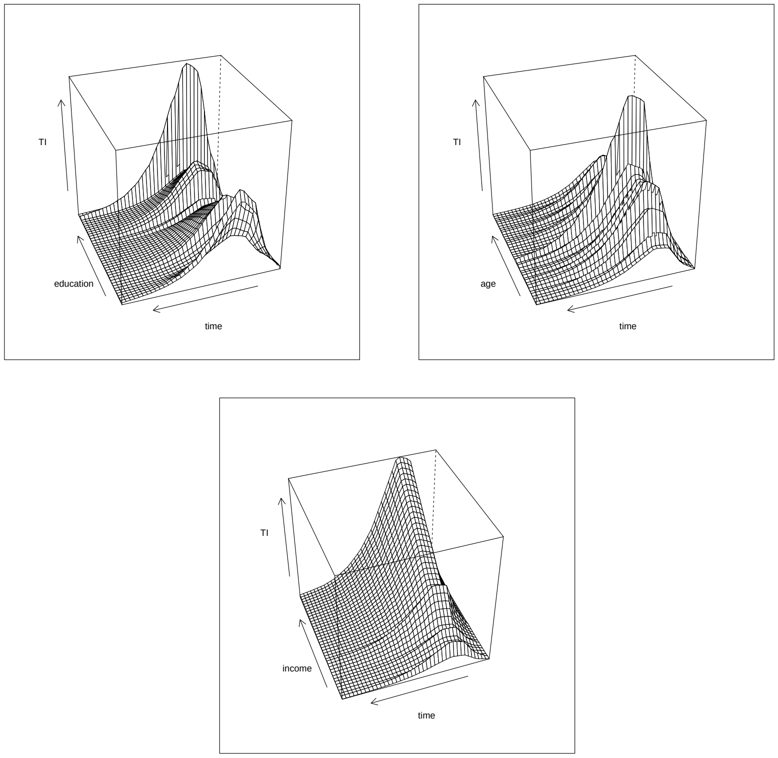

Figure 7: Information Transfer under consideration of different time lags

5. Conclusion

This paper presents a way to apply information theory namely the concept of *transfer entropy* by Schreiber (2000) to consumers surveys. Using self-organizing Kohonen maps the repeated cross-section structure of the University of Michigan consumer survey data set was transformed into a pseudo panel with 64 cells. Subsequently the information theoretic measure of transfer entropy was used to measure the information flow between all pairs of cohorts in the context of business expectations. It was shown that social influences is strongly determined by the socio-demographic situation of an agent: Social influence on other agents increases with education and income. As far as age is concerned agents between forty and sixty years are the opinion leaders exerting influence on other groups.

Looking only at the strongest ties in terms of information transfer between the different cohorts within the University of Michigan survey data set allows to assess the underlying network structure. It turns out that the estimated social network is scale-free and follows a power-law with an exponent γ of 2.277632. This means the number of agents falls exponentially with the number of their degrees. Such a network structure is realistic and often observed. We further saw that high influence coincides with high connectivity. This means that highly influential agents exert their influence not only on a few other cohorts but play a central rule within the network structure. Social influence reaches a peak when including three months of past data but diminishes beyond this date.

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