Externalities in Endogenous Sharing Economy Networks

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Abstract

This paper investigates the impact of link formation between a pair of agents on the resource availability of other agents (that is, externalities) in a social cloud network, a special case of endogenous sharing economy networks. Specifically, we study how the closeness between agents and the network size affect externalities.

We conjecture, and experimentally support, that for an agent to experience positive externalities, an increase in its closeness is necessary. The condition is not sufficient though. We, then, show that for populated ring networks, one or more agents experience positive externalities due to an increase in the closeness of agents. Further, the initial distance between agents forming a link has a direct bearing on the number of beneficiaries, and the number of beneficiaries is always less than that of non-beneficiaries.

KEYWORDS
endogenous; sharing economy; network; externalities; social cloud

1. Introduction

The sharing economy (Puschmann and Rainer 2016) is not free from externalities, the effects of actions of individual agents on other agents. Studies (for example, Jing and Sun (2018)) have investigated externalities and its sources in the sharing economy. However, these studies have mainly focused on platform-mediated sharing models where consumers and providers are matched. Numerous studies have looked at sharing platforms with negative externalities (Katz 2015; Cohen and Sundararajan 2017; Frenken and Schor 2017) and with positive externalities too (Basselier, Langenus, and Walravens 2018).

Externalities in endogenous network formation are usually studied in determining which network structure is likely to emerge, and to understand the tension between network stability and its efficiency (Buechel and Hellmann 2012). However, in this paper, we study externalities with a different motivation — to study how closeness and network size affect externalities.

To study the above aspects, we consider the social cloud model proposed by Mane, Ahuja, and Krishnamurthy (2014), a sharing economy network (Georgiadis, Iosifidis, and Tassiulas 2017), different from platform-mediated sharing models and endogenously formed. On the one hand, we have online data backup services like Buddy-

Backup[1] and CrashPlan[2], which are examples of such social clouds, where two agents share or trade resources directly with each other, without an intermediary third-party. On the other hand, we have traditional cloud service providers like Amazon's AWS S3[3] and Microsoft's Azure[4], which are examples of players in a horizontal market where different cloud providers compete for customer requests of computational resources.

2. Social Cloud Model

A social cloud $\mathfrak{g}$ is a storage or computational resource sharing network of N agents connected by $\mathcal{L}$ links, that evolves endogenously when agents build their resource sharing connections. According to Chard et al. (2012), agents could limit resource sharing with friends who are close to them. Mane, Ahuja, and Krishnamurthy (2014) capture this closeness by using the harmonic centrality measure (Boldi and Vigna 2014), as

$$\Phi_i(\mathfrak{g}) = \sum_{j \in \mathfrak{g} \setminus \{i\}} \frac{1}{d_{ij}(\mathfrak{g})},$$

where $d_{ij}(\mathfrak{g})$ is the distance between agents i and j, that is, the length of any shortest path between them.

Similar to Mane, Ahuja, and Krishnamurthy (2014), we define the probability that agent i obtains a resource from j as

$$\alpha_{ij}(\mathfrak{g}) = \frac{\frac{1}{d_{ij}(\mathfrak{g})}}{\Phi_j(\mathfrak{g})}.$$

The probability that agent i will get the resource from at least one agent in the network $\mathfrak{g}$ is

$$\gamma_i(\mathfrak{g}) = 1 - \prod_{j \in \mathfrak{g}} (1 - \alpha_{ij}(\mathfrak{g})).$$

Based on the definition of externalities by Jackson and Wolinsky (1996), we define the following for the social cloud model.

Definition 2.1. Suppose $\mathfrak{g}$ is a social cloud, with distinct agents i, j, k such that $\langle jk \rangle \notin \mathfrak{g}$. If j and k add a link, the resulting network denoted by $\mathfrak{g} + \langle jk \rangle$, then i experiences

(1) no externalities if $\gamma_i(\mathfrak{g} + \langle jk \rangle) = \gamma_i(\mathfrak{g})$,
(2) negative externalities if $\gamma_i(\mathfrak{g} + \langle jk \rangle) < \gamma_i(\mathfrak{g})$, and
(3) positive externalities if $\gamma_i(\mathfrak{g} + \langle jk \rangle) > \gamma_i(\mathfrak{g})$.

[1] buddybackup.com
[2] crashplan.com
[3] aws.amazon.com/s3
[4] azure.microsoft.com

Our objective is to investigate the impact of a newly added link $\langle jk \rangle$ in $\mathfrak{g}$ on the relation between changes in

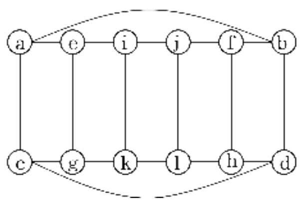
(1) Φ_i and γ_i,
(2) N, d_{jk} and γ_i,

for all $i \in \mathfrak{g}$.

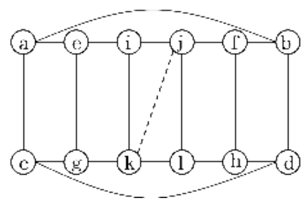
3. Findings

3.1. *Externalities and Closeness*

On first glance, it seems that the harmonic centrality would lead to only negative externalities. However, a careful analysis reveals that both positive and negative externalities are exhibited. This is an important motivation of our study. Consider the network $\mathfrak{g}$ (Figure 1(a)). On adding link $\langle jk \rangle$, we get $\mathfrak{g} + \langle jk \rangle$ (Figure 1(b)). $\gamma_i(\mathfrak{g} + \langle jk \rangle) - \gamma_i(\mathfrak{g})$



(a) Network $\mathfrak{g}$



(b) Network $\mathfrak{g} + \langle jk \rangle$

Figure 1. Example: Externalities and Closeness

provides a basis for the study of externalities. As shown in Table 1, the link $\langle jk \rangle$ is advantageous for agents f and g (shown in blue), and for j and k themselves, but disadvantageous for the remaining agents (shown in red).

agent (x)	$\Phi_x(\mathfrak{g})$	$\gamma_x(\mathfrak{g})$	$\Phi_x(\mathfrak{g} + \langle jk \rangle)$	$\gamma_x(\mathfrak{g} + \langle jk \rangle)$	$\gamma_x(\mathfrak{g} + \langle jk \rangle) - \gamma_x(\mathfrak{g})$
a	6.25	0.654	6.25	0.646	-0.008
b	6.25	0.654	6.33	0.650	-0.004
c	6.25	0.654	6.33	0.650	-0.004
d	6.25	0.654	6.25	0.646	-0.008
e	6.25	0.654	6.25	0.644	-0.011
f	6.25	0.654	6.50	0.657	0.003
g	6.25	0.654	6.50	0.657	0.003
h	6.25	0.654	6.25	0.644	-0.011
i	6.25	0.654	6.25	0.637	-0.017
j	6.25	0.654	7.00	0.687	0.033
k	6.25	0.654	7.00	0.687	0.033
l	6.25	0.654	6.25	0.637	-0.017

Table 1. Externalities and Closeness

Observation 1. *Addition of a link ($\langle jk \rangle$, above) results in the same closeness for some agents (for example, h and i) and an increased closeness for the others (for example, b and c). Addition of a link cannot decrease the closeness of any agent, and always increases the closeness of the agents who add the link (j and k).*

Conjecture 1. *For an agent to experience positive externalities, an increment in its closeness is necessary.*

Finding 1. *For an agent to experience positive externalities, an increment in its closeness is not a sufficient condition. For example, although the closeness of agents b and c increases, their chance of obtaining a resource does not improve.*

3.2. *Network Size Analysis*

For our second objective, we focus on the ring network with sizes varying from 4 to 30 agents, considered reasonably large in the literature on experimental research on economic networks (Choi, Gallo, and Kariv 2016). Very large networks may encode a very limited amount of information (Chandrasekhar 2016).

We focus on the ring network as its harmonic centrality is uniform. This helps us investigate the relation between externalities and network size.

To obtain data, we adopt a single computer program-based simulation (Naylor, Burdick, and Sasser 1967; Friedman and Cassar 2004) method due to unavailability of data of real world networks like BuddyBackup or CrashPlan, and because of the endogeneity issue (Choi, Gallo, and Kariv 2016) faced by various studies.

We, initially, compute $\gamma_i(\mathfrak{g})$ for all agents in a ring network $\mathfrak{g}$. Then, we select an agent j arbitrarily and add a link with another agent k whose distance is two hops from j. We compute $\gamma_i(\mathfrak{g} + \langle jk \rangle) - \gamma_i(\mathfrak{g})$, and count the number of beneficiaries (NOB) i for whom this difference is positive. We repeat the above for all agents k who are located at distance two hops from agent j in $\mathfrak{g}$. Then, we increment the distance between j and k by one and follow the same procedure. We do this until we exhaust all agents j.

Figure 2 summarises our results. The *x-axis* represents the shortest distance between two agents involved in link formation. The *y-axis* represents the NOB. The *z-axis* represents the network size (the number of agents in the network).

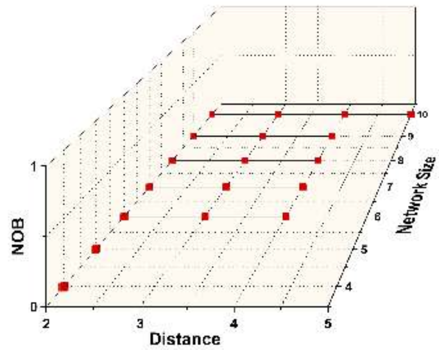
Finding 2. *In "less" populated ring networks, no agent experiences positive externalities.*

In networks with size varying from 4 to 10 (Figure 2(a)), no agent experiences positive externalities. From Conjecture 1, positive externalities require an increase in closeness, which is absent here. However, from network size 11 to 30 (Figures 2(b) and 2(c)), a significant number of agents experience positive externalities.

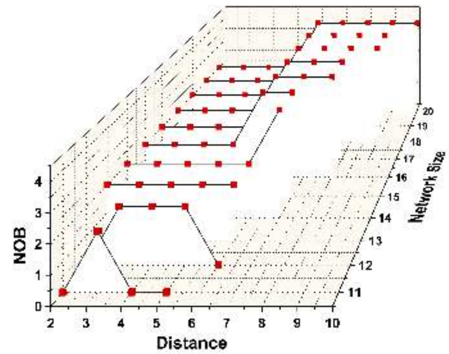
Finding 3. *In ring networks of size greater than 10, as the distance between the agents involved in link addition increases, the number of beneficiaries increases in most cases, and in all cases for small distances.*

Plots in Figures 2(b), 2(c) and 2(d) are of this type. It is clear that, if an agent experiences positive externalities, its closeness should increased (from Conjecture 1). This is intuitive — if a pair of agents who are far from each other in $\mathfrak{g}$ form a link then, this link reduces the mutual distances among other agents, and therefore, their closeness increase. As discussed in Finding 1, an increase in closeness is not a sufficient condition for positive externalities. We believe that an increase in closeness together with some conditions will always imply positive externalities, and leave open this question of finding the other conditions of sufficiency.

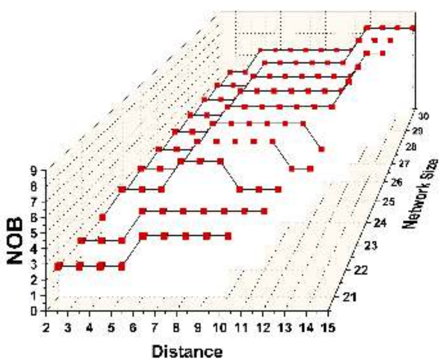
Finding 4. *In ring networks, the number of beneficiaries is always less than the*



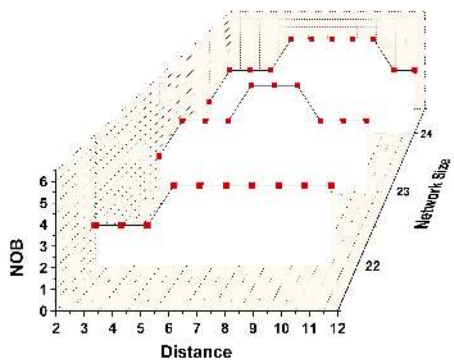
(a) Network Size 4-10



(b) Network Size 11-20



(c) Network Size 21-30



(d) Network Size 22-24

Figure 2. Externalities and Network-Size

number of non-beneficiaries.

In all our experiments, the percentage of beneficiaries varies from 0% to 26% of the total number of agents in the network.

4. Conclusion

Though our investigations are on a small scale, our findings have many applications and implications. Our study enhances our understanding of externalities in the sharing economy network model. Our findings show that network size is also a key factor in determining externalities.

Our approach of relating externalities and group well-being (that is, measuring the percentage of beneficiaries versus non-beneficiaries) enriches the transfer-based network formation model (where agents subsidise others to form or not to form a link with others), (Bloch and Jackson 2007) by incorporating group subsidisation. In particular, agents can subsidize a pair of agents involved in a link formation, instead of individual subsidization. For example, in some research and development settings, where a set of beneficiary-firms are willing to pay a pair of firms that would like to collaborate (Jackson 2008). Using the approach and results discussed in the paper, one can model this situation either as collective subsidization or as bargaining on link formation. In this case, a set of non-beneficiary-firms will pay for the pair of firms to not collaborate with each other, or a set of beneficiary-firms will pay for the pair of firms to collaborate with each other. Alternatively, both beneficiaries and non-beneficiaries may bargain for link formation.

Our result regarding the network size and the distance between agents can be used to formulate resource allocation policy in social clouds. Specifically, the policy may include the use (or recommendation) of friends as backup partners, so as to avoid negative externalities or minimize the number of non-beneficiaries (for example, by choosing agents for data backup who are far away from the agent requesting backup). Although our results are for ring networks, they can be extended to other network structures too.

Existing literature has not looked at resource availability in social networks where links (connections) are endogenously formed. We believe that our study is a first step towards enhancing our understanding of externalities in social clouds, and hence in endogenous sharing economy networks.

References

Basselier, R., G. Langenus, and L. Walravens. 2018. "The rise of the sharing economy." *Economic Review* iii: 57–78.

Bloch, F., and Jackson, M. O. 2007. "The formation of networks with transfers among players." *Journal of Economic Theory* 133 (1): 83–110. doi:10.1016/j.jet.2005.10.003

Boldi, P., and S. Vigna. 2014. "Axioms for Centrality." *Internet Mathematics* 10 (3-4): 222–262. doi:10.1080/15427951.2013.865686.

Buechel, B., and T. Hellmann. 2012. "Under-connected and Over-connected Networks: The Role of Externalities in Strategic Network Formation." *Review of Economic Design* 16 (1): 71–87. doi:10.1007/s10058-012-0114-x.

Chandrasekhar, A. 2016. "Econometrics of Network Formation." In *The Oxford Handbook of the Economics of Networks*, Oxford University Press.

Chard, K., K. Bubendorfer, S. Caton, and O. F. Rana. 2012. "Social Cloud Computing: A Vision for Socially Motivated Resource Sharing." *IEEE Transactions on Services Computing* 5 (4): 551–563. doi:10.1109/TSC.2011.39.

Choi, S., S. Kariv, and E. Gallo. 2016. "Networks in the Laboratory." In *The Oxford Handbook on the Economics of Networks*, edited by Y. Bramoullé, A. Galeotti, and B. Rogers, 440–475. New York: Oxford University Press.

Cohen, M., and A. Sundararajan. 2017. "Self-regulation and innovation in the peer-to-peer sharing economy." *University of Chicago Law Review Online* 82 (1): 116–133.

Frenken, K., and J. Schor. 2017. "Putting the sharing economy into perspective." *Environmental Innovation and Societal Transitions* 23: 3–10. doi:10.1016/j.eist.2017.01.003.

Friedman, D., and A. Cassar. 2004. "Economists go to the laboratory: who, what, when, and why." In *Economics Lab*, edited by D. Friedman, and A. Cassar, 26–36. Routledge.

Georgiadis, L., G. Iosifidis, and L. Tassiulas. 2017. "On the Efficiency of Sharing Economy Networks." Available at: arXiv:1703.09669v.

Jackson, M. O. 2008. "Social and economic networks". Princeton University Press.

Jackson, M. O., and A. Wolinsky. 1996. "A Strategic Model of Social and Economic Networks." *Journal of Economic Theory* 71 (1): 44 – 74. doi:10.1006/jeth.1996.0108.

Jing, W., and B. Sun. 2018. "Negative externalities in the sharing economy: sources, paths and recommendations." *International Journal of Crowd Science* 2 (2): 149–163. doi:10.1108/IJCS-08-2018-0016.

Vanessa, K. 2015. "Regulating the sharing economy." *Berkeley Technology Law Journal* 30 (4): 1067–1126. doi:10.14763/2016.2.414.

Mane, P., K. Ahuja, and N. Krishnamurthy. 2014. "Externalities and Stability in Social Cloud." In *5th International Conference on Game Theory for Networks*, Beijing, China, Nov, pp.1–6. IEEE. doi:10.1109/GAMENETS.2014.7043730.

Thomas N. H., D. S. Burdick, and W. E. Sasser. 1967. "Computer simulation experiments with economic systems: the problem of experimental design." *Journal of the American Statistical Association* 62 (320): 1315–1337. doi:10.1080/01621459.1967.10500937.

Puschmann, T., and A. Rainer. 2016. "Sharing economy." *Business & Information Systems Engineering* 58 (1): 93–99. doi:10.1007/s12599-015-0420-2.