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HOW ROBUST ARE THE STARS?
NETWORK FORMATION UNDER SHOCK AND GROUP EFFECTS

A MASTER'S THESIS

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ABBREVIATIONS

BG: Bala and Goyal

CN: Complete Network

CSS: Center Sponsored Star

EN: Empty Network

FN: Flower Network

LS: Linked Star

MSS: Minimally Sponsored Star

PSS: Periphery Sponsored Star

SNN: Strict Nash Network

LIST OF SYMBOLS

N	:	set of agents
n	:	number of agents
G	:	set of strategies
Z_+	:	non-negative integers
Π	:	payoff function
c	:	cost of link formation
b	:	benefit of a link
v	:	value accessed through a link
$\mu(g)$	:	number of total links
$\mu_i^d(g)$	:	number of links that agent i has formed
BR	:	set of best responses
w	:	wealth, sum of the agents' payoff
δ, Φ	:	decay function
d	:	distance

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RÉSUMÉ

L'homme est un «animal social» et intégré dans la dynamique complexe de la société qui contient également de nombreuses structures de réseaux dynamiques en tant que plate-forme où une quantité excessive d'information ou de bénéfices circulent de personnes en personnes. Dans ces réseaux, les gens partagent des informations, donnent et prennent des conseils sur de nombreux sujets tels que les téléphones portables qu'ils utilisent, les livres qu'ils lisent et ainsi de suite. Par conséquent, non seulement les individus, mais aussi les réseaux sociaux qu'ils s’intègrent jouent un rôle important en expliquant une partie importante des processus décisionnels humains. L’importance des réseaux sociaux a conduit à la proposition de nombreux modèles différents pour déterminer comment les réseaux sociaux se forment. Les chercheurs ont affirmé que les réseaux sociaux sont des facteurs cruciaux dans de nombreux domaines tels que le vote, la recherche d'emploi, l'élaboration de politiques, l'immigration et même le bonheur.

Il existe également différentes approches dans l'étude économique des réseaux sociaux. Sadler (2015) délimite deux extremités opposées. La première extremité est l'hypothèse de la présence d'un agent (entièrement) rationnel qui a des croyances détaillées sur la structure de son réseau. Il est important de souligner que l'agent rationnel a une tâche difficile car elle doit tenir encompte de toutes les actions et croyances possibles de tous les autres agents du réseau. Seulement si son point de vue est illimité, ses actions ne dépendent pas d'hypothèses incomplètes. Cependant, un tel point de vue illimité n'est pas possible pour notre enquête en raison de la complexité des structures de réseau. D'autre part, les règles heuristiques qui sont motivées comme une forme de meilleure réponse myopique représentent la deuxième extremité. En conséquence, tout agent est myope sur les actions d'autres agents dans une période de

temps donnée. Bien qu'elle puisse observer les actions d'autres agents dans son réseau, elle ne reçoit pas d'informations détaillées sur les raisons ou l'impulsion derrière les actions. Par conséquent, elle est susceptible de régler ses actions par règle générale. Il est vrai que la deuxième extremité fournit évidemment une description plus simple et plus réaliste des interactions humaines au sein d'un réseau, mais elle présente certains inconvénients issus de l'arbitraire de la règle de base. Sadler, en mettant l'accent sur la nature évolutianiste du comportement rationnel, suggère l'hypothèse de la rationalité limitée comme une mi-chemin, ce suivi dans cette thèse entre ces deux extremités. L'hypothèse de rationalité bornée reconnaît les limites inhérentes à la connaissance humaine. Dans ce point, il faut souligner que si une vision évolutiniste est adoptée, les théoriciens ne disposent pas seulement d'une plus grande liberté, mais aussi d'une plus grande responsabilité de considérer attentivement les hypothèses.

Il existe deux principaux flux dans la théorie des réseaux sociaux: les modèles coopératifs et non coopératifs. Les deux modèles ont fourni des résultats intuitifs et cohérents. Jackson et Wolinsky (1996) ont étudié sur le modèle coopératif dans lequel deux agents (individus, entreprises, etc.) forment un lien si et seulement si les deux agents s'entendent d'un commun accord sur la formation de ce lien. Les agents impliqués, en revanche, peuvent rompre unilatéralement les liens. Les coûts d'un lien formé sont payés par les deux agents. D'autre part, Bala et Goyal (2000) (ce après rèfèrè comme BG) ont étudié un modèle non coopératif où le consentement mutuel n'est pas nécessaire, une hypothèse qui est probablement plus réaliste dans les petits réseaux qui consistent en relativement peu d'agents. Les agents impliqués font une décision de liaison unilatéiraux en se liant à d'autres agents. Les agents se rendent simultanément sur la question de savoir s'ils forment des liens uniiatetaux avec un ou plusieurs autres agents ou non afin de collecter les avantages autant que possible. Seul l'agent qui lance le lien encourt le coût de la formation des liens. Bala et Goyal ont démontré que les réseaux vides et la roue dans le modèle de flux de benéfices unidirectionnel et l'étoile parrainée par le centre dans le modèle de flux de benéfices bidirectionnels sont les équilibres stricts de Nash de leur modèle.

En plus des modèles proposés pour étudier la formation des réseaux, la méthode expérimentale est apparue comme une méthode spécifique pour tester les validités des modèles proposés. Un nombre croissant de publications expérimentales évalue certaines des prédictions déclarées du modèle BG, en particulier celles concernant la convergence vers l'architecture stricte de Nash. Cependant, il n'est résumé ici que deux articles pertinents pour notre enquête. L'étude expérimentale de Falk et Kosfeld (2003) a montré que les prédictions basées sur l'équilibre strict Nash de Bala et Goyal fonctionnent bien dans le modèle de flux unidirectionnel alors qu'elles échouent largement dans le modèle à flux bidirectionnel. Goeree et al. (2009), d'autre part, ont indiqué que l'introduction d'agents hétérogènes dans le modèle permet de former des réseaux en forme d'étoile dans le modèle à flux bidirectionnel.

Cette thèse rapporte les résultats d'une étude expérimentale qui cherche à avancer quelques pas de plus ce que Goeree et al. Le premier objectif de cette thèse est d'obtenir des réseaux en étoile dans les mêmes conditions avec le traitement V dans l'étude de Goeree et al: flux bidirectionnel de bénéfices, informations complètes et présence d'un agent de haute valeur. Une fois que le premier but est accompli et que les étoiles attendues sont obtenues, nous progressons, mesurer la robustesse de ces étoiles. Ce processus, que nous appelons la «robustesse de l'étoile», exige une adhérence aux agents à haute valeur en con de facteurs exogènes et endogènes potentiels. La robustesse de l'étoile est acceptée si les agents forment de manière déterminée des réseaux en forme d'étoile en résistant à des facteurs exogènes ou endogènes. Par conséquent, on s'attend à ce que les agents s'adaptent rapidement et commodément à leurs «tâches» perpétuellement modifiées pour l'observation d'étoiles robustes tout au long de l'expérience. Dans ce cas, il faut élucider quels sont ces facteurs exogènes et endogènes possibles pour forcer la robustesse des étoiles. Le premier est ce que nous appelons l' «effet de choc». Le principal choc exogène dans notre étude est que les valeurs des agents changent constamment à travers les périodes de notre jeu expérimental. L'effet de choc est étudié en divisant chaque traitement en différentes parties qui consistent en différents mélanges de types d'agents (seulement un agent de haute valeur (HV) avec des agents ordinaires, deux agents de moyen valeur (MV) avec des agents ordinaires, et seulement des agents ordinaires (OV)). Le deuxième facteur (endogène) pour forcer la robustesse des étoiles est ce que nous appelons l’ "effet de groupe". Ce que nous recherchons dans ce cas, c'est une tendance partisane issue de l'effet du groupe. On pourrait soutenir que l'action partisane est hors des prédictions BG et elle affecte négativement l'utilité attendue de l'agent dans la plupart des cas. L'effet de groupe est étudié tout au long de deux traitements effectués. Dans le premier traitement, il n'y a pas d'effet de groupe alors que dans notre deuxième traitement, les agents d'un réseau sont informés qu'ils sont divisés en deux sous-groupes en fonction du parti qu'ils soutiennent.

En ce qui concerne notre attention principale, la robustesse des étoiles, les résultats indiquent que l'effet de choc crée des fluctuations périodiques dans la formation de réseaux en forme d'étoile à travers les périodes. Par conséquent, il (en chaque transition de la HV à MV), détériore temporairement et efface les étoiles. Cependant, avec l'effet de choc défavorable (de MV à HV), les étoiles sont réformées par les agents. Le dernier choc (du MV à l'OV) termine la formation d'étoiles. En outre, notre deuxième concept, l'effet de groupe (endogène) est susceptible de se révéler comme une diminution générale du niveau de centralités du réseau. Par conséquent, on peut conclure que deux concepts que nous avons introduits (effet de choc et effet de groupe) s'opposent à un autre concept introduit par nous, la robustesse de l'étoile à travers deux plans différents: horizontale et verticale.

ABSTRACT

Human is a “social animal”, and is embedded in the complex dynamics of their society which also contains many dynamic network structures as a platform where an excessive amount of information or benefit flows from people to people. In these networks, people share information, give and take advices on many topics such cell phones they use, books they read and so on. Therefore, not only individuals but also social networks they are embedded in play a significant role in explaining an important part of human decision-making processes. Given significance of social networks has led to proposition of many different models to determine how social networks form. Researchers have asserted that social networks are crucial factors in many fields such as voting, finding job, policy-making, immigration, and even happiness.

There exist different approaches in the economic investigation of social networks, as well. Sadler (2015) delineates two opposite horns. First horn is the assumption of presence of (fully) rational agent who has detailed beliefs about structure of her network. It is significant to emphasize that the rational agent has a challenging task since she must consider all possible actions and beliefs of all other agents in the network. Only if her vantage point is unlimited, her actions do not depend on incomplete hypotheses and assumptions. However, such an unlimited vantage point is not possible for our inquiry due to the complexity of network structures. On the other hand, heuristic rules which is motivated as a form of myopic best response represent the second horn. Accordingly, any agent is myopic about other agents’ actions in a given period of time. Although she can observe the actions of other agents in her network, she is not provided with a detailed information about the reasons or impetus lying behind theır actions. Therefore, she is likely to set her actions by rule-of-thumb. It is true that the second horn obviously provides a simpler and more realistic description of human interactions within a network, however it has some drawbacks originated from the arbitrariness of rule-of-thumb. Sadler, by emphasizing the

evolutionary nature of rational behavior, suggests the assumption of bounded rationality as a midway that is mostly followed in this thesis between these two horns. Bounded rationality assumption acknowledges the inherent limits of human cognition. In this point, it is necessary to point out that if an evolutionary view is embraced, theorists are not only provided with greater freedom but also imposed by greater responsibility to carefully consider assumptions.

There are two main streams in social network theory: cooperative and non-cooperative models. Both of two models have provided intuitive and consistent results. Jackson and Wolinsky (1996) have studied on cooperative model in which two agents (individuals, firms etc.) form a link if and only if both agents mutually agree upon the formation of this link. Involved agents, on the other hand, are able to break links unilaterally. The costs of a link formed are paid by both agents. On the other hand, Bala and Goyal (2000) have studied a non-cooperative model where the mutual consent is not required, and which provides realistic results mostly in relatively small group. Involved agents make unilateral linking decision by linking to other agents. Agents simultaneously decide on whether they form unilateral links to any other agent(s) or not for the aim of collecting benefit as much as possible. Only the agent who initiates the link payss the cost of link formation. Bala and Goyal have demonstrated that the non-empty strict Nash network is empty the wheel in the one-way flow model, and the center-sponsored star in the two-way flow model.

In addition to proposed models to investigate formation of networks, experimental method has appeared as a specific method to test the validities of proposed models. A growing body of experimental literature tests some of the stated predictions of the BG model, especially those concerning convergence to the strict Nash architecture. However, it is summarized here only two papers relevant for our inquiry. Experimental study of Falk and Kosfeld (2003) has showed that the predictions based on strict Nash equilibrium of Bala and Goyal work well in the one-way flow model whereas they largely fail in the two-way flow model. Goeree et al. (2009), on the other hand, have indicated introduction of heterogeneous agents into the model enable star-shaped networks to be formed in two-way flow model.

This thesis reports the results belonging to an experimental study which seeks for taking a few steps further from what Goeree et al. have proposed. The first purpose of this thesis is to obtain star-shaped networks under the same conditions with the treatment V in the study of Goeree et al: two-way flow of benefit, complete information, and the presence of one high-value agent. After the first purpose is accomplished and expected stars are obtained we, taking a few steps further, measure the robustness of these stars. This process what we call “star robustness” requires a very stickiness to the high-value agents against potential exogenous and endogenous factors. Star robustness is accepted if agents determinedly form star-shaped networks by resisting any exogenous or endogenous factors. Therefore, agents are expected to promptly and conveniently adapt to their perpetually changing “tasks” for the observation of robust stars throughout the experiment. In this point, it is required to elucidate what these possible exogenous and endogenous factors to force the robustness of the stars are. The first one is what we call the “shock effect”. Main exogenous shock in our study is that values of agents perpetually change across the periods of our experimental game. Shock effect is investigated by dividing each treatment into various parts consisting different mixture of agent types. The second (endogenous) factor to force the robustness of stars is what we call “group effect”. What we are searching for in this point is a partisan tendency originating from the group effect. It could be argued that partisan action is out of BG predictions and it adversely affects expected utility of the agent in most case. The group effect is investigated throughout two treatments conducted. In the first treatment, there is no group effect whereas in our second treatment the agents in a network are informed that they are divided into two sub-groups in terms of the party they support.

The experimental sessions were conducted between April and July 2017 at Bahcesehir University Financial Research and Implementation Center. In total, 108 subjects participated in the experiment. This thesis presents results concerning the connectedness, stability, architecture and robustness of networks as relating devices our primary issue of concern. We first present a few preliminary observations. Participants in our experiments actively link with each other: throughout the first and the second treatments and all periods we never observe the empty network. On the other hand, neither do we observe the complete network. In two treatments, we observe that in HV, number of links formed increases whereas in OV, number of links formed by the participants dramatically decreases. In MV part, since there are two agents who have relatively high value agents remain in limbo. Furthermore, this limbo is an illusion since the expected utility from a link with mid-value agent is negative. Ironically, results show that MV has been the part in which participants have formed the maximum number of links. Goeree et al. (2009) have defined the relative stability of a network as "the number of agents who do not change any links from round $(t - 1)$ to round t divided by the total number of agents" (2009, p. 458). We, in our study, investigated relative stability within each part. As we have expected, networks formed in HV parts are statistically more stable than in MV. Depending on BG model, we have predicted various strict Nash networks (SNN) for different parts of our experimental design and we have also mentioned about potential deviations from the strict Nash networks. Starting with the results of the first treatment, in HV, 26.8% of all observed networks were strict Nash, whereas in MV and OV no Nash network was formed at all. In the second treatment, on the other hand, in HV, 14.8% of all observed networks was strict Nash. Similarly, in MV and OV, no strict Nash network was formed at all. In HV, stars were the prevailing network architecture; 33.3% of all networks were star. In MV, 17.5% and in OV only 3.7% of all observed networks were star. In the part HV, the difference in percentages of stars between the first and second treatments is mostly due to the tendency of ordinary agents to form additional links with other ordinary agents (mostly from their party) in the second treatment. This action, which could be defined as quasi-partisan, has led to formation of flower networks (FN) together with the PSS in HV of the second treatment.

Concerning our main focus, star-robustness, results indicate that shock effect creates periodic fluctuations in the formation of star-shaped networks across the periods. Therefore, it (in each transition from the HV to MV), temporarily deteriorates and eliminates the stars. However, with the adverse shock effect (from MV to HV), stars are reformed by the agents. The very last shock (from the MV to OV) finishes the formation of stars. In addition, our second concept, (endogenous) group effect is likely to reveal itself as a general decrease in the level of network centralities. Therefore, it could be concluded that two concepts we introduced (shock effect and group effect) force to another concept introduced by us, star robustness, through two different planes; respectively horizontal and vertical.

ÖZET

İnsanoğlu doğası gereği "*sosyal bir hayvan*"dır ve toplumunun karmaşık dinamikleri ile bütünleşik durumdadır. Bir toplum, insanlardan insanlara oldukça fazla miktarda bilgi ya da fayda akışının gerçekleştiği birçok dinamik ağ yapısı içerir. Bu ağlarda insanlar kullandıkları cep telefonları, okudukları kitaplar gibi pek çok konuda bilgi paylaşır, tavsiye verir ve tavsiye alır. Bu nedenle, sadece bireyler değil bütünleşik oldukları sosyal ağlar da insanların karar alma süreçlerinin büyük kısmının açıklanmasında önemli rol oynar. Sosyal ağların bu denli önemli olması sosyal ağların oluşumu hakkında birçok farklı modelin ortaya atılmasını beraberinde getirmiştir. Araştırmacılar oy verme, iş bulma, politika yapma, göç dinamikleri ve hatta mutluluk gibi sayısız alanda sosyal ağların oldukça kritik bir etmen olduğunu ortaya koymuşlardır.

Sosyal ağların ekonomik analizinde değişik yaklaşımlar mevcuttur. Sadler (2015) birbiriyle zıt iki uç tasvir eder. Bir uçta ağ yapısı hakkında detaylı çıkarımlara sahip olan rasyonel bireyin varlığı varsayımı bulunur. Rasyonel birey ağdaki diğer tüm bireylerin olası davranış ve inançlarını göz önünde bulundurmak zorunda olduğundan zorlu bir göreve sahiptir. Yalnızca bakış açısı sınırsız ise davranışları eksik hipotez ve varsayımlara dayanmaz. Fakat, böyle sınırsız bir bakış açısı ağ yapılarının karışıklığı nedeniyle mümkün değildir. Sezgisel kurallar, en iyi miyopik tepkinin bir çeşidi olarak, ikinci ucu temsil eder. Buna göre bir birey diğer bireylerin davranışlarını göremez (miyopiktir). Ağındaki diğer bireylerin davranışlarını gözlemleyebilse de diğer bireylerin davranışlarının arkasında yatan itici güç ve nedenler hakkında detaylı bilgiye sahip değildir. Bu nedenle, görünen o ki davranışlarını "göz kararı" belirler. İkinci ucun bir ağ yapısı içindeki insanların etkileşimlerine dair daha basit ve gerçekçi tanımlamalar yaptığı doğrudur. Fakat fakat göz kararı hesaplamanın kesin sınırlarının bulunmamasından kaynaklanan bazı olumsuz tarafları da mevcuttur. Sadler, mantıksal

davranışın evrimsel doğasına vurgu yaparak sınırlı rasyonalite varsayımını bu iki uç arasında bir orta yol olarak ortaya koyar. Sınırlı rasyonalite yaklaşımı insan bilişselliğinin fıtri limitlerini göz önünde bulundurur. Unutulmamalıdır ki evrimsel bakış kabul edilirse teorisyenler yalnızca daha özgür kılınmayacak ayrıca varsayımların daha dikkatli gözden geçirilmesi konusunda daha ciddi sorumluluklar yükleneceklerdir.

Sosyal ağlar teorisinde iki ana akım mevcuttur: işbirlikli ve işbirliksiz modeler. İki model de sezgisel ve tutarlı sonuçlar sağlamıştır. Jackson ve Wolinsky (1996) iki ajanın (birey, firma vb.) yalnızca karşılıklı rıza ile bağlantı kurabildiği işbirlikli model üzerine çalışmışlardır. Ote yandan, mevcut ajanlar bağlantıları tek taraflı olarak bozabilirler. Kurulan bağlantının maliyeti iki ajan tarafından da ödenir. Öte yandan Bala ve Goyal bir bağlantının kurulması için rızaya gereksinim duyulmayan işbirliksiz bir model üzerine çalışmıştır ki bu model görece az ajanın bulunduğu daha küçük ağlar için daha gerçekçidir. Mevcut ajanlar diğer ajanlarla kurdukları bağlantılar üzerinden mümkün olduğunca fazla fayda kazanmak amacıyla eş zamanlı olarak tek taraflı bağlantı kararları verirler. Ajanlar bir sınırlama olmaksızın diğer ajanlar ile bağlantı kurabilirler. Kurulan bağlantının maliyeti yalnızca bağlantı kuran ajan tarafından üstlenilir. Bala ve Goyal tek yönlü fayda akışının olduğu modelde “boş ağ” ve “çark”, iki yönlü fayda akışının olduğu modelde ise “merkez sponsorlu yıldız” ın katı Nash dengesi olduğunu gösterirler. Deneysel ekonomi, sunulan teorilerin geçerliliğinin ölçülmesi konusunda oldukça değerli bir yaklaşım olarak öne çıkmıştır. Bala ve Goyal modelinin tahminlerini, ki özellikle de katı Nash dengelerine yakınsallık üzerine olanları, test eden mevcut ve sürekli büyüyen bir deneysel literature bulunmaktadır. Fakat, burada yalnızca bizim araştırmamızla ilişkili iki makaleden söz edilecektir. Falk ve Kosfeld (2003)’in deneysel çalışması gösterir ki Bala ve Goyal’in (katı) Nash dengesi tahminleri tek yönlü fayda akışı durumunda isabetli olurken çift yönlü fayda akışı durumumda sonuç vermezler. Öte yandan Goeree ve arkadaşları (2009) ortaya koyar ki ajanların heterojen olması durumunda Bala ve Goyal’in tahminlerine parallel olarak çift yönlü fayda akışı durumunda yıldız yapılı ağların gözlemlenmesi mümkündür.

Bu tez Goeree ve arkadaşlarının çalışmasını birkaç adım ileriye taşımayı amaçlayan bir deneysel çalışmamıza ait sonuçlar sunar. Bu bağlamda, bu tezin ilk amacı Goeree ve arkadaşlarının çalışmasındaki V bölümü ile aynı şartlar altında, ki bu şartlar çift yönlü fayda akışı, ajanların oyunun ana hatları hakkında tam bir bilgiye sahip olmaları ve bir yüksek değerli ajanın varlığıdır, yıldız yapılı ağların oluşumunu sağlamaktır. İlk amaç başarı ile tamamlandıktan ve beklenen yıldızlar gözlemlendikten sonra, birkaç adım öteye giderek, bu yıldızların dayanıklılığının ölçülmesi amaçlanmaktadır. Bizim "yıldız dayanıklılığı" adını verdiğimiz bu süreç olası dış ve içsel etmenlere karşın yüksek değerli ajana sıkı bir bağlılık gerektirir. Eğer ajanlar herhangi bir dış ya da içsel etmene karşı direnip kararlı bir şekilde yıldız yapılı ağlar oluştururlar ise yıldızlar dayanıklıdır sonucuna varılır. Bu nedenle, dayanıklı yıldızların gözlemlenmesi için ajanların sürekli değişen "görevlerine" hızlı ve sorunsuzca adapte olması gereklidir. Bu noktada yıldızların dayanıklılığını zorlaması olası dış ve içsel etmenlerden bahsetmek gerekliliği doğar. İlki bizim "şok etkisi" adını verdiğimiz etmendir. Deney boyunca, yıldızların dayanıklılığını ölçmek amacıyla çeşitli dış şoklar uygulanmıştır. Çalışmamızdaki başlıca dış şok ise deneysel oyunumuz boyunca ajanların değerlerinin periyodlar boyunca sürekli değişmesidir. Şok etkisi deneyimizin ajan tiplerinin farklı karışımlarını içeren çeşitli bölümlere ayrılması ile ölçülür. Yıldız dayanıklılığını zorlayacağı öngörülen ikinci (içsel)etmeni ise "grup etkisi" olarak isimlendirdik. Bu noktada aradığımız, grup etkisinden kaynaklanan bir partizan yatkınlık olacaktır. Bu bağlamda söyleyebiliriz ki partizan davranışlar Bala ve Goyal tahminleri dışına çıkar ve çoğunlukla ajanların beklenen faydasında olumsuz sonuçlara neden olur. Grup etkisi ise yürütülen iki uygulama (geliştirim) üzerinden incelenir. İlkinde grup etkisi yok iken ikincisinde bir ağdaki ajanlar destekledikleri partilere göre iki alt gruba ayrıldıkları konusunda bilgilendirilirler.

Deney oturumları 2017 yılı Nisan ve Temmuz ayları arasında Bahçeşehir Üniversitesi Finansal Araştırma ve Uygulama Merkezi'nde gerçekleştirilmiştir. Toplamda 108 denek deneye katılım sağlamıştır. Bu tezde ölçümlenmek istenen asıl konu (yıldız dayanıklılığı) ile yakından ilgili olarak deney seansları boyunca kurulan ağların bağlılık, stabilite, yapı ve dayanıklılıklarına ilişkin sonuçlar sunulmuştur. Öncelikle birkaç ön gözlem sunmak adına söylenebilir ki deneyimizin katılımcıları aktif bir şekilde birbirileriyle bağlantı kurmuşlardır. Tüm seanslar boyunca boş ağ yapısına rastlanmamıştır. Öte yandan, eksiksiz ağ yapıları da gözlemlenmemiştir. Ajanlar, bir yüksek değerli ajanın bulunduğu HV periyodlarında tüm ajanların homojen ve sıradan değerli olduğu OV partında kurduklarından daha fazla sayıda bağlantı kurmuşlardır. iki orta değerli ajanın bulundu MV periyodları ise en fazla sayıda bağlantı kurulan kısım olmuştur.

Bir ağın göreceli stabilitesi t-1 periyodundan t periyoduna herhangi bir bağlantı değiştirmeyen ajanların sayısının toplam ajan sayısına bölünmesiyle bulunur. Çalışmamızda her bir bölüme ait (HV, MV ve OV) ağ stabiliteleri kendi içlerinde incelenmiştir. Öngördüğümüz üzere HV periyodlarında kurulan ağlar diğerlerine nazaran daha stabildir. Bala ve Goyal modeline dayanarak her bir bölüm için (katı) Nash dengeleri öngörülmüş ve bahsedilmiş olan iki etmenden ötürü bu dengelerden belirli derecede sapmalar görülebileceği ve bu olası sapma ve değişimlerin gözlemlenmesi gerekliliği tarafımızca vurgulanmıştır. Ilk treatment (geliştirim) ait sonuçlarla başlamak gerekirse, HV bölümünde gözlenen tüm ağ yapılarının %26.8'i katı Nash dengesinde iken MV ve OV bölümlerinde Nash dengesinde ağlar kurulmamıştır. İkinci treatmentta (geliştirim), HV bölümünde kurulan tüm ağların %14.8'i katı Nash dengesindeyken benzer şekilde MV ve OV bölümlerinde Nash dengesi gözlenmemiştir. Oyunun genelinde HV bölümünde yıldızlar yaygın olarak kurulan yapılardır ki bu bölümde oluşturulmuş ağların üçte biri yıldız yapılı ağlardır. MV bölümünde bu oran %17.5 iken OV bölümünde kurulan ağlardan yalnızca % 3.7si yıldızdır. HV bölümünde oluşturulan yıldızların oranlarında iki treatment arasında belirgin bir fark gözlemlenmiştir ki bu fark büyük oranda sıradan ajanların kendi partilerinden diğer sıradan ajanlarla bağlantı kurmaya olan eğilimlerinden kaynaklanır. Yarı-partizan davranış olarak adlandırılabilecek olan bu davranış çevreden sponsorlu yıldız ile birlikte çiçek yapılı ağların yaygın şekilde oluşumuna yol açmıştır.

Tezin esas odak noktası olan yıldız dayanıklılığına gelecek olursak sonuçlar gösterir ki şok etkisi star yapılı ağların oluşturulmasında yarattığı periyodik dalgalanmalar üzerinden gözlemlenebilir. Şok etkisinin (HV bölümünden MV bölümüne her geçişte) yıldızları geçici olarak zedelediği ve yok ettiği kanaatine varılabilir. Fakat takriben gelen ters yönlü şok etkisi (MV bölümünden HV bölümüne geçişte) ile yıldız yapılı ağlar yeniden oluşur. En son şok ise (MV bölümünden OV bölümüne geçişte) yıldız oluşumunu sonlandırır. Ek olarak, ikinci (içsel) etmen olan grup etkisi kendisini ağ merkeziliklerinin seviyesindeki genel bir düşüş olarak kendini gösterir. Bu da demektir ki grup etkisi daha düşük merkeziliklere sahip ve dolayısıyla yıldız yapısından daha uzak ağların oluşumuna neden olur. Bu nedenle söylenebilir ki tanıttığımız iki kavram (şok etkisi ve grup etkisi) tanıttığımız bir diğer kavram olan yıldız dayanıklılığına karşı sırasıyla yatay ve dikey olmak üzere iki farklı düzlemde işler.

CHAPTER 1: INTRODUCTION

"*Man is by nature a social animal; an individual who is unsocial naturally and not accidentally is either beneath our notice or more than human. Society is something that precedes the individual. Anyone who either cannot lead the common life or is so self-sufficient as not to need to, and therefore does not partake of society, is either a beast or a god*."

― Aristotle, Politics

It is sure that the quotation above has taken place in many times in a lot of papers in the field of social sciences. Seemingly, we could not avoid from making such a cliché in order to make an impressive introduction which aims to emphasize how man, as a *social animal*, is embedded in networks (of relations, neighborhoods etc.) within the society. The society which "man partakes of" contains many dynamic network structures where an excessive amount of information or benefit flows from people to people: People share information, give and take advices on many topics such cell phones they use, books they read and so on. Therefore, social networks play a significant role in explaining an important part of decision-making process of people. Researchers have also found social networks to be a crucial factor in many fields such as voting (Berelson, Lazarsfeld, & McPhee, 1954), finding job (Granovetter, 1973), policy-making (Caldeira & Patterson, 1987), immigration (Sanders, Nee, & Sernau, 2002), diffusion of innovation ((Golsbee & Klenow, 2002), (Acemoglu, Ozdaglar, & Yildiz, 2011)) and even happiness (Fowler & Christakis, 2008). In this sense, social networks have become a significant topic for sociological, political and economic analysis. Jackson (2014) asserts that the main impetus of economists to study on networks is the fact that networks reflect human behaviors in a good way:

> They cannot ignore that humans are fundamentally a social species with interaction patterns that shape their behaviors. People's opinions, which products they buy, whether they invest in education, become criminals, and so forth, are all influenced by friends and acquaintances" (Jackson, 2014, pp. 3-4).

As Jackson states, analyzing interactions of individuals who connect each other within a network structure and whose behaviors might be shaped by other individuals in this network would provide deep insights about human decision-making. Also, these interactions seem to be suitable for investigating by using game theory. Jackson and Zenou (2014) refer games on networks as a special perspective: "*this particular view of games on networks, where an agent chooses an action and then the payoffs of each player are determined by those of his or her neighbors is a special perspective*" (p. 2).

This thesis, depending on such *a special perspective*, reports a network experiment of non-cooperative model of Bala and Goyal (2000). The central result presented by Bala and Goyal (BG) is that there are only two non-empty network structures that are strict Nash equilibria: the wheel in the one-way flow model, and the center-sponsored star in two-way flow model. Experimental study of Falk and Kosfeld (2003) shows that the prediction based on strict Nash equilibrium of BG works well in the one-way flow model whereas it largely fails in the two-way flow model. Goeree et al. (2009), on the other hand, indicate that introduction of heterogeneity to the model enables us to observe compatible results with BG predictions in two-way flow model. Results of their study indicate that starts are frequently observed when at least one high-value or low-cost agent does exist in the network while almost no star networks are formed by homogenous agents. In their treatment where one high-value agent exists, a specific star which is called periphery-sponsored-star is extensively observed as strict Nash network. In a network with n agent $n \geq 3$, periphery-sponsored-star implies that $(n-1)$ agents are sponsor for connecting one specific (central) agent. That the central agent has a relatively high-value (benefit-to-others) make her an obvious target. In this way, the process of formation star-shaped networks become smoother.

The starting point of this thesis is the point where Goeree et al. (2009) have concluded. Goeree et al. (2009), in their paper "In search of stars: Network formation among heterogeneous agents", as the name implies, search for star-shaped networks among heterogenous agents. They assert that when at least one high-value agent exists, star-shaped networks are observed. We take a few steps further from Goeree et al. and analyzed two main scenarios. Goeree et al. assert that if there is a high-value agent in a network, ordinary agents undertake the cost to form a link and surround the high-value agent. As a result, they create periphery-sponsored stars. What if the high-value agent periodically changes? Do ordinary agents insistently continue to be sponsor for ever-changing high-value agent? In this way, do they continue to form star-shaped networks? In order to observe this scenario, we set our design in a way that each agent in the network alternately becomes the high-value agent. In addition, we created a mid-stage in which the high-value agent is downgraded to become a mid-value agent, and an ordinary agent is upgraded to become a mid-value agent. Therefore, this mid-stage consists of two mid-value agents maintaining the same value and the remaining agents are ordinary. In these parts, it is also significant to observe whether agents immediately adapt to their new "task" in a smooth way. There is a last part in our design in which all agents are ordinary.

The partite structure of our design is intended for observing potential impacts of what we call "shock effect" on the network structures. Indeed, these shocks are quite similar toreal life. In real life, there are certain power balances embedded in a society. Some people have more power (which denotes information or benefit in our study) and this situation makes them more valuable to interact in the eyes of other people in their networks. Furthermore, existing power balances are not everlasting; they might change from time to time. People with more power might lose their values as a consequence of exogenous shocks and new people might substitute them. In this context, fluctuations in the values of agents from period to period which are considered as determining exogenous shock in our design, might lead to deformation or reformation of stars. We aim in our first step to test we call the "star robustness"; the resistance of the stars which are expected to be formed in the first part against (exogenous) shock effect.

As the second scenario, this thesis aims to measure star robustness against another factor, group identity. We conducted two treatments which differ in terms of this factor and investigated potential impacts of what we call "group effect" on the architecture of starts. We aim to investigate whether stars deteriorate or meliorate due to partisan trends originating from the group effect. The group effect is investigated throughout two treatments we conducted. In our first treatment, there is no identity factor whereas in our second treatment the agents are informed that they are divided into two in terms of the party they support. By comparing the results belonging to two treatments, we aim to investigate whether agents arrived a group consciousness that creates a partisan tendency. The second scenario, as well, is in line with empirical fact. In a society, people knowingly or unknowingly get involved in many groups in respect to their socioeconomic status, their gender (or sexual orientation), their political and ideological opinions etc. This fact might create some biases having a significant impact on interaction map and volume in a network. People might automatically eliminate a part of their social networks to interact. In a general perspective, if group effect outweighs in the human interactions and in the processes of benefit flow, networks might be divided in themselves. Therefore, group effect might also lead to deformation of stars or reformation of differently shaped stars.

In this context, the first purpose of this thesis is to observe star-shaped networks under complete information, two-way flow and value heterogeneity. The second purpose, after obtaining the stars, is to measure the robustness of these stars against two effects: the shock effect and group effect. In this context, this paper contributes to existing literature by introducing the concept of star robustness as well as two factors which have the potential to force the star robustness. The shock effect is sought to be measured by dividing each treatment into various parts consisting different mixtures of different value-agents. The group effect is investigated throughout two treatments which differ in terms that agents have the information about their group identites. As a result, our game design consists of two treatments which have various parts in themselves.

After this first introduction chapter, the rest of the thesis is organized as follows. The second chapter aims to provide a starting point for our experimental study on network games by delineating the network theory and various approaches to social networks. The third chapter examines the BG model in detail and a few experimental studies following BG model to test its validity for various circumstances. In the fourth chapter, our experimental study (the model, experimental design, predictions and results) is introduced. The fifth chapter concludes the methods and results of our network formation game.

CHAPTER 2: THEORY OF SOCIAL NETWORK

Hungarian poet and writer Frigyes Karinthy, in his 1929 short story "*L\'aancszemek*" ("Chains"), has asserted that any two individuals, among all inhabitants on earth, were distanced by at most six (friendship) links or were linked through at most five acquaintances. Hence, with this assertion, the network theory has been initiated as a new field of inquiry. After the John Guare's eponymous award-winner play premiered in 1990, Karinthy’s idea has stuck as the phrase "six degrees of separation". However, before Guare’s play has been premiered, the sociologist Stanley Milgram has elaborated Karinthy’s idea in his study “The Small World Problem” (1967). Milgram, in his famous experiment, has asked people to route a postcard to a targeted recipient by passing it only through direct acquaintances who would then do the same etc., until the target person was reached. By this way, Milgram has measured how many intermediate nodes (acquaintances) would be required to link the original sender with the target person. The average number of intermediaries is measured between 4.4 and 5.7, depending on the sample of people chosen. Hence was born the idea of “six degrees of separation”. As a result of Milgram's study and Guare's play, it is assumed that "degrees of separation" equals to "distance minus one", where "distance" is the usual path length-the number of arcs in the path.

In this regard, this chapter introduces network theory whose nascence is summarized above by particularly focusing on social networks, in terms of its basic concepts, dynamics and graphical representations. Basic questions are addressed: What is a network? What are the essential dimensions along which networks meaningfully vary? How are networks measured? In addition, game theoretical approaches to social networks as well as cooperative and non-cooperative models of network formation games are investigated.

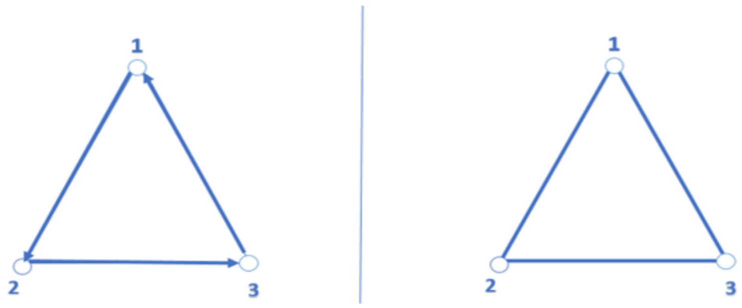
2.1. Basic concepts and representing networks

The question "what is a network?" is a beneficial starting point to examine the social and economic networks. In the related literature, a network describes the interaction structures among a set of agents (Wasserman & Faust, 1994). Taking a step further, to analyze various elements within a network would provide an explicit understanding on networks.

Nodes. The set $N = \{1, \dots, n\}$ is the set of agents which are called "nodes". In economic and social networks, nodes might represent individuals, firms, organizations, countries etc.

Ties. Nodes might be connected by "ties" which may also be referred to as "edges" or "links". There is a broad range of ties that network researchers have investigated: communication ties (who gives information to whom), formal ties (who reports to whom), material flow ties (who gives resources to whom) etc. (Katz, Lazer, Arrow, & Contractor, 2004). A fundamental characteristic of ties among the agents depends on whether ties are undirected or directed. Two nodes in an undirected (network) graph are either connected or not. In directed graphs, on the other hand, possibilities about the connection between two nodes are doubled. There are four situations to consider: (i) two nodes are not connected, (ii) the first node is connected to the second one while the second node is not connected to the first one, (iii) the second node is connected to the first one while the second node is not connected to the first one, (iv) two nodes are connected. Granovetter (1973) classifies the ties in terms of their strength. Accordingly, ties among agents may be strong (with family, close friends etc.) or weak (with acquaintances etc.). Granovetter (1973), in his study conducted to examine the role of social networks in finding a job, records that the job-seekers are mostly provided with a job through their weak ties (relations with acquaintances), instead of "strong" ones (relations with family or close friends). He relates the strength of a tie to a set of factors such as "*amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie*" (Granovetter, 1973, p. 1361).

Graphs. A network is represented by a graph (N, g) in which N denotes the set of nodes $N = \{1, \ldots, n\}$ and g denotes a real-valued matrix that demonstrates the relations between the nodes. For all as $i, j \in N$, $g_{ij} \in \{0, 1\}$ represents the availability of a ties between the nodes i and j and it is referred as adjacency matrix because it shows which nodes are adjacent to one another. A graph is directed if $g_{ij} \neq g_{ji}$ (as in Figure 2.1.a) and undirected if $g_{ij} = g_{ji}$ (as in Figure 2.1.b) (Jackson, 2008, p. 41).



$$g = \begin{matrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{matrix} \qquad g = \begin{matrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{matrix}$$

Figure 2.1. **(a)** Matrix representation of a directed graph. **(b)** Matrix representation of an undirected graph.

A network graph might also be described as a pair given by (N, E) where E denotes the collection of ties which are just listed as a subset of N of size 2. In directed graphs, E is the set of "directed" ties, i.e., $\{i, j\} \in E$ while in undirected graphs, E is the set of "undirected" edges, i.e., $\{i, j\} \in E$. Then pair representations of networks in Figure 2.1 are following: for the directed graph in Figure 2.1.a, $E_d = \{(1, 2), (2, 3), (3, 1)\}$ and for the undirected graph in Figure 2.1.b, $E_u = \{1, 2\}, \{1, 3\}, \{2, 3\}$ (Jackson, 2008, p. 42).

Walks, paths and cycles. For an undirected graph (N, g), a sequence of ties $\{i_1, i_2\}, \{i_2, i_3\}, \ldots, \{i_{K-1}, i_K\}$ represents a "walk". A "path" between nodes i and j is "a sequence of ties $\{i_1, i_2\}, \{i_2, i_3\}, \ldots, \{i_{K-1}, i_K\}$ such that $\{i_k, i_{k+1}\} \in g$ for each $k \in \{1, \ldots, (K-1)\}$, with $i_1 = i$ and $i_K = j$, and such that each node in the sequence $i_1, \ldots, i_K$ is distinct" (Jackson, 2008, p. 43). A "cycle" represents "a walk that starts and ends at the same node" (Jackson, 2008, p. 44). A geodesic between nodes i and j is the "shortest path" between i and j (Jackson, 2008, pp. 43-44).

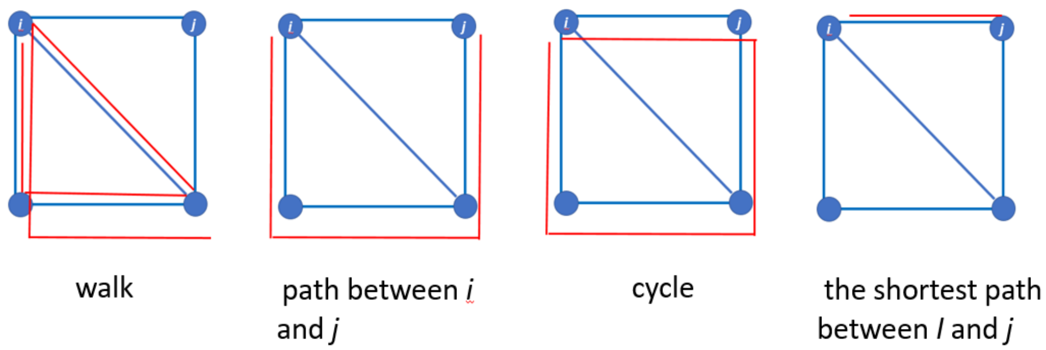


Figure 2.2. Walk, path, cycle and geodesic.

Trees, stars, circles and complete networks. As a result of networking decisions of the agents, a network might be shaped in a few particular structures. Figure 2.3 depicts some of these structures that Jackson (2008) defines as follows:

- *"A tree is a connected network that has no cycles".*
- *"A star is a network such that there exists some node i such that every link in the network involves node i".*
- *"A circle is a network that has a single cycle and such that each node in the network has exactly two neighbors".*
- *"The complete network is one where all possible links are present, so one where $g_{ij} = 1$ for all $i \neq j$"* (Jackson, 2008, pp. 49-50).

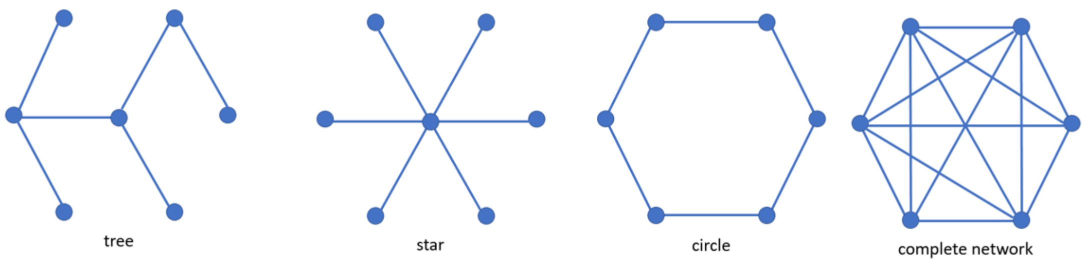


Figure 2.3. Tree, star, circle and complete network.

Neighborhood. As Jackson defines “the neighborhood of a node i is the set of nodes that i is (directly) linked to” (Jackson, 2008, p. 50). It might be represented as $N_i(g) = \{j: g_{ij} = 1\}$.

2.2. Different Approaches to Social Networks

Social networks are not only characterized by a pattern of linkages, but also by the interactions formed within a network structure. Decision-making processes in a network are expected to include a lot of strategic decisions to make: Should the individual follow the advice of her friend (or any individual in her network)? Should she imitate the behavior of other individuals in her network? Theory depends on normative foundations in which any rational agent is expected to observe actions of other agents in her networks, gather information and conduct in a sophisticated manner as a result of all these observations and experiences. However, this is a restricted scenario which ignores how dynamics of a network are complicated. A network structure includes myriad potentialities to consider whose outcomes are sensitive to even tiny changes. Considering the complexity of network structures, expectations depending on the very existence of rational man seem not only cumbersome but also unrealistic. Instead of such an unrealistic approach, Kahneman et al. (1982) propose that explaining actions of the agents in a network through heuristics and biases provides a simpler setting. They investigate whether it is possible to obtain economical and effective outcomes by following heuristic rules. Relating the heuristic assumption with one of the masterpieces of Kahneman, *Thinking, Fast and Slow*, it might be asserted that decision-making processes are the results of a compelling interaction between the automatic System 1 and the effortful System 2. Accordingly, since System 2 requires a high-level attention, people are prone to follow System 1 which is compatible with the "lazy" nature to accomplish routine tasks (Kahneman, 2011, p. 45).

Sadler (2015) addresses a significant dilemma that network economists have to deal with. The dilemma lies between the assumption of fully rational agents and the existence of heuristic rules. Sadler entitles them as "two horns". In the first horn, there is the assumption of fully rational agent who has detailed beliefs about overall network structure. The rational agent has a challenging task since she must consider all possible actions and beliefs of all other agents in the network. Only if her vantage point is unlimited, her actions do not depend on incomplete hypotheses and assumptions. However, such an unlimited vantage point is not possible due to the complexity of network structures. On the other hand, the rational agent might adapt and learn through experience and by this way, she might approximate the rational actions. The main insight of the study of Jadbabaie et al. (2012) is that with a constant flow of new information, social learning depends on agents taking their personal signals into account in a rational way. As a result of repeated interaction in a social network, learning would be obtained and the gap between the opinions would vanish. They highlight the significance of local updates; however, this approach is also unrealistic for network games since it requires fully, accurate and timely feedback:

> Agents do not need to have any information (or form beliefs) about the structure of the social network nor the views or characteristics of most agents, as they only update their opinions *locally* and do not make any deductions about the world beyond their immediate neighbors. Moreover, the individuals do not need to know the signal structure of any other agent in the network, besides their own. Thus, individuals eventually achieve full learning through a simple local updating rule and avoid the highly complex computations that are essential for full Bayesian updating over the network (Jadbabaie, Molavi, Sandroni, & Tahbaz-Salehi, p. 218).

Heuristic rules which is motivated as a form of myopic best response represent the second horn. Accordingly, any agent is myopic about other agents' actions in a given period of time. She seeks to earn the possible highest payoff by following expected utilities. Also, although she can observe the actions of the other agents in her network, she is not provided with detailed information about the reasons or impetus laying behind the actions of other agents. Therefore, she is likely to set her actions by rule-of-thumb. It is true that his second horn obviously provides a simpler and more realistic description of human interactions within a network, it has some drawbacks originated from the arbitrariness of rule-of-thumb. Accordingly, different rules would create different performances and it is all arbitrary to choose among such performances (Jackson, 2008, pp. 223-250). In addition to this arbitrariness, Osborne (2003) argues that any individual decision making process in a network, and the results of its experimental study, might deviate from the Nash equilibria since the agents' action might be affected by a set of social preferences such as altruism (receiving utility from being nice to others), fairness (receiving utility from being fair to others) and vindictiveness (individuals' tendency to punish those who deviates from accepted norms) etc (Osborne, 2003, pp. 411-418). Therefore, Sadler (2015) suggests the bounded rationality literature as a middle path between these two horns to solve this dilemma economists face with:

> I have advocated a particular view on the role of rationality in economics emphasizing the evolutionary nature of rational behavior, while acknowledging the limits inherent in this perspective. If we embrace an evolutionary view, then it becomes sensible to describe separately the environment to which behavior is adapted, and the environment in which behavior occurs. Such an approach offers greater freedom to theorists on one hand, but imposes greater responsibility to carefully consider assumptions on the other (Sadler, 2015, p. 35).

2.3. Cooperative and non-cooperative models of network formation

As already discussed, the economic significance of social networks has made the network formation an important field in economic research. One of the key question within economic inquiry of social networks has become how networks emerge. There exist two main streams which have been proposed to analyze the network formation: cooperative network formation (Jackson and Wolinsky, 1996; Jackson, 2003) and non-cooperative network formation (Bala and Goyal, 2000). Both theoretical models have provided intuitive and consistent results and experimental economics appears as a particularly valuable approach to test the validity of provided theories. Since the non-cooperative model of Bala and Goyal is going to be widely discussed in the next chapter, cooperative model (Jackson and Wolinsky (1996), Jackson (2003)) is focused in this part.

Jackson and Wolinsky (1996) study on a model in which two agents (individuals, firms etc.) form a link if and only if both agents mutually agree upon the formation of this link. Involved agents, on the other hand, are able to break links unilaterally. The costs of a link formed are paid by both agents. The notion of stability has a significant place in the study of Jackson and Wolinsky. They state that the main purpose of the study is "*to understand which networks are stable, when self-interested individuals choose to form new links or to sever existing links*" (Jackson & Wolinsky, 1996, p. 45). Their stability analysis is based on the notion of pairwise stability. A pairwise-stable network emerges if no agent wishes to break a link she involves; and (ii) all non-existing links are stable if at least one of the involved agents on the non-existing link suffers from its existence (Jackson & Wolinsky, 1996).

Jackson (2003) propounds two main models: the connections model and the co-author model. In the connections model, links represent social relationships between the agents. These relationships provide benefits such as favors, information, etc., and require some costs. Moreover, agents do benefit from not only direct but also indirect relationships but the benefit deteriorates in the "distance" of the relationship. In the co-author model, each agent is a researcher who spends time for research projects. If two researchers are connected, then they are working on a project together. As two researchers spend more time together, their synergy increases. The value of a project also increases as the researchers spend more time on it. On the other hand, each researcher has a fixed time to spend on projects and as the number of projects she studies on increases at the same time interval, the time she separates for each project decreases. The total value produced by the researchers depends on both the number of project they study on and time they separated for each project (Jackson, 2003, pp. 10-14). The common point in two models which distinguishes the cooperative model of Jackson and Wolinsky from non-cooperative model of Bala and Goyal is, as stated above, that any link formation requires mutual consent of the involved agents. Next chapters focus the latter one which is the non-cooperative games of Bala and Goyal (BG). In BG model, initiative of only one agent is required and sufficient for the formation of a link.

CHAPTER 3: BALA AND GOYAL'S (BG) MODEL AND THE EXPERIMENTAL LITERATURE ON BG MODEL

This chapter gives a short introduction to BG model of non-cooperative network formation. After BG model is introduced, several experimental studies to test the predictions of BG model are investigated.

3.1. BG model

Bala and Goyal study a game-theoretic model where agents possess complete information about the network. BG model is expected to provide more realistic predictions in relatively small networks. Involved agents simultaneously decide on whether they form unilateral links or not to collect as much information as possible. They are able to unrestrictedly initiate links with other agents. If the network consists of n agents, then each agent has 2^{n-1} pure strategies. If we call an agent who initiates a link to any other agent as the initiator, the initiator pays the costs of the link she has formed. In this situation, the other agent who is initiated a link by the initiator is called as the receiver. Then, this is a direct link formed between the initiator and the receiver and enables information to flow from the receiver to the initiator (in one-way flow of information model) or both from the receiver to the initiator and vice versa (in two-way flow of information model). In addition, the agents gain access to information that other agents have throughout indirect links. For instance, let's we have three agents in a network: i, j and k. If there is a direct link between i and j, as well as j and k, then i and k are indirectly linked and have access to each other's information. Information to which agents gain access represents some benefits. Benefit function is a monotone function of the number of individuals to whom an individual is linked, either *directly* or *indirectly*.

Let $N = \{1, \dots, n\}$ be a set of agents and let i and j be typical members of this set and assume that $n \geq 3$. A *strategy* of agent $i \in N$ is a row vector $g_i = (g_{i1}, \dots, g_{in})$ where $g_{ij} \in \{0, 1\}$ for each $j \in N \backslash \{i\}$. Agent i has a link with j if $g_{ij} = 1$. The set of all strategies of agent i is denoted by G_i since the agent i has the options forming or not forming a link with each of the remaining $(n-1)$ agents, the number of strategies of i is obviously $|G_i| = 2^{n-1}$. The set $G = G_1 \times \dots \times G_n$ is the space of pure strategies of all the agents.

Denote the set of nonnegative integers by Z_+. Let $\phi : Z_+^2 \rightarrow R$ be such that $\phi(x, y)$ is strictly increasing in x and decreasing in y. Define each agent's payoff function $\Pi_i : G \rightarrow R$ as: $\mu_i^d(g)$ denotes the number of agents i has chosen to link to (denotes the "cost" associated with maintaining these links, as well). $\mu_i\,(g)$ denotes the ''benefit'' that agent i receives from her (direct and indirect) links. Then, the payoff function in BG model is strictly increasing in the "benefit", and strictly decreasing in the "cost" that agent i has as a result of linking decisions in her network.

$$\prod_i(g) = \phi\left(\mu_i\,(g), \mu_i^d(g)\right) \tag{3.1}$$

If $\phi(x, y)$ is defined as "$x - yc$" (as c denotes the cost of link formation), a linear payoff function is obtained as follows:

$$\prod_i(g) = \mu_i\,(g) - \mu_i^d(g)c \tag{3.2}$$

The BG model demonstrates results of two settings: one-way flow and two-way flow of information. In one-way flow of benefits, only the initiator of the link receives the values through it whereas in two-way flow version, no matter which agent forms the link, both parties (the initiator and the receiver) are provided with values through the link. In both settings, BG studies Nash and strict Nash stability. The networks corresponding to the strict Nash equilibria of such a game are called strict Nash networks. Nash networks are either empty or connected. In both settings, Nash network is *minimally connected*, i.e., all agents are connected with each other and the removal of any direct link destroys this property. Thus, for a network to be Nash in both information conditions, all agents have to be connected and there are no isolated (groups of) individuals.

A reasonable refinement is the notion of strict Nash equilibrium, where each agent plays his unique best response to the strategy profile of the other agents. BG assert that "*In the one-way flow model, the only strict Nash architectures are the wheel or the empty network*" (Bala & Goyal, 2000, p. 1182). In the wheel, each agent is linked to her adjacent agent on a one-directional path. Thus, each agent pays the cost of only one connection while receiving all the information from the other agents. Note that there are many action profiles that correspond to a wheel configuration. In the empty network, there are no links among the agents. As c denotes the cost of a link formed and b denotes the marginal benefit of a connection, the wheel is the unique strict Nash network if the c does not exceed b. If $c > (n-1)b$, only the empty network is strict Nash. If $(n-1)b > c > b$, both the wheel and the empty network are strict Nash networks. BG states that "*In the two-way flow model, the only strict Nash architectures are the center-sponsored star and the empty network*" (Bala & Goyal, 2000, p. 1182). The center-sponsored star in which every link is initiated or "sponsored" by the center is the unique strict Nash network if $c < b$ and the empty network is the unique strict Nash network if $c > b$. Both the wheel and the center-sponsored star are efficient networks, where an efficient network is defined as a network that maximizes the sum of players' payoffs.

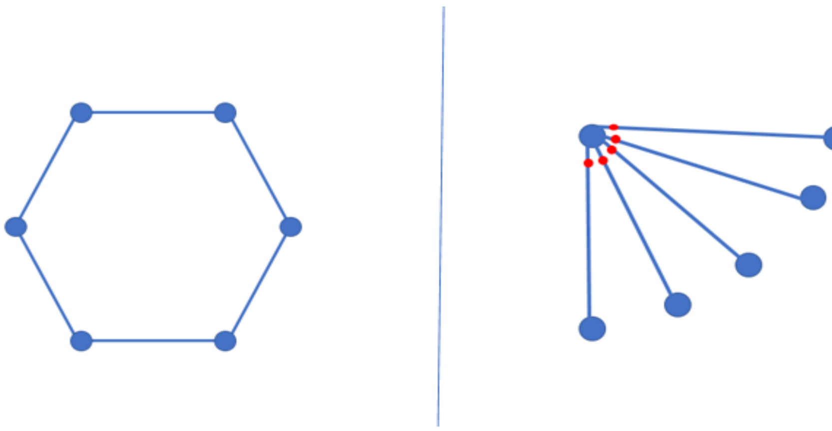


Figure 3.1. (a) Wheel, and **(b)** Center-sponsored star. (Dots indicate the direction of information flow)

In the benchmark model of BG, there is no decay which is explained as "*if an agent i is linked with some other agent j via a sequence of intermediaries, $\{j_1, \ldots, j_s\}$, then the benefit that i derives from j is insensitive to the number of intermediaries*" (Bala & Goyal, 2000, p. 1182). The decay function is introduced to the model in terms of a parameter $\delta \in [0, 1]$. In the model without decay, $\delta = 1$. On the other hand, when the decay is initiated, if each agent offers benefits V and the cost of forming a link is c, they suppose that if the shortest path from agent j to agent i involves q links, then the value of agent j's benefits to i is given by δ^{qV}. For low levels of decay, strict Nash networks expand both in the one-way and two-way models. Strict equilibria mostly are extensions of the wheel and the center-sponsored star. In the one-way flow model, a class of networks with a *flower* architecture is strict Nash since these networks trade-off the higher costs of more links (as compared to a wheel) against the benefits of shorter distance between different agents that is made possible by a ''central agent.'' The wheel and the star are special cases of this architecture. In the case of two-way model, networks with a *single star* and *linked stars* are strict Nash.

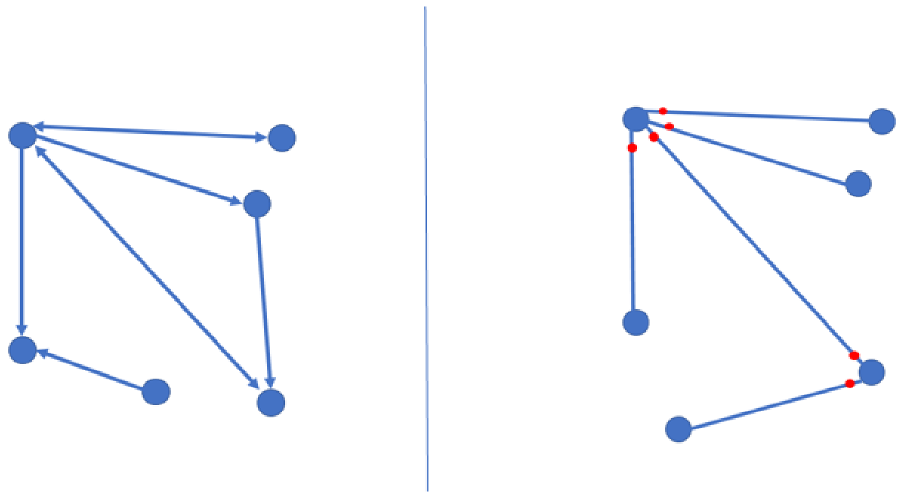


Figure 3.2. (a) Flower and **(b)** linked star networks (Dots indicate the direction of information flow)

Some further significant Nash networks in models with decay are following:

Let us consider a modification of the linear payoff structure given above i.e. where the value of information is $V \equiv 1$ and its cost is $c > 0$. A parameter $\delta \in (0,1)$ measures the decay. The payoffs to an agent i from a network g are given by

$$\prod_i(g) = 1 + \sum_{j \epsilon N(i;g)\{i\}} \delta^{d(i,j;g)} - \mu_i^d(g)c \qquad (3.3)$$

- *"In one-way model with decay, let the payoffs be given above. Then a strict Nash network is either connected or empty. Furthermore, (a) the complete network is strict Nash if and only if* $0 < c < \delta - \delta^2$, *(b) the star network is strict Nash if and only if* $\delta - \delta^2 < c < \delta$, *(c) if* $c \in (0, n-1)$, *then there exists* $\delta(c) \in (0,1)$ *such that the wheel is strict Nash for all* $\delta \in (\delta(c), 1)$, *(d) the empty network is strict Nash if and only if* $c > \delta$*"*[1] (Bala & Goyal, 2000, pp. 1210-1211).

$$\overline{\prod}_i(g) = 1 + \sum_{j \epsilon N(i;\bar{g})\{i\}} \delta^{d(i,j;\bar{g})} - \mu_i^d(g)c \qquad (3.4)$$

[1] See the Proposition 5.1 in Bala and Goyal (2000).

- *"In two-way model with decay, let the payoffs be given above. Then a strict Nash network is either connected or empty. Furthermore, (a) if* $0 < c < \delta - \delta^2$*, then the two-way complete network is the unique strict Nash, (b) if* $\delta - \delta^2 < c < \delta$*, then all three types of stars (center-sponsored, periphery-sponsored, and mixed) are strict Nash, (c) if* $\delta < c < \delta + (n-2)\delta^2$*, then the periphery-sponsored star, but none of other stars (d) if* $c > \delta$*, then the empty network is strict Nash"*[2] (Bala & Goyal, 2000, pp. 1215-1216).

- *"Let the payoffs be given above and let* $c \in (0, 1)$ *and suppose* g *is a linked star. Then there exists* $\delta(c, g) < 1$ *such that for all* $\delta \in (\delta(c, g), 1)$ *the network* g *is strict Nash. (b) Let* $c \in (1, n-1)$ *and suppose that* $n \geq 4$*. Then there exists* $\delta(c) < 1$*, such that* $\delta \in (\delta(c), 1)$ *then the periphery-sponsored star and the empty network are the only two strict Nash networks"*[3] (Bala & Goyal, 2000, p. 1219).

In this point, the question is whether agents really act as they do in the Nash networks. BG asserts that this question could be explained by learning dynamics of the agents who repeatedly play the networking game and learn from their previous experiences and accordingly modify their linking decisions over time. Although it might seem as a naïve assumption that an agent believes with probability one that the other agent would repeat her previous action, BG proves that if all agents use their best response with inertia, a non-strict Nash network could not be a steady state. They use a version of the best response dynamic with inertia that they explain as follow:

> In particular, when making his decision an individual chooses a set of links that maximizes his payoffs given the network of the previous period. Two

[2] See the Proposition 5.3 in Bala and Goyal (2000).
[3] See the Proposition 5.4 in Bala and Goyal (2000).

> features of our model are important: one, there is some probability that an individual exhibits inertia, i.e., chooses the same strategy as in the previous period. This ensures that agents do not perpetually miscoordinate. Two, if more than one strategy is optimal for some individual, then he randomizes across the optimal strategies (Bala & Goyal, 2000, p. 1184).

3.2. The experimental literature on the BG model

A growing body of experimental literature tests some of the stated predictions of the BG model, especially those concerning convergence to the strict Nash architecture. For instance, Berninghaus et al. (2007) investigate the role of star-shaped structures in both discrete and continuous time. However, it is summarized here only two papers relevant for our inquiry.

Falk and Kosfeld (2003)'s study is the first paper that offers a rigorous experimental result on noncooperative games of network formation. Depending on BG model, they study both one-way and two-way flow model without decay. The contribution of Falk and Kosfeld is to vary the cost parameter ($c = 5;\ 15;\ 25$) and to fix the marginal benefit of a link to 10. They had groups of four agents in their all treatments. Agents decide whether they form a direct link during 15 rounds. Where μ_i denotes the number of agents to whom is connected (it includes agent i himself) and μ_i^d denotes the number of direct links i maintains and c is the cost of forming a direct links, the payoff function is linear and equals to:

$$\prod_i(g) = 10\mu_i - c\mu_i^d \tag{3.5}$$

Falk and Kosfeld (2003) conduct three one-way information treatments where the cost of a direct link is either 5, 15 or 25 (called the 1c5, 1c15, and 1c25 treatment) and two two-way information treatments with cost of direct links equal to 5 and 15 (called 2c5 and 2c15 treatment). The theoretical prediction depends on whether the cost of a direct link is larger or smaller than 10.

- In the one-way information flow model, depending on predictions of BG, for 1c5 treatment, the only strict Nash network is the wheel whereas for 1c15 and 1c25 treatments, there are two strict Nash network structures, the wheel and the empty network (Falk & Kosfeld, 2003, pp. 9-10).

- In the two-way flow model, depending on predictions of BG, for 2c5 treatment, the only strict Nash network is the center-sponsored star whereas for the 2c15 treatment, only strict Nash network is the empty network (Falk & Kosfeld, 2003, pp. 9-10).

Falk and Kosfeld (2003)'s study shows that the BG predictions based on Nash and strict Nash equilibrium work well in the one-way flow model but they largely fail in the two-way flow model. The first explanation for the discrepancy between one-way and two-way models is the fact that coordination within the center-sponsored star might be more challenging due to the "*strategic asymmetry"* (p. 2). Accordingly, in center-sponsored star not all agents are expected to conduct the same strategic action. One of the agent is expected to initiate links with all other agents while remaining agents are expected not to maintain any link with other agents. On the other hand, the wheel is a symmetric equilibrium. The second explanation for the failure of the two-way flow model is the "*asymmetry with respect to payoffs"* (Falk & Kosfeld, 2003, p. 3). Falk and Kosfeld (2003) highlight that in two-way flow model, every nonempty Nash equilibrium (the center-sponsored star) is payoff-asymmetric, i.e., the payoffs differ among the agents. The agent who is at the center is expected to pay for all links she initiates while the remaining agents enjoy the benefits provided by links they maintain without paying any cost. In one-way information flow, on the other hand, the strict Nash equilibrium (the wheel) is payoff-symmetric, i.e., each agent obtains the same payoff. Since each agent is expected to initiate one link and since she incurs the cost as well as earns the benefit of this one link, each involved agent obtains the same payoff as a result of their rational actions. Similarly, Callander and Plott (2005) assert that the center-sponsored star almost never emerges in laboratory settings due to the inequality aversion (the central agent pays the cost for all the links and so obtains a lower payoff than the others) and coordination problems (the dynamics which converge to the center-sponsored star require very specific patterns of play among the agents).

Goeree et al. (2009*)* extend the BG model with decay and two-way flow of benefits by allowing for agents with lower costs or higher benefits to other agents. For these settings, BG model predicts that the unique Nash network is a form of *star*. Therefore, Goeree et al. seek for arriving a star-shaped Nash architecture in their study. As mentioned above, in the perspective of Falk and Kosfeld, star-shaped networks are difficult to obtain. However, as opposed to Falk and Kosfeld's prediction of the low frequency of Nash networks with two-way flow setting, Goeree et al. argue that entry of heterogeneity to the setting has a dramatic effect on obtaining Nash equilibrium. Heterogeneity in the study of Goeree et al. indicates the presence of high-value and low-cost agents together with those called ordinary agents in the same network.

Goeree et al. (2009) conduct five treatments to test for the effects of heterogeneity by using the payoff function above. Each treatment group has six agents who play for 30 periods and retain the same characteristics throughout all 30 periods. They study both complete information treatments where agents are informed about the costs, benefits and decay functions and incomplete information where the agents are merely aware of their own types; but not the types of other involved agents in their network.

- (B) the first treatment is baseline where all the subjects are homogeneous,
- (C & Ci) The second treatment features one low-cost agent, implemented under complete and incomplete information,
- (V & Vi) The third treatment features a high-value agent, implemented under complete and incomplete information,
- (VV) The fourth treatment features two high-value agents.
- (CV & CVi) The fifth treatment features one a high-value agent and one low-cost agent, implemented under complete and incomplete information (Goeree, Riedl, & Ule, 2009, p. 350).

In all treatments, the (efficient) equilibrium network has a "star" structure. Goeree et al. (2009), in parallel to Falk and Kosfeld's study, find that in the baseline treatment with homogeneous agents, equilibrium predictions on BG model largely fail. However, when the heterogeneity factor gets involved in the setting, frequency of star-shaped networks increases. Existence of at least one high-value agent particularly increases the possibility of formation of star-shaped network structures, Furthermore, these star-shaped networks are often efficient which means that high-value agent is in the center. Individual differences in benefits-to-others seem as dealing with some of the strategic challenges faced by the agents. When there is a high-value agent in the network, the high-value agent would be more potentially targeted to be linked by the other agents, and a periphery-sponsored star (PSS) whose center is high-value agent is predictably a Nash network.

Results of the study of Goeree et al. (2009) are briefly as follows:

- Heterogeneity has a significant impact on the agents' behaviors and hence; formation of star architectures. Especially, the existence of at least one high-value agent increases the frequency of star networks. In treatments B, Ci, CV and CVi, star architectures are not observed. In treatment C, star-shaped networks in which low-cost agent is in the center are rarely observed. As opposed, the proportion of stars formed in the treatments V and Vi is quite higher. Furthermore, they find that all star-shaped networks are efficient, i.e. the high-value agent is in the center of the star (Goeree, Riedl, & Ule, 2009, p. 455).

- Appearances of star-shaped networks require time. Goeree et al. (2009) assert that "*Stars are not born, however, but grow over time*" (Goeree, Riedl, & Ule, 2009, p. 460). Briefly, star architecture which is absent at the beginning (and remains absent when the agents are homogenous), repetition and experience enable agents to coordinate and to form star-shaped networks towards the end of the experiment.

- Information conditions are also significant on the results of experiment. Accordingly, incomplete information generally has a negative impact on the formation of the stars. However, in treatments V and Vi, there is a slight impact. In treatments with a low-cost agent (C&Ci), under incomplete information, occurrence of star-shaped networks slightly raises. In treatments CV and CVi, information condition is more significant. Under incomplete information, fewer stars are observed (Goeree, Riedl, & Ule, 2009, p. 455).

The treatments V and VV that Goeree et al. (2009) have conducted constitute the baseline of our experimental study. So, these treatments require a more detailed attention for the sake of our inquiry. Accordingly, depending on the predictions of BG model with a low-level decay, in the treatment V where one high-value agent does exist in a network the only strict Nash equilibrium is the periphery-sponsored star (Figure 3.3). If the network is minimally-sponsored-star (MSS) in which each link is sponsored either center or periphery agent and the high-value agent is in the center of the star (Figure 3.3.a), network is efficient. In the treatment VV where two high-value agents do exist in the network, the strict Nash network is either star or linked star. Nash network is efficient if it is MSS and the high-value agents are in the center. In sum, Goeree et al. (2009) mostly observed the stars they search for by the introduction of heterogeneity (and especially of the high-value agent) to the setting. Accordingly, 75% of all networks formed in V and 56% of all networks formed in VV are star-shaped networks (Goeree, Riedl, & Ule, 2009, p. 455).

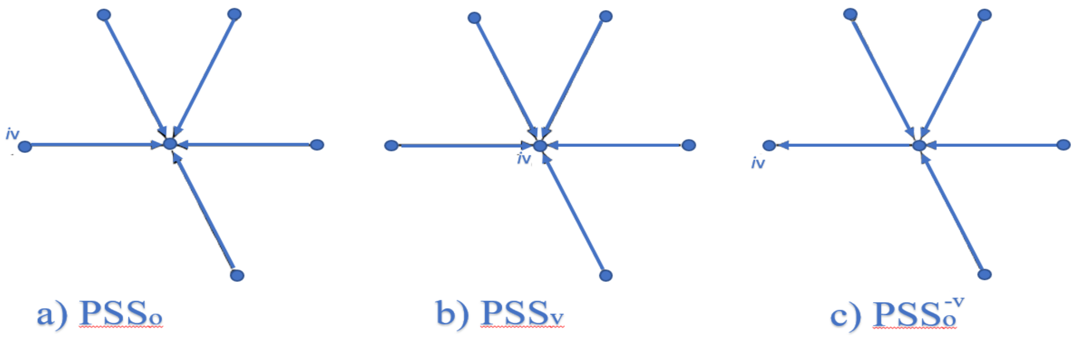


Figure 3.3. Strict Nash networks for treatment V (Source: Goeree et al. (2009), pg. 448)

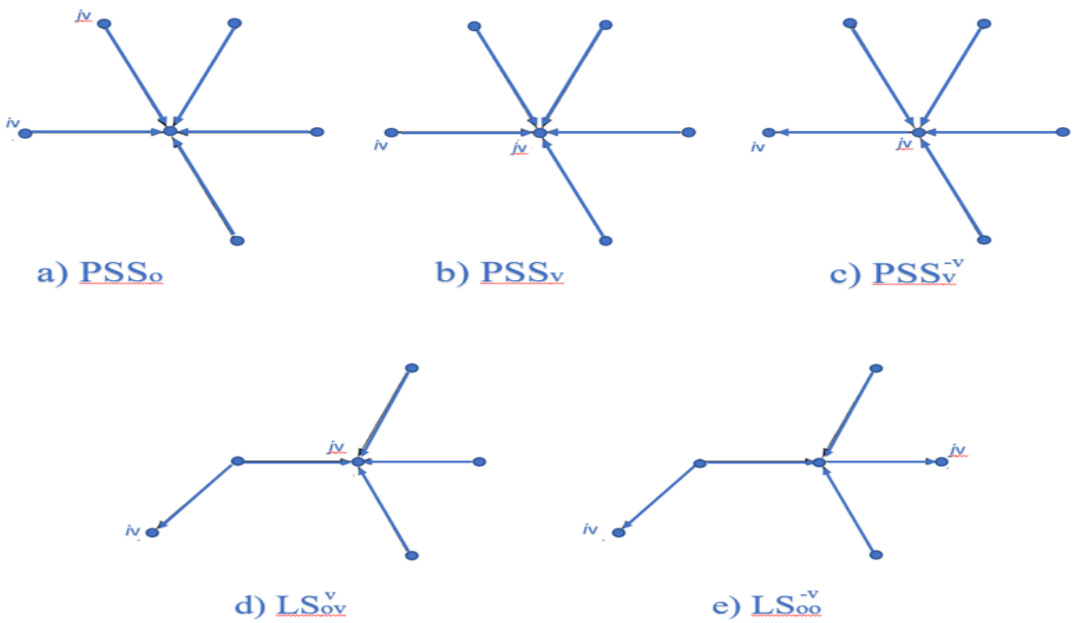


Figure 3.4. Strict Nash networks for treatment VV (Source: Goeree et al. (2009), pg. 449)

CHAPTER 4: OUR MODEL, EXPERIMENTAL DESIGN, THEORETICAL PREDICTIONS and RESULTS

Goeree et al. (2009) have searched for the stars that Falk and Kosfeld (2005) have failed to observe. This thesis seeks for taking a few steps further from what Goeree et al. have concluded. First purpose in this thesis is to obtain stars under two-way flow of benefit, complete information and value-heterogeneity. Second, we aim to measure the robustness of the stars that are obtained under various effects. In this context, this paper contributes to existing literature by introducing two concepts into the literature on the network formation games: shock effect and group effect as two factors having the ability to alter the structures of star-shaped networks.

4.1. Star robustness, shock effect and group effect

The first purpose of this thesis is to obtain star-shaped networks under the same conditions with the treatment V in the study of Goeree et al: two-way flow of benefit, complete information, and the presence of one high-value agent. Goeree et al. (2009) indicate that if there is a high-value agent in a network, ordinary agents undertake the cost of form a link and they create a star-shaped network by “surrounding” the high-value agent. Similarly, under these circumstances, we predict the formation of periphery-sponsored stars, as well.

After the first purpose is accomplished and expected stars are obtained, we, by taking a few steps further, aim to measure the robustness of these stars. This process that we call “star robustness” implies a stickiness to the high-value agents against potential exogenous and endegonous factors. If the agents determinedly form star-shaped networks by resisting any exogenous or endogenous factors, it could be reached the conclusion that stars are robust. Therefore, agents are expected to promptly and conveniently adapt to their perpetually changing “tasks” in order to maintain the robust stars.

In this point, it is required to elucidate what are these possible exogenous and endogenous factors to force the robustness of the stars. The first one is what we call the “shock effect”. Main exogenous shock in our study is that values of agents perpetually change across the periods of our experimental game. The shock effect is investigated by dividing each treatment of our experiment into various parts consisting different mixture of agent types (See Table 4.1). In our design, each agent in the network alternately becomes the high-value agent. In addition, there are mid-stages in which the high-value agent is downgraded to become a mid-value agent, and an ordinary agent is upgraded to become a mid-value agent. These mid-stages consist of two mid-value agents whose values are the same and remaining ordinary agents. There is a last part in our design in which all agents are the ordinary value. We are searching for the answers of a set of questions: Do ever-changing ordinary agents insistently continue to be sponsor for ever-changing high-value or mid-value agent(s)? Do they continue to form star-shaped networks? Are the stars robust enough to cope with this shock effect? Therefore, partite structure of our design is intended for observing potential impacts, that we call “shock effect” on the network structures (See Table 4.3). We expect to observe a dynamic process involving formations, deformations and reformations of the star-shaped networks resulting from the shock effect. Indeed, these shocks are quite similar to real life. In real life, there are certain power balances embedded in a society. Some people have more power (which denotes information or benefit in our study) and this situation makes them more valuable to interact in the eyes of other people in their networks. Furthermore, existing power balances are not everlasting; they might change from time to time. People with more power might lose their values as a consequence of exogenous shocks and new people might substitute them. In this context, fluctuations in the values of agents across periods which are considered as a determining exogenous shock in our design, might lead to deformation or reformation of stars.

The second (endogenous) factor to force the robustness of stars is what we call "group effect". What we are searching for in this point is a partisan tendency originating from the group effect. In this context, it could be said that partisan action drives the network structures out of BG predictions on strict Nash networks and mostly deteriorate the expected utility of the agents who tend to partisan action. The group effect is investigated throughout two types of treatments conducted. In the first treatment, there is no group effect whereas in our second treatment the agents in a network are informed that they are divided into two sub-groups in terms of the party they support. Accordingly, the agents "A", "B", and "C" are the supporters of the "X party" while the agents "D", "E" and "F" are the supporters of the "Y party". Agents, on the other hand, are neither rewarded if they especially form links to other supporters of their party nor punished if they do not avoid from maintaining links to supporters of the other party. By comparing the results belonging two treatments, we aim to investigate whether agents arrived a group consciousness that creates a potential partisan action as a strong group effect. Furthermore, as we have already mentioned, partisan action might decrease agents' payoff. The second scenario, as well, is in line with empirical line. In a society, people knowingly or unknowingly get involved in many groups in respect to their socioeconomic status, their gender (or sexual orientation), their political and ideological opinions etc. This fact might create some biases having a significant impact on interaction map and volume in a network. People might automatically eliminate a part of their social networks to interact. In a general perspective, if group effect outweighs in the human interactions and in the processes of benefit flow, networks might be divided in themselves. Therefore, group effect might also lead deformation of stars or reformation of differently shaped stars.

4.2. Basic network concepts

For these purposes, we built our study on the predictions of BG model on Nash networks. Our model is a natural variation of network formation model of BG in which there are two-way-flow of benefit and a low-level decay factor (see Table 4.2). Each agent would like to enhance their benefit by gathering values from other agents via their links formed. If the agent i forms a link with the agent j, i obtains access to the value available not only in the agent j; but also in other agents who has a connection via agent j. The cost of link formation is incurred only by the agent who initiates the link. In our model, the cost is fixed for all agents and level of distances; i.e. it does not vary in regard of the agents, distance etc.

Let $N = \{1, \ldots, n\}$ be a set of agents and let i and j be typical members of this set. We assume that $n \geq 3$. A *strategy* of agent $i \in N$ is a row vector $g_i = (g_{i1}, \ldots, g_{in})$ $g = (g_1, \ldots, g_n)$ where $g_{ij} \in \{0, 1\}$ for each $j \in N \backslash \{i\}$. Agent i has a link with j if $g_{ij} = 1$. The set of all strategies of agent i is denoted by $G_i = g = (g_1, \ldots, g_n)$. The set of all strategies of agent i is denoted by G_i, since the agent i has the options forming or not forming a link with each of the remaining $(n - 1)$ agents, the number of strategies of i is obviously $|G_i| = 2^{n-1}$.

In our model, the benefit that agent i receives from agent j depends both on the value v_j and on the distance $d(i, j;\ g)$. The distance between i and j, $i \neq j$, as given by the decay function $\Phi(v_j, d(i, j; g))$, is the length of the shortest path between i and j. If j is inaccessible for i then the distance is $d(i, j;\ g) = \infty$. If i and j are (directly) linked, that is, if $g_{ij} = 1$, then $d(i, j;\ g) = 1$. Decay function, $\Phi : \mathbb{R}_+ \times \{\{0, 1, 2, \ldots, (n - 1)\} \cup \{\infty\}\} \to \mathbb{R}$, is strictly increasing in value and decreasing in distance, with $\Phi(v_j, 0) = \Phi(v_j, \infty) = 0$. Accordingly, any agent receives no value both from herself and from those other agents she does not have a (direct or indirect) link (see Table 4.2). In similar to the BG model (2000), we assume a linear payoff function. The payoff to agent i equals to the sum of the values accessed through her direct and indirect links minus the costs of links she initiates. Let $\mu_i(g) = |\{\, j \in N;\ g_{ij} = 1\}|$ be the number of links that agent i maintains. Then the payoff to agent i in the network g is given by

$$\prod_i(g) = \sum_{j \in N} \Phi\left(v_j, d(i,j;\ g)\right) - \mu_i(g)c_i\ . \qquad (4.1)$$

The set of pure strategies of agent i, G_i, is the set of all her possible linking vectors g_i. The set $G = G_1 \times \ldots \times G_n$ is the space of pure strategies of all the agents. Under complete information which agents' values, costs and decay function are common knowledge, Nash networks are established in the (pure-strategy) Nash equilibria of the game $\langle N, G, (\pi_i)_{i=1}^n \rangle$. Given a network g let g_{-i} denote the network obtained when all links maintained by agent i are removed. The network g can thus be written as $g = g_i \oplus g_{-i}$, where the symbol '$\oplus$' represents that g is formed by the union of links in g_i and g_{-i}. A strategy g_i is a best response of agent i to network g if

$\pi_i(g_i \oplus g_{-i}) \geq \pi_i(g_i' \oplus g_{-i})$ for all $g_i' \in G_i$.

The set of all best responses of agent i to g is denoted by $BR_i(g_{-i})$. A network $g = (g_1, \ldots, g_n)$ is a Nash network if $g_i \in BR_i(g_{-i})$ for each i. A Nash network is strict Nash if $|BR_i(g_{-i})| = 1$ for each i, i.e. each agent is playing her unique best response to the network established by the other agents. Efficiency can be measured with the sum of agents' payoffs. Let $w\colon G \to R$ be defined as $w(g) = \sum_{i=1}^n \pi_i(g)$. A network g is efficient if $w(g) \geq w(g')$ for all $g' \in G$.

4.3. Experimental parameters and design

Our experimental design consists of two treatments: the first treatment and the second treatment. In both treatments, there are three main parts of the experiment:

- **HV:** The periods in which there is one high-value and five ordinary agents (12 periods).
- **MV:** The periods in which there are two mid-value and four ordinary agents (12 periods).

- **OV:** The periods in which all six agents in a group are ordinary agents (3 periods).

Table 4.1. Experimental parameters for three parts of treatments

-Parameters-	HV	MV	OV
Types of Agents	1 high-value & 5 ordinary	2 mid-value & 4 ordinary	6 ordinary
Values	High-value → 32 Ordinary → 16	Mid-value → 23 Ordinary → 16	Ordinary → 16
Cost	24	24	24

Table 4.2. Values (per agent accessed) from accessing different types of agents at different distances

Distance	1	2	3	4	5	∞
High-value agent	32	24	18	14	10	0
Mid-value agent	23	17	13	10	7	0
Ordinary agent	16	12	9	7	5	0

We set the values of agent in our game design as seen in the Table 4.3. Our design includes three main part: HV, MV and OV. As indicated in Table 4.1 in HV part there are one high-value and five ordinary agents. MV part is quite significant in terms of being illusionary. In MV, mid-value agents have 23 points value and the cost is 24 points ($b < c$); therefore, in theory MV has equal condition with OV. However, we have created a type of illusion by introducing mid-value agents which have a relatively higher value than others. MV part provides crucial insights about general framework of human perception. In the last three periods (OV), the agents are asked to play our network formation game under value homogeneity. For the sake of our second treatment, in each MV part, one of the mid-value agents is the supporter of the X party and the other one is the supporter of the Y party.

Table 4.3. Values of agents have for each part of the game both in the first and the second treatment

	HV1	MV1	HV2	MV2	HV3	MV3	HV4	MV4	HV5	MV5	HV6	MV6	OV1
A	16	16	16	16	16	**23**	**32**	**23**	16	16	16	16	16
B	16	**23**	**32**	**23**	16	16	16	16	16	16	16	16	16
C	16	16	16	16	16	16	16	16	16	**23**	**32**	**23**	16
D	**32**	**23**	16	16	16	16	16	16	16	16	16	**23**	16
E	16	16	16	16	16	16	16	**23**	**32**	**23**	16	16	16
F	16	16	16	**23**	**32**	**23**	16	16	16	16	16	16	16

4.4. Predictions

Connectedness and group effect. In the second treatment where agents are told that they are the supporters of two different party (group), there are two prominent strategies: the rational strategy depending on BG predictions (see Table 4.3) and the partisan strategy resulting from indigenization of the group identity. Although agents are neither rewarded nor promoted if they specifically connect with the supporters of their party (group), we expect to observe partisan inclinations to a certain extent. In OV, agents are predicted to minimally connect with other member of their own party (group). As seen in Table 4.3 in each MV part, two mid-value agents are set in a way that one of them is the supporter of the X party whereas the other mid-value agent is the supporter of Y party. Therefore, in this part, ordinary agents might tend to form links to the mid-value agent from their own party. In MV as a reflection of group identity, agents might form minimally connected linked stars. Especially in OV as well as MV, the idea of being supporter of a specific party would affect linking decision of the agents.

Architecture. BG model indicates that Nash networks are either minimally connected or empty. Table 4.4 summarizes the predictions depending on BG for different parts of our experiment. In the part HV, the only strict Nash network is periphery-sponsored star (PSS). If the high-value agent is at the center of the star, the network is efficient, as well. On the other hand, in MV and OV, Nash is periphery-sponsored star (PSS) or empty network (EN) (See Proposition 5.3 and 5.4 of BG model mentioned in the Chapter 3). In HV part, formation of PSS is relatively smooth since the existence of one high-value agent provides a strong stimulus that makes the ordinary agents become sponsor for forming a link with the high-value agent. In MV, predictions depending on BG model points out that empty networks and minimally-connected periphery sponsored star are the Nash for this part (see Table 4.4). However, in MV part, since there are two agents who have relatively high value (see Table 4.3)., effect of stimulus decreases and agents remain in limbo. Furthermore, this limbo is an illusion since the expected utility from a link with mid-value agent is negative. Falk and Kosfeld (2003) have highlighted how complicated the task of the participants under value and cost homogeneity and two-way flow of information is. In the light of Falk and Kosfeld's study, it could be predicted that it is challenging to obtain star-shaped structures in OV.

Table 4.4. Nash network predictions based on the BG model.

-Predictions-	***HV***	***MV***	***OV***
Strict Nash Networks	*Periphery-sponsored star (PSS)*	*Periphery-sponsored star (PSS) or Empty Network (EN)*	*Periphery-sponsored star (PSS) or Empty Network (EN)*
Efficient	*All minimally sponsored stars (MSS) that the high-value agent is at the center*	*All minimally sponsored stars (MSS) that the mid-value agent is at the center*	*All minimally sponsored stars (MSS)*

Relative stability. Goeree et al. (2009) have defined the relative stability of a network as "*the number of agents who do not change any links from round* $(t-1)$ *to round* t *divided by the total number of agents"* (2009, p. 458). We predict that networks formed are more stable in HV where one best response does exist for the agents than in the other parts where agents has multiple responses to the equilibrium strategies of other agents in their network.

4.5. Experimental procedures

The experimental sessions were conducted between April and July 2017 at Bahcesehir University Financial Research and Implementation Center. In total, 108 subjects participated in the experiment, 54 in each treatment. All subjects were students from Bahcesehir University. Each experimental session lasted between 45 and 60 minutes. Subjects played the game for 27 periods after three trial periods. At the beginning of each session, subjects were told the rules of conduct and provided with detailed instructions. The instructions were read aloud and shown on the board. We attached importance to minimize differences in the instructions for different treatments. In all treatments, subjects knew the size of their group, the numbers of normal, mid-value and high-value types in their group, the type-conditional payoff functions, and the number of periods. After having finished the instructions, and been sure about subjects' understanding of the game, the payoff calculations, and the computer interface, we conducted a few trial periods. The experiment started after all subjects confirmed they had no further questions.

At the beginning of the experiment, subjects were randomly assigned to a group of six participants. To increase anonymity and avoid framing, each participant's screen displayed herself and the other five participants in her group as "A," "B," "C," "D," "E," and "F". Each letter corresponded to the same subject in the group throughout the session, and this was common knowledge. In each period, each subject simultaneously decides whether she form direct links with other subjects. Therefore, each subject could form no direct link as well as one, two, three, four or five direct links. This was done with the help of a computer screen, which displays all subjects together with two boxes, “Yes” and “No”. To form a link with a particular subject in their group, subjects had to click the “Yes”-box next to the corresponding subject. Accordingly, clicking the “No”-box meant that one did not want to form a link to corresponding subject. After all subjects made their decisions, they were presented a second screen. On this screen, they were informed about all direct links which all group members had formed in the given period. In other words, subjects were informed about the entire network that had been formed in that period. In addition to the direct links, the second screen also informed each subject about with whom she was directly or indirectly connected, the total cost of the direct links, the benefit (stemming from being connected) and profits (benefit minus total cost). After subjects read the information, they pressed an OK-button on the screen. Once all subjects pressed the OK-button, the next period began. We used the experimental software z-Tree (Fischbacher, 2007) to run the experiment[4].

4.6. Results

Connectedness. We first present a few preliminary observations. Participants in our experiments actively link with each other: throughout the first and the second treatments and all periods we never observe the empty network. On the other hand, neither do we observe the complete network, as well. Furthermore, in both of two treatments, we observe that in HV, number of links formed (which is 6.6 on average) increases whereas in OV, number of links formed by the participants (which is 3.2 on average) dramatically decreases. MV has been the part in which participants have formed links most (6.8 links on average). In this point, it could be asserted that the agents are deceived by the illusion. Despite the fact that, MV and OV has the same Nash network predictions, there is a wide gap between the number of links formed in these parts.

[4] Screen shots belonging to first trial period of the 2nd treatment is presented in the Appendix.

In addition, group effect has impact on nature of connectedness of the networks which have been formed in particularly MV and OV parts of our design. In MV, agents have mostly preferred to form links with the mid-value agent from their party (group) rather than the other mid-value agent. In OV, agents have partly formed links with the ordinary agent(s) from their party (group) rather than those from the other party. In these parts, we observe partisan actions to some extent by deviating network structures from BG prediction. In MV, for instance, agents tend to form linked stars and in OV, connectedness among the agents increases. On the other hand, in HV, group effect is not sufficient for agents who completely deviate from BG predictions. In other words, agents are not partisan enough not to form a direct link with the high-value agent from the other party. Although the stars are the prevailing network architecture in HV, group effect makes agents to create flower-shaped networks since ordinary agents tend to form additional links with other agents from their own party (See Table 4.5). Also, we observe that group effect slightly increases the number of links formed in HV part because of another partisan action in which the high-value agent forms a link with ordinary agent(s) in her party (group).

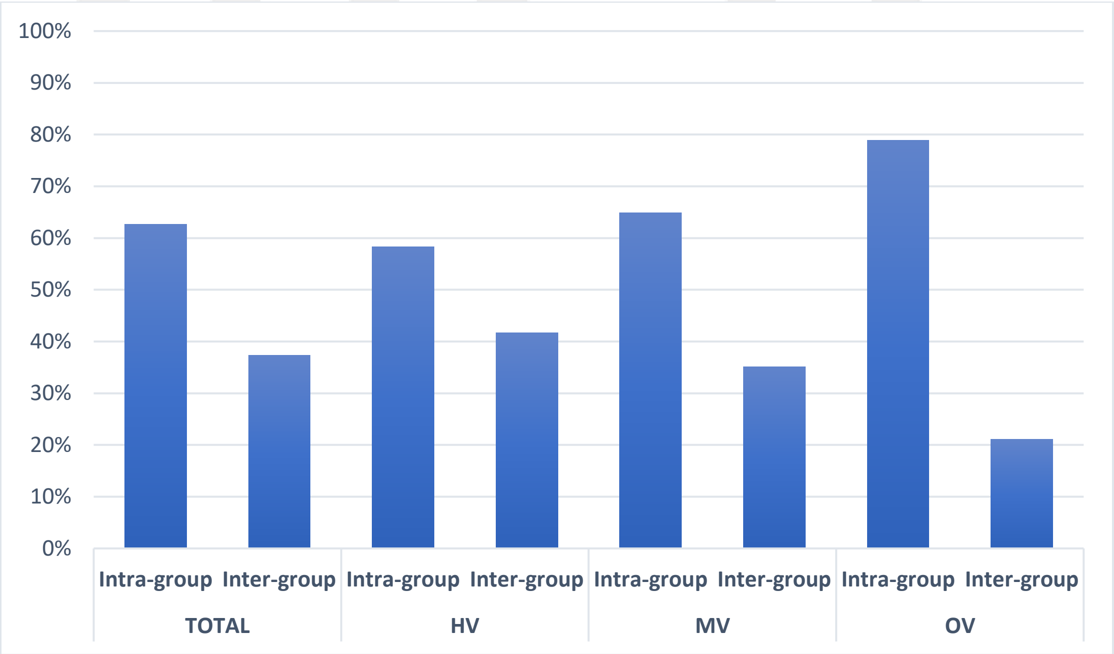


Figure 4.1. Percentages of intra-group and inter-group links

In parallel with the implications above, and as seen in Figure 4.1, agents have formed different number of intra-group and inter-group links in each part of the second treatment. In MV 65% of all formed links were intra-group links. In OV, this ratio was even higher, 78.8% of all formed links were intra-group. On the other hand, in HV, percentage of intra-group links is below the level of 60%.

Relative stability. Goeree et al. (2009) have defined the relative stability of a network as "*the number of agents who do not change any links from round* $(t - 1)$ *to round* t *divided by the total number of agents"* (2009, p. 458). Hence, if no agent changes a link, relative stability is 1 while it is 0 if all agents change at least one link. We, in our study, investigated relative stability within each part. As we have expected, networks formed in HV parts are statistically more stable than in MV ($p = 0.012$; two-sided Wilcoxon signed-rank test). (See Figure 4.2).

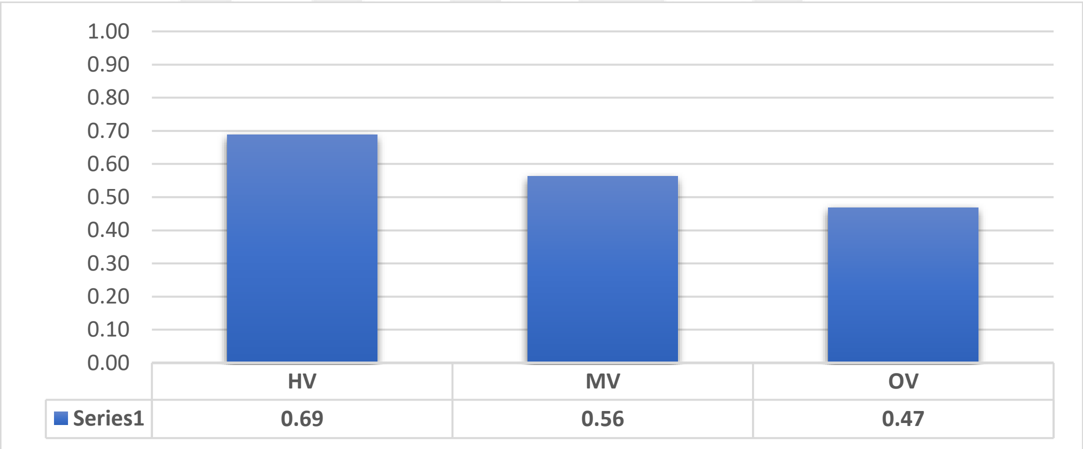


Figure 4.2. Average relative stabilities of networks formed in HV, MV and OV.

Architecture. We then present results concerning the architecture of networks. We investigate the occurrence of Nash networks as well as frequency of formation, deformation and reformation of star-shaped networks across different parts and treatments. We briefly discuss the stability of the observed networks.

Strict Nash networks. Depending on BG model, we have predicted various strict Nash networks (SNN) for different parts of our game (see Table 4.3) and we have also mentioned about some potential deviations from SNN in the second treatments due to potential partisan actions of participants. Starting with the results of the first treatment, in HV, 26.8% of all observed networks were strict Nash, whereas in MV and OV, no Nash network was formed at all. In the second treatment, on the other hand, in HV, 14.8% of all observed networks was strict Nash. Similarly, in MV and OV, no strict Nash network was formed at all. In total, 20.8% of all observed networks was strict Nash in HV, whereas no Nash was observed in MV and OV.

Stars. Goeree et al. (2009) have observed PSS in which all agents are sponsor for connecting to one central agent, in their treatment with one high-value and five ordinary agents. Similary, in HV part of our setting, PSS is extensively observed as the prevailing network architecture: 33.3% of all networks were (72/216) PSS. In MV, 17.5% (38/216) and in OV only 3.7% (2/54) of all observed networks were star. Starting with the first treatment, in HV 44.4% (48/108), in MV 24% (26/108) of all networks are stars. In the second treatment, in HV 22.2% (24/108), in MV 11% (12/108) of all networks are stars. In HV, the difference in percentages of PSS between the first and second treatments is mostly due to the tendency of ordinary agents to form additional links with other ordinary agents (mostly from their party). This action which could be defined as *quasi*-partisan action leads to formation of flower networks (FN) (see Figure 3.2.a) together with the PSS is the prevailing networks in HV of the second treatment.

Table 4.5. Equilibrium Networks (in percent).[5]

		Equilibrium Networks (in percent)						
Treatment	**Part**	**EN**	**PSS**	**CSS**	**LS**	**FN**	**CN**	**#Obs**
First	**HV**		44%					108
	MV	0%	1%		23%			108
	OV	0%	0%					27
Second	**HV**		22%			13%		108
	MV	0%	1%		10%			108
	OV	0%	0%	7%				27
Total	**HV**		33%			7%		216
	MV	0%	1%		17%			216
	OV	0%	0%	4%				54

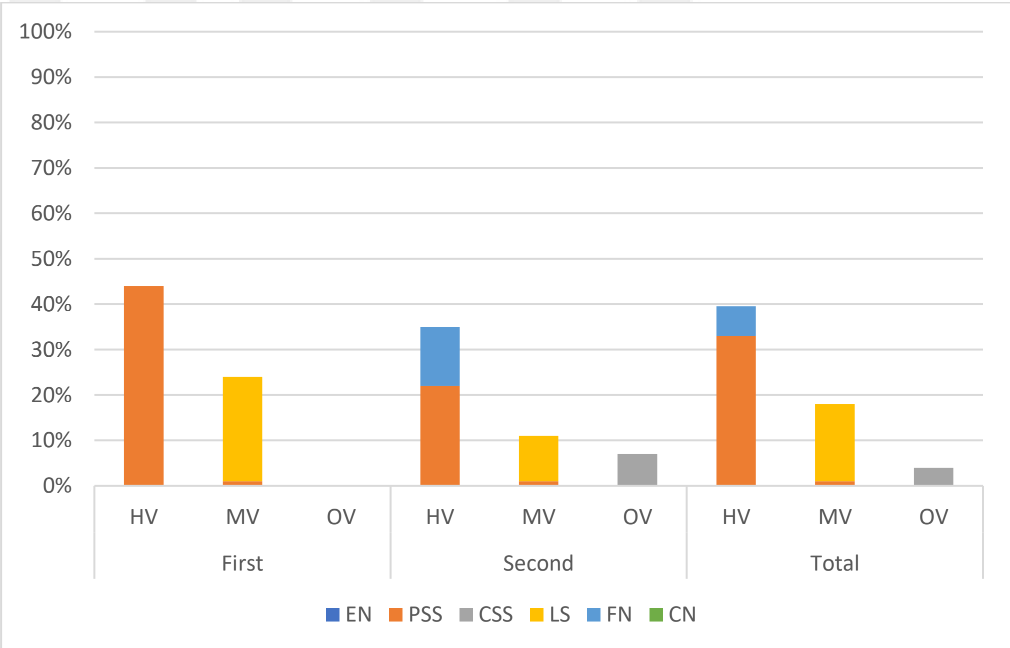


Figure 4.3. Equilibrium networks in HV, MV and OV in the first and second treatment and in total.

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[5] *Empty network (EN)*: No links are made.
Complete network (CN): All links are made
Periphery-sponsored star (PSS): A minimally-sponsored star where all links with the central agent *i* are sponsored by the periphery agents.
Center-sponsored star (CSS): A minimally-sponsored star where the central agent *i* sponsors all the links.
Linked star (LS): There are two linked non-periphery agents *i* and *j* while all other agents are periphery, linked with either *i* or *j*.

Network centrality. Since searching for 'exact' star-shaped networks might be too restrictive given the complexity of coordination that subjects face in the network formation experiments, we also investigate a less restrictive measure: 'centrality'. As The degree-centrality (Freeman, 1978-79) is one of the main measures of network studies and its significance depends on itsto to provide insights how central (hence, important or strong) position of any agent in a network (Goeree, Riedl, & Ule, p. 456) has. 'Degree-centrality' is defined as the sum of the differences in degrees between the most central agent and all other agents. Formally,

$$cent(g) = \frac{1}{(N-1)(N-2)} \sum_{i \in N} \left[max\, deg_j(g) \text{-} deg_i(g) \right] \text{ where } i, j \in N. \quad (4.2)$$

If centrality of a network is 1, then the network is star-shaped whereas centrality is 0, meaning that network is wheel or empty. Therefore, how centrality of a network approaches to 1, this could be interpreted as a tendency to star or star-like networks. The average centralities formed in the parts HV, MV and OV *in the first and second treatment* were 0.8, 0.47 and 0.33 respectively. Since the group effect and potential partisan trends are originating this, we are particularly interested in if there is a difference of centrality of networks in the first and second treatments. As seen in the table below, in the second treatment, centrality of networks in HV and MV decreased whereas increases in OV. Therefore, it indicates that group effect deteriorates the star robustness to an extent. We have emphasized that agents have a more challenging task in MV parts in which there are two-mid value agents whose values are slightly smaller than the cost of forming a link and four ordinary agents (see Table 4.3). A high-degree coordination is required to form strict Nash networks in a rather limited time and in our first treatment, agents fail to coordinate around one of the mid-value agents and star-shaped networks are barely observed. Moreover, it is likely that group effect does lower the network centralities and likelihood of formation of star-shaped structures. For the parts HV and MV, difference in network centralities of the first and second treatments is statistically significant ($p = 0.033$; Mann-Whitney test). If the part OV is included in the analysis, there is no statistically significant difference ($p = 0.240$; Mann-Whitney test).

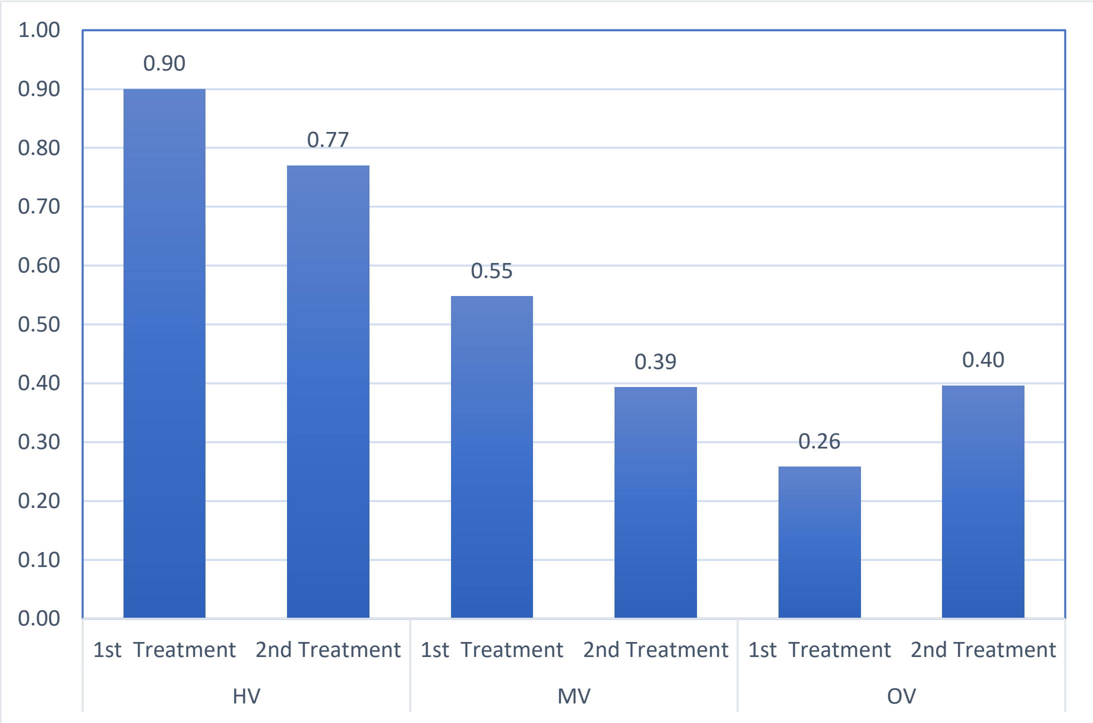


Figure 4.4. Average network centrality in HV, MV and OV in the first and second treatments.

Star robustness. We have proposed to take a step further from Goeree et al. (2009) by measuring robustness of the stars that Goeree et al have searched for. Are agents adaptive enough to reform star shaped networks in a perpetually changing design? For HV part, agents in an adaptive way and no matter who is the high value agent tend to stick to the high-value agents as centrality measure also points out. Across the periods, we can also observe a learning trend. As mentioned above, since searching the exact star is a tough process, we investigated the formation of stars through the network centralities. As network centrality measure approaches to 1, it represents the formation of star-like network structures.

From the general perspective comparing the first and second treatments, we observed that the average network centralities in the first treatment are higher than in the second treatment (see Figure 4.4 and Figure 4.5). Comparing the HV and MV parts, we observe a regular trend in formation stars across the period in HV part whereas in MV part, any regular trend in forming star-shaped networks could not been observed. This might be due to the complexity of required coordination among the agents.

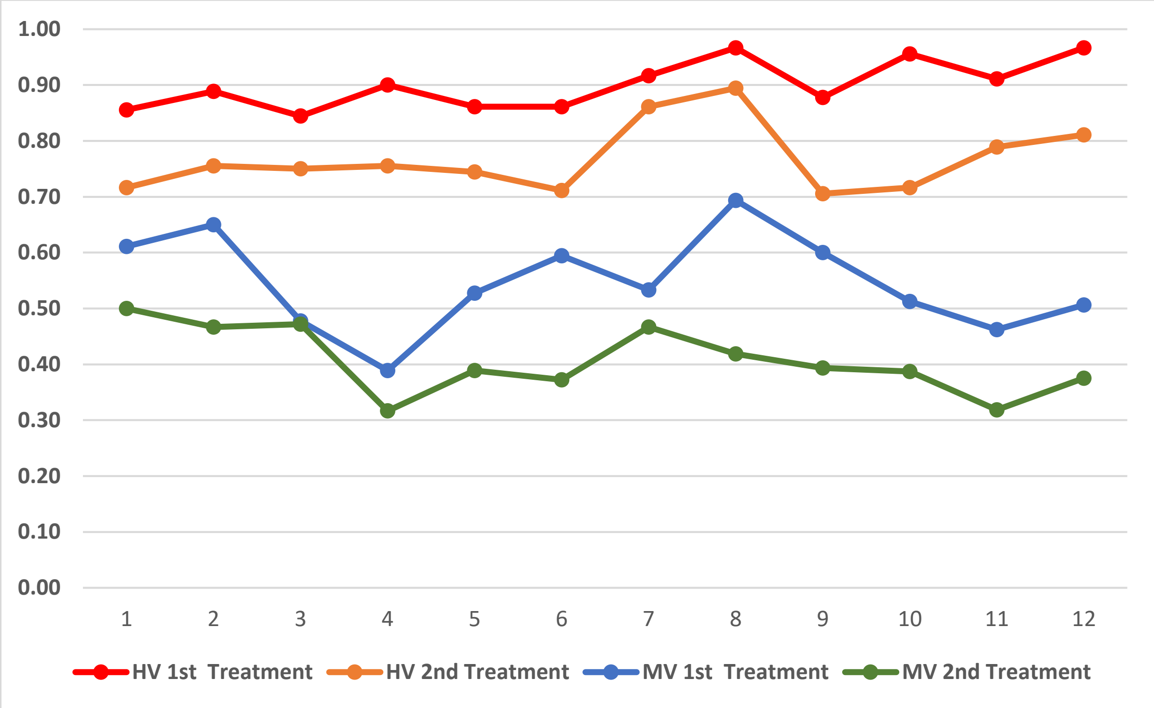
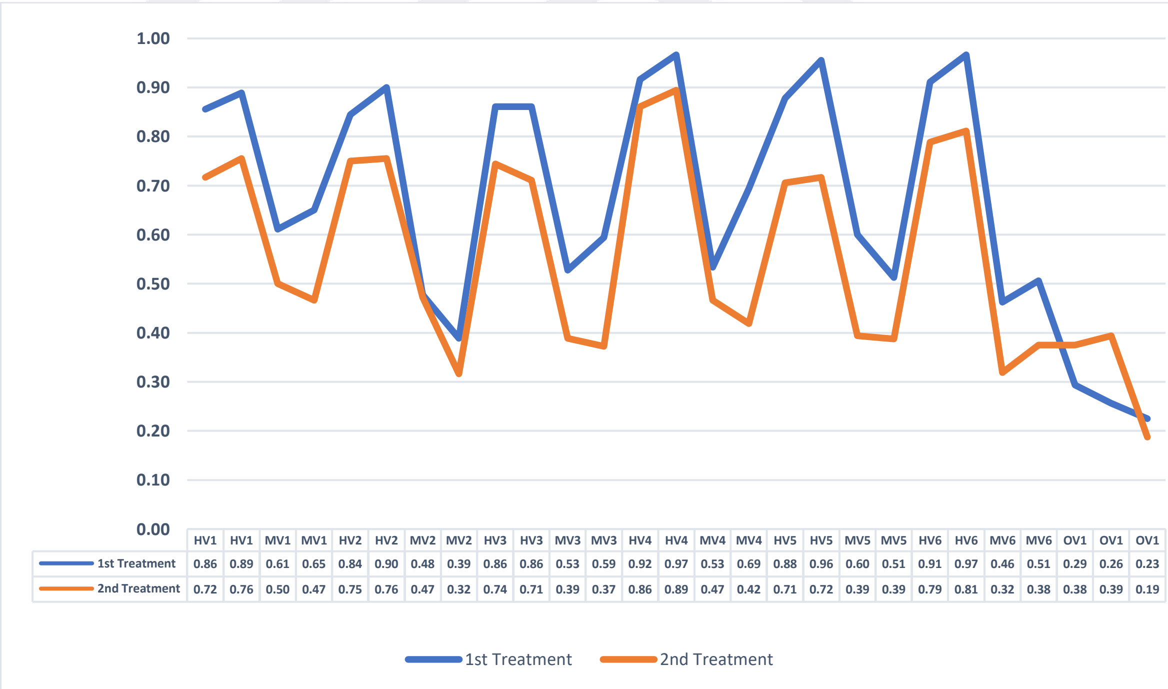


Figure 4.5. Average network centrality in each period of HV and MV parts in in the first and second treatment.



	HV1	HV1	MV1	MV1	HV2	HV2	MV2	MV2	HV3	HV3	MV3	MV3	HV4	HV4	MV4	MV4	HV5	HV5	MV5	MV5	HV6	HV6	MV6	MV6	OV1	OV1	OV1
1st Treatment	0.86	0.89	0.61	0.65	0.84	0.90	0.48	0.39	0.86	0.86	0.53	0.59	0.92	0.97	0.53	0.69	0.88	0.96	0.60	0.51	0.91	0.97	0.46	0.51	0.29	0.26	0.23
2nd Treatment	0.72	0.76	0.50	0.47	0.75	0.76	0.47	0.32	0.74	0.71	0.39	0.37	0.86	0.89	0.47	0.42	0.71	0.72	0.39	0.39	0.79	0.81	0.32	0.38	0.38	0.39	0.19

Figure 4.6. Network centralities across the periods.

Figure 4.6 provides a clear figuration of ups-and-downs of star formation trends in the natural flow of our design. We have mentioned about fluctuations in the values of people across the periods. These fluctuations representing the (exogenous) shock effect concept of our study could clearly be observed in the Figure 4.5. It could be concluded that shock effect (in each transition from the HV to MV), temporarily eliminates the stars. However, with the adverse shock effect (from MV to HV), stars are reformed by the agents. The very last shock (from the MV to OV) finishes the formation of stars. In this way, shock effect vertically interrupts the formation of star-shaped networks across the periods.

In addition, our second concept, (endogenous) group effect is likely to reveal itself as a general decrease in the level of network centralities. In each part of our setting, group effect deteriorates the network centralities. Considering that network centrality is a significant device to measure the formation of star-shaped networks, a decrease in the level of network centrality implies that stars deteriorate. Figure 4.6 indicates that this decrease is maintained across the periods. If we ignore the slight increase in the centrality of networks in OV, group effect causes to horizontal results on robustness of the stars. effect creates a slight increase in the centrality of networks. Therefore, two concepts we introduced (shock effect and group effect) force to another concept introduced by us star robustness through two different planes: horizontal and vertical respectively.

CHAPTER 5: CONCLUSION

Human is a "social animal", and is embedded in the complex dynamics of their society which contains many dynamic network structures where an excessive amount of information or benefit flows from people to people. Therefore, social networks play a significant role in explaining an important part of information sharing and decision-making process of people in many fields such as voting, finding a job, new technologies etc. Analyzing interactions of the individuals who are connected via a network and whose behaviors are shaped by other individuals in this network does provide deep insights about decision-making processes of human-beings which could not have been ignored by the economists. Such interactions are likely to be quite suitable to model by using game theory. This thesis depending on such a special perspective reports a network experiment of noncooperative model of Bala and Goyal (BG).

The central result presented by BG is that there are only two nonempty network structures that are strict Nash equilibria: the wheel in the one-way flow model, and the center-sponsored star in two-way flow model. Experimental study of Falk and Kosfeld (2003) shows that the prediction based on strict Nash equilibrium of BG works well in the one-way flow model whereas it largely fails in the two-way flow model. Goeree et al. (2009), on the other hand, indicate that introduction of heterogeneity in the model plays a crucial role in observation of star-shaped networks in two-way flow model. While almost no star networks are formed by homogenous agent, stars are frequently observed when at least one high-value or low-cost agent does exist in the network.

The first purpose of this thesis was to obtain star-shaped networks under the same conditions with the treatment V in the study of Goeree et al: two-way flow of benefit, complete information, the presence of one high-value agent. After the first purpose is accomplished and expected stars are obtained we, taking a few steps further, measured the robustness of these stars. This process what we call “star robustness” requires a strong stickiness to the high-value agents against potential exogenous and endogenous factors. If agents determinedly form star-shaped networks by resisting any exogenous or endogenous factors, it could be reached the conclusion that stars are robust. Therefore, agents are expected to promptly and conveniently adapt to their perpetually changing “tasks” for the observation of robust stars throughout the experiment. In this point, it is required to elucidate what are these possible exogenous and endogenous factors to force the robustness of the stars. The first one is what we call the “shock effect”. Throughout the experiment, various exogenous shocks are implemented to measure the star robustness. Main exogenous shock in our study is that values of agents perpetually change across the periods of our experimental game. Shock effect is investigated by dividing each treatment of our experiment into various parts consisting different mixture of agent types. The second (endogenous) factor to force the robustness of stars is what we call “group effect”. What we are searching for in this point is a partisan action originating from the group effect. The group effect is investigated throughout two treatments conducted. In the first treatment, there is no group effect whereas in our second treatment the agents in a network are informed that they are divided into two sub-groups in terms of the party they support.

It was presented results concerning the connectedness, stability, architecture and within and across the periods. Each of these results is related to our primary issue of concern: star robustness. Star robustness requires first the formation of stars, so the results concerning the architecture has been quite crucial. Then, obtained stars must have been stable not only within each part of our experiment but also across the periods against the determined shock and group effects.

We have mentioned about fluctuations resulting from shock effect in the values of people across the periods. The first fluctuation (in the transition from the HV to MV), temporarily eliminates the stars. However, with the following fluctuation (in the transition from MV to HV), stars are reformed by the agents. The very last shock (from the MV to OV) finishes the formation of stars. It could be concluded that shock effect (in each transition from the HV to MV), temporarily eliminates the stars. However, with the adverse shock effect (from MV to HV), stars are reformed by the agents. The very last shock (from the MV to OV) finishes the formation of stars. In this way, shock effect horizontally interrupts the formation of star-shaped networks across the periods.

In addition, our second concept, (endogenous) group effect is likely to reveal itself as a general decrease in the level of network centralities. In each part of our setting, group effect deteriorates the network centralities that means the deterioration of star-shaped networks, as well. If we ignore the slight increase in the centrality of networks in OV, group effect causes vertical results on robustness of the stars. effect creates a slight increase in the centrality of networks. Therefore, two concepts we introduced (shock effect and group effect) force to another concept introduced by us star robustness through two different planes: horizontal and vertical respectively.

In this thesis, agents have not been rewarded or promoted for their intra-group, partisan or quasi-partisan actions in the second treatment. As a further study, a design in which agents are provided with some reward or promotion would be exciting in terms of its results. In this study, group effect would reveal itself in a much more severe way.

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