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Infectious happiness in heterogeneous social networks: evidence from rural China

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Abstract

We investigate infectious effects in happiness using a novel panel of data from a village in China. We construct a complete and heterogeneous social network that includes all households, and use spatial econometric models to estimate the infectious effect. We find that both infectious and contextual effects within social networks are significant for household happiness. Household happiness is not positively influenced by the happiness of the household's closest family, but rather by others from the social network who are not particularly close to the household. We also provide evidence for envy effects between the closest families.

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1. Introduction

There is an emerging literature focused on the infectiousness of happiness, referring to an observed positive correlation between individual-level and group-level happiness (Tumen and Zeydanli, 2015), that is largely motivated on related policy implications (Povey, 2015). Research on infectious happiness began with a 20-year psychological study that found that an individual's happiness is positively correlated with the happiness of others, and attributed the observed happiness clustering to the spread of happiness (Fowler and Christakis, 2008). However, Manski (1993) shows that it is not straightforward to separate spillovers in outcomes from the social context, and economists that have explored this issue have come to conflicting conclusions. For example, Knight and Gunatilaka (2017) use data from rural China and find that individual happiness is positively dependent on the happiness of other people in the village; they use an IV approach to determine causality. Yet, Tumen and Zeydanli (2015) did not find evidence of the spread of happiness in the UK, finding instead that clustering patterns of happiness is determined by contextual effects – that is, the spread of happiness is related to the characteristics of others in the group, not the happiness of others in the group.

The impact of peer happiness on an individual is complex. One can imagine positive mechanisms like emotional contagion among people that interact (e.g., Sato and Yoshikawa, 2007), though at the same time the happiness of one's peers may have a negative impact on individual happiness on account of jealousy. Furthermore, the characteristics of one's peers can influence one's happiness; for example, higher peer income may lead to a reduction in one's happiness (e.g., Ferrer-I-Carbonell, 2005). We emphasize that previous studies focused on the infectious and contextual effects of happiness have done so through a group-structured "peer effects" model, and not through a specified social network structure. The group-structured approach treats all individuals within each group homogeneously, whereas the network approach is capable of examining the heterogeneous links between individuals within a social structure, thereby garnering a deeper understanding into the nature of the infectiousness of happiness.

Based on a unique panel dataset from a village in China with an explicit network structure, we investigate heterogeneity in the infectious effects of happiness through the network. In the survey, we obtained information on social relationships among all households in the village and constructed a complete and heterogeneous social network. This data allows us to eschew the assumption that individuals are equally influenced by all peers, and analyze the infectiousness of happiness among people with different social relationships; meanwhile, we employ network (spatial) econometric models so as to avoid the reflection problem (Bramoullé et al. 2009) and to identify both the infectious effects (endogenous social effects) and the contextual effects of happiness.

2. Data

Our data come from a long-running, multiple-period survey of the rural Hong Village that is located in Gansu Province in northwestern China; this region is characterized by the topography of the Loess Plateau. Households are scattered across ridges and valleys of dry mountains, and clustered in six sub-villages. A map of Hong Village is provided in the appendix.

There are a total of 206 households in Hong Village, and from 2010 to 2016, we repeatedly interviewed all households annually, and constructed a seven-phase, balanced panel dataset.

In the annual survey, we measured household happiness via the question "How would you rate the overall happiness of your family in the previous year?" The scoring ranged from 1 to 10, in which a score of 1 reflects "very unhappy" and a score of 10 reflects "very happy".

We also surveyed the social network structure within Hong Village through a self-nomination method in which we asked each household with which of the other 205 households they had a social relationship, the type of that relationship, and the timeline through which that relationship was established or dissolved. The social relationships fall into five distinct categories: distant neighbors, close neighbors, distant relatives, friends, and close relatives. Based on these data, we construct three different types of social networks.

The first is the complete social network. Let W be a 206×206 matrix representing the social network, where the (i,j)th element of W, denoted as w_{ij}, is a binary indicator that equals one if there are any of the above social relationships between households i and j, and zero otherwise. Simultaneously, w_{ii} is defined as 0 to exclude self-relations within the network.

We refer to the other two networks as the close network and the non-close network. As part of the survey, we obtained gift flow records from 9 households for the years 2014-2016, detailing 503 gift exchanges with other families within the village (specifically, monetary values of gifts given). We find that the average gift value given to close neighbors, distant relatives, friends, and close relatives was 1.46, 1.81, 1.82, and 3.47 times greater than those given to distant neighbors, respectively. Anthropologists have found that in reciprocity gift-giving networks the closer the relationship between the giver and the recipient, the higher the value of the gift (Yan, 1996). Thus, with this intuition and our data, we see that compared to the other four types of social relationships, families have a much closer social distance with close relatives (because the gift values are so much larger). Therefore, based on social distance, we define close relatives as close relationships, and distant neighbors, close neighbors, distant relatives, and friends as non-close relationships, leading to the construction of the close and the non-close network. Specifically, for the close network, we reassign a value of 1 to w_{ij} if there is a close relationship between household i and j, and 0 otherwise, and construct the close network. Similarly, for the non-close network, we assign a value of 1 to w_{ij} if there is a non-close relationship between household i and j, and 0 otherwise.

In Table 1, we report descriptive statistics for several network-related variables over the 2010 to 2016 period, and in Figure 1 we plot the complete social network connections from 2016. The figure makes clear that the households in Hong Village are very well-connected, without any isolated nodes. Further, each household has, on average, more than 70 connections with other households; as expected, households have significantly fewer close relationships than non-close relationships.

Table 1 Descriptive statistics of the social networks

	2010	2011	2012	2013	2014	2015	2016
Complete Social Network							
Average Degree of Centrality	70.93	71.09	71.31	71.51	71.55	71.66	71.71
Average Geodesic Distance	1.66	1.66	1.66	1.66	1.66	1.66	1.66
Maximum Geodesic Distance (Diameter)	3	3	3	3	3	3	3
Close Network							
Average Degree of Centrality	14.39	14.46	14.49	14.49	14.50	14.50	14.53
Average Geodesic Distance	2.72	2.72	2.70	2.70	2.70	2.70	2.70
Maximum Geodesic Distance (Diameter)	6	6	6	6	6	6	6
Non-Close Network							
Average Degree of Centrality	56.44	56.59	56.76	56.96	57.00	57.17	57.38
Average Geodesic Distance	1.76	1.76	1.76	1.75	1.75	1.75	1.75
Maximum Geodesic Distance (Diameter)	3	3	3	3	3	3	3

Notes: Indicators are calculated by Node XL.

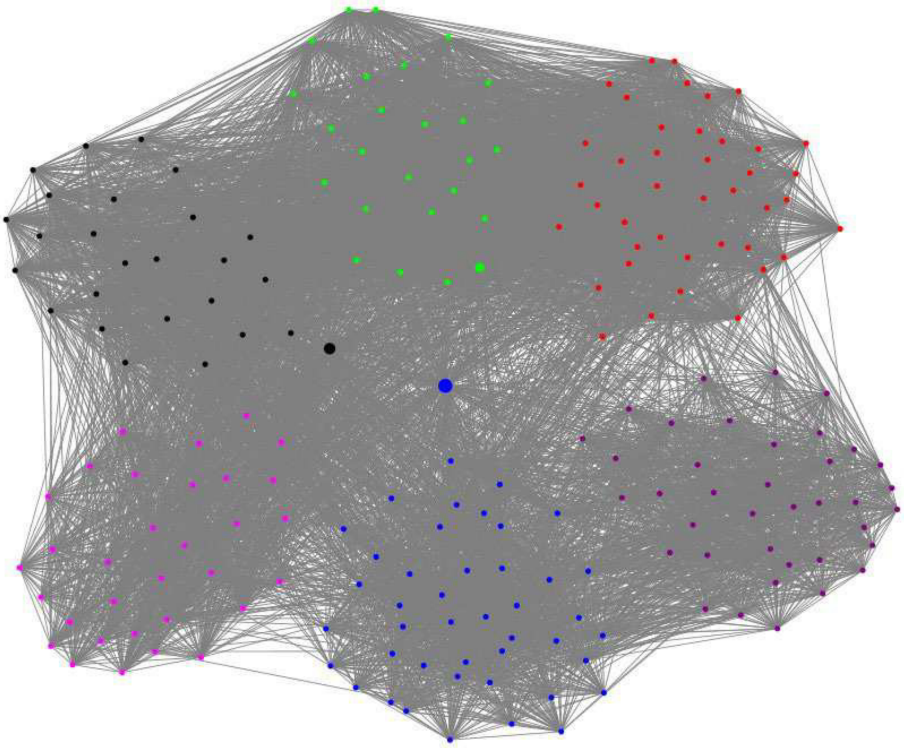

Fig. 1 Visualization of the Complete Social Network in 2016

Note: Each dot represents a household, the different colors indicate the six sub-villages, and the lines connecting the dots represent the social relationships between households.

3. Model

Our infectious happiness model is:

$$H_{it} = \rho \sum_{j=1}^{n} w_{ij} H_{jt} + \sum_{k=1}^{K} \beta_k x_{itk} + \sum_{k=1}^{K} \sum_{j=1}^{n} \theta_k w_{ij} x_{jtk} + \alpha_i + \lambda_t + \varepsilon_{it} \qquad (1)$$

where for n households, H_{it} represents the happiness of household i in time t and x_{itk} represents the k-th characteristic of household i in time t; the definitions and descriptive statistics of characteristic are reported in Table 2. w_{ij} represents the social relationships between households i and j introduced above. In Hong Village, social relationships are primarily kinship relationships that are determined by clan relation and/or neighbor relationships determined by geography (since the village area is mountainous and therefore not easily traversed); hence, w_{ij} is largely formed on exogenous attributes and so in our econometric analysis we treat it as exogenous. Additionally, these particular social networks are stable over time (see the limited temporal variation in Table 1), and so we fix w_{ij} according to the 2016 social networks. α_i is the time-invariant fixed effect for household i, λ_t is the time fixed effect that affects all households, and ε_{it} is the error term.[1]

[1] The correlated unobservables, or correlated effects, refer to the observable convergence in happiness that may be driven by a common shock to all households (through the λ_t term) or similar family

The coefficient ρ captures the infectious effect of happiness, and θ_k captures the contextual effects (e.g., Manski 1993). For network (spatial) econometric models, the infectious effect can be identified if the network diameter isn't less than 3 (Bramoullé et al., 2009); this condition is satisfied in our three social networks (see Table 1). We estimate the model using quasi-maximum likelihood.

Table 2 Definitions and descriptive statistics of variables

Variable	Description	Mean	St. Dev.	Min	Max
Happiness	Self-reported index of family happiness. Ranges from 1 (minimum) to 10 (maximum)	6.618	2.246	1	10
Income	Natural log of net per capita family income	8.051	2.240	0	13.461
Asset	Standardized indicator for household asset	0.000	1.000	-2.112	4.517
Age	Age in years of the household head	48.888	7.712	21	79
Edu	Education in years of the household head	5.562	3.372	0	15
Married	Marital status of the household head, 1=yes, 0=no	0.900	0.300	0	1
Members	Number of family members	4.361	1.439	1	11
Health	Proportion of family member that are healthy	0.782	0.256	0	1
Cadre	Village cadre, 1=yes, 0=no	0.015	0.120	0	1
Party	Party member , 1=yes, 0=no	0.140	0.347	0	1
$Respondent_1$	Whether the respondent is the spouse of the household head, 1=yes, 0=no	0.249	0.433	0	1
$Respondent_2$	Whether the respondent is the child of the household head, 1=yes, 0=no	0.058	0.234	0	1
$Respondent_3$	Whether the respondent is another family member, 1=yes, 0=no	0.033	0.179	0	1

Notes: “Asset” is constructed by applying principal component analysis to a set of variables (television, air conditioning, refrigerator, computer, mobile phone, truck, car, motorcycle, tractor, agricultural machinery, and land). We take the household head as the baseline for the “Respondent”. The survey for each household is conducted separately, and the type of respondents does not affect the happiness of other households, so, the spillover effects of respondent types are not considered in the model. More detailed information about the respondents is provided in the appendix.

4. Results

Table 3 reports the estimation results of the panel fixed effects model following Eq. (1) under the three social networks.[2] We find that, for the complete social network, there is no evidence of infectious happiness. Further analyzing heterogeneity in the social relationships, we also find no infectious effect in the close network. Instead, our results provide evidence for an envy effect: as shown in Table 3 Column 2, the assets of other households have a negative effect on happiness as a household’s happiness decreases as the economic level of other households within the close network increases. In contrast, for the non-close network, there is a significant infectious effect on happiness,

characteristics (through α_i), and needs to be controlled for when isolating the infectious effect (see Manski, 1993).

[2] A Hausman test indicates that the fixed-effect model provides a better fit than a random-effects model.

even after controlling for family characteristics, contextual effects, and unobservable factors. This implies that household happiness is positively impacted by the happiness levels of other families with whom they have a non-close relationship. Specifically, as shown in Column 3 of Table 3, for every 1 unit increase in the average happiness of other families from the non-close network, the happiness of a family increases by 0.292 units. Meanwhile, the negative externality of assets does not persist in the non-close network.

Table 3 Regression results

	(1) Complete Social Network	(2) Close Network	(3) Non-close Network
Infectious Effect (ρ)	0.170	0.081	0.292***
	(0.138)	(0.056)	(0.113)
Own (β)			
Income	-0.003	-0.009	0.009
	(0.024)	(0.024)	(0.024)
Asset	0.209*	0.241**	0.208*
	(0.112)	(0.114)	(0.113)
Age	0.015	0.020	0.014
	(0.014)	(0.014)	(0.014)
Education	0.169***	0.176***	0.144**
	(0.059)	(0.059)	(0.059)
Married	0.334	0.365	0.402
	(0.250)	(0.251)	(0.251)
Members	-0.114	-0.120*	-0.109
	(0.071)	(0.072)	(0.071)
Health	0.807***	0.670***	0.826***
	(0.239)	(0.237)	(0.240)
Cadre	0.713	0.363	0.537
	(0.668)	(0.660)	(0.664)
Party	0.418	0.406	0.354
	(0.371)	(0.374)	(0.371)
Respondent_1	-0.009	-0.014	-0.025
	(0.137)	(0.138)	(0.138)
Respondent_2	-0.247	-0.255	-0.288
	(0.230)	(0.232)	(0.230)
Respondent_3	0.129	0.209	0.058
	(0.335)	(0.338)	(0.337)
Contextual (θ)			
Income	-0.160	0.058	0.130
	(0.185)	(0.057)	(0.147)
Asset	0.119	-0.590*	0.642
	(0.954)	(0.333)	(0.823)
Age	0.212	0.027	0.354***
	(0.172)	(0.038)	(0.128)

Education	3.379***	0.423**	1.834***
	(0.662)	(0.168)	(0.459)
Married	-2.055	-0.373	4.711**
	(3.128)	(0.697)	(2.082)
Members	0.845	0.379**	0.151
	(0.810)	(0.178)	(0.661)
Health	2.594*	1.151*	0.927
	(1.461)	(0.683)	(1.331)
Cadre	12.644	-1.545	2.813
	(8.510)	(2.221)	(5.635)
Party	3.030	0.854	0.672
	(3.472)	(1.132)	(3.071)
Observations	1442	1442	1442
Household Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes

Note: Networks are contiguity networks. Standard errors in parentheses; * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.

We conduct placebo tests to strengthen the reliability of the results from the non-close network, as this is where we find a significant infectious happiness effect. We create 5000 placebo networks in which households were randomly connected, and estimate the same panel fixed-effects model for each placebo network. As shown in Table 4, 24.60% of placebo trials show significant infectious effects at the 5% statistical level, which seemingly contradicts our empirical results. Drawing on the analysis strategy for small and tightly connected networks proposed by Fang et al. (2023), we further analyze the relationship between the overlap degree between the placebo network and the real network (the proportion of true connections also present in the placebo network) and the contagion effects in the placebo regression.[3] The second row of Table 4 shows a positive correlation between these two indicators, indicating that as the placebo network gets closer to the real network, the likelihood of significant infectious effects in the placebo test increases. Taking stock, we believe that these placebo test results are supportive of our empirical findings.

Table 4 Results of the placebo test

	Non-close Network
Percent with infectious effects p-value less than 0.05	24.60%
Correlation coefficient of the true percentage with whether the p-value is less than 0.05	0.132

Notes: The true percentage refers to the proportion of fake connections in the placebo network that overlap with true connections in networks.

[3] Because the non-close network is small and well connected, it is easy for the randomly-generated placebo connections overlap with true connections.

5. Conclusion

Based on a complete and heterogeneous social network of a village in China, we show heterogeneity in the infectious effects of happiness. We find that happiness spreads through less intimate social relationships, but does not spread through close relationships. That is, household happiness is influenced positively by the happiness of others in non-close social networks, but not by those closest to the household. We further provide evidence for envy effects in close social networks. The heterogeneity of infectious happiness implies a smaller social multiplier than found in linear group-structure models, but still has implications for welfare policies, especially in relatively isolated rural areas of developing countries where people are closely connected. In closing, we note that our research focuses on the infectiousness of happiness within social networks among households, and the heterogeneity of happiness contagion within individual networks deserves further exploration.

References

Bramoullé, Y., Djebbari, H., and Fortin, B. (2009) "Identification of peer effects through social networks" *Journal of Econometrics* **150**, 41-55.

Fang, H., Chen, Q., Delgado, M., and He, Q. (2023) "Peer correlations in income: Evidence from a *Guanxi* network in rural China" *Economics Letters* **222**, 110959.

Ferrer-I-Carbonell, A. (2005) "Income and well-being: an empirical analysis of the comparison income effect" *Journal of Public Economics* **89**, 997–1019.

Fowler, J. H., and Christakis, N. A. (2008) "Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study" *British Medical Journal* **337**, a2338.

Knight, J., and Gunatilaka, R. (2017) "Is happiness infectious?" *Scottish Journal of Political Economy* **64**, 1-24.

Manski, C. F. (1993) "Identification of endogenous social effects – The reflection problem" *Review of Economic Studies* **60**, 531-542.

Povey, R. (2015) "The welfare economics of infectious happiness" *Economics Letters* **133**, 1-3.

Sato, W., and Yoshikawa, S. (2007) "Spontaneous facial mimicry in response to dynamic facial expressions" *Cognition* **104**, 1–18.

Tumen, S., and Zeydanli, T. (2015) "Is happiness contagious? Separating spillover externalities from the group-level social context" *Journal of Happiness Studies* **16**, 719-744.

Yan, Y. (1996) *The Flow of Gifts: Reciprocity and Social Network in a Chinese Village*, Stanford: Stanford University Press.