ESSAYS ON FORMATION AND USE OF JOB-CONTACT NETWORKS

by

David S. Powers
A Dissertation
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of
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DEDICATION

This work is dedicated to my loving wife, Megan, my son, Gavin, my mother, Henrietta, and the memory of my father, Robert.

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

ESSAYS ON FORMATION AND USE OF JOB-CONTACT NETWORKS

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This dissertation contributes to the understanding of endogenous job network formation and utilization under varying job-market conditions. It is composed of three chapters, each of which examines different aspects of networking in the pursuit of employment.

A large body of research documents the importance of social ties in finding jobs around the world, in periods of economic expansion and contraction, among developed and less-developed countries, and within urban and rural areas. This dissertation studies the impact of job-market conditions on the effectiveness of social ties in obtaining jobs and on peoples' choices of networking behavior. It examines the use of networks and the network formation process, including the incentives, perceived and/or real, for individuals to form connections in order to share jobs, while others simultaneously choose for themselves. This work compares individual choices relative to predicted behavior in networking and network use and tries to interpret and explain any differences.

The first chapter, entitled, "Network-Formation Theory, Experiments, and an Application," discusses literature related to networks and endogenous network formation, reporting on a group of theoretical and empirical works about job markets, matching, and networking. The majority of works considered are from within the economics of networks framework. The chapter targets a particular application: job-contact networks or referral-based hiring. It highlights the widespread use of social contacts for finding jobs in many settings, considers the importance of social tie strength, and discusses related effects on wages, productivity and job turnover. Finally, the chapter reviews a variety of job-contact models in detail, including their main assumptions, advantages and drawbacks, which provides overall perspective for the main job-contact model to be presented and tested in the next chapter.

The second chapter, entitled, "A Laboratory Test of Endogenous Job-Contact Networks," describes a laboratory implementation and evaluation of endogenous job-contact networks under varying job-market conditions. Specifically, it tests for a non-monotonic relation between the job separation rate (as well as the job offer rate) and peoples' choices of network investment, which consequently affect the likelihood of finding jobs through social networks. The data are drawn from a laboratory enactment of a published theoretical framework under controlled conditions. The chapter details the experimental procedures undertaken, presents the collected data and an empirical model, and discusses the statistical results and overall findings. The outcomes are examined under multiple information levels and linking-cost levels, and post-experiment questionnaire responses are also considered.

The third chapter, entitled, "Extensions of Job-Contact Network Formation in the Laboratory," describes and tests augmentations of the base case job-contact networks setup which step beyond the formally derived theory in order to rule out some alternative explanations of the laboratory-observed phenomena and to assess the overall robustness of the base case results. In particular, three variations are considered: (1) Higher payoffs for jobs found via network matching than for jobs found through other sources; (2) Human players grouped with computer players that follow predetermined strategies (i.e., instead of with other people); (3) Heterogeneous job loss and offer rates among players.. The chapter closes with a discussion motivating additional extensions related to job-contact networks that could merit further model development and/or experimentation in the future.

Taken together, the main contributions of this dissertation are: (1) To synthesize a wide range of readings that are foundational or related to job-contact networks and related theory; (2) To document peoples' networking behavior in laboratory job-contact networks under varying job-market conditions that influence network productivity; and (3) To illustrate useful extensions to the basic laboratory testing of the theory and to help stimulate continued related research in this important area. The results of this project could, at the margin, improve the economics of networks field's collective understanding about the formation and use of job-contact networks. This work could also aid in the discovery and application of some individual and/or policy remedies that improve worker-job matching and job-market outcomes, though also being mindful of possible unintended consequences.

CHAPTER ONE: NETWORK-FORMATION THEORY, EXPERIMENTS, AND AN APPLICATION

In this chapter, after an overview about job matching, I review mechanisms by which social ties can be important to finding jobs and the reasons why people use job-contact networks, using illustrations from economics of networks theory and corresponding empirical work.

1   Job-Contact Networks: Their Value and Effects

In this section I discuss the reasons for and effects of job-contact networks, starting with a discussion of formal and informal labor markets. I then review some terms and discuss commonly cited motivations for job seekers and employers to use job-contact networks. I close with a discussion of strong versus weak ties and their relative importance.

1.1   Formal and Informal Labor Market

The topic of job creation, particularly, for the right kinds of jobs (e.g., by industry, occupation, pay level), is perennially popular in politics, casual conversation, and in the media, including in newspaper articles, television segments, web broadcasts, talk radio, and podcasts. There is also a large volume of related academic literature in economics and other disciplines. Recent U.S. job-creation figures total about 6 million job openings

and around 5.4 million hires per month (Bureau of Labor Statistics (BLS), 2017a), as shown in Figure 1, and these numbers are up a bit from a few years ago.
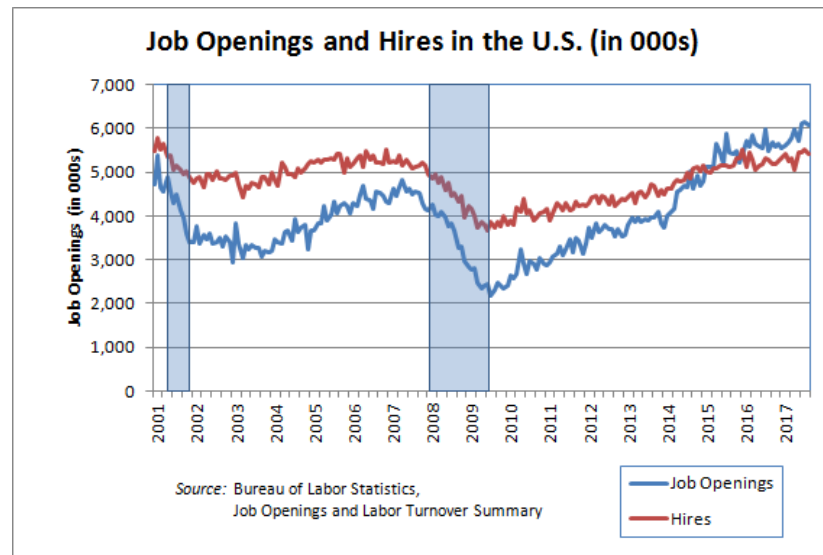
Figure 1. Job openings and hires in the United States.
Source: Bureau of Labor Statistics, Job Openings and Labor Turnover Summary

Even among those currently employed, about 3.6 percent of jobs turn over per month (BLS, 2017a), and median employee tenure is around 4.2 years (BLS, 2016). A recent study of workers born between 1957 and 1964 showed these workers to change jobs about 6 times, on average, between ages 25 and 50 (BLS, 2017b). Given that job churn is a standard part of economic life, so is job *matching*, the alignment of prospective workers to employers' job vacancies. The efficiency of the hiring process and the ultimate quality of the job-worker match are critically important, since hiring costs are a material part of firms' budgets, since employee productivity depends on which workers enter which jobs, and since job and/or occupational fit can affect feelings of self-worth and life fulfillment.

As described in much of the related literature, including Rees (1966), job seekers and hiring managers typically arrange hiring through the following approaches:

(1) Traditional job market, i.e., most of the formal market, including (anonymous) job posts through centralized or limited-access job sites, company websites, career fairs, and newspaper advertisements, and walk-ins.[1]

(2) Job-contact network, i.e., most of the informal market, including referrals from friends, family, acquaintances 'insider information' about job openings, preference for obtaining an interview among applications, preference for hiring among top candidates.[2]

(3) A mix of **(1)** and **(2)**. For example, this might include hearing about a job opening from a friend but then applying competitively, or being waived past the first-round interview.

A job seeker or hiring manager may optimize or balance his/her time and energy spent *across* these approaches, subject to the best information he/she has about the expected marginal returns for each approach, for particular jobs or positions. Where social contacts can produce a quality match at a low cost, social contacts would be favored over the traditional job market, and vice versa.

Furthermore, a job seeker or hiring manager may optimize his/her efforts *within* each approach. For instance, regarding traditional job markets, the employee may strive

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[1] Rees (1966) considered walk-ins as part of the informal job market, not the formal job market. However, the distinction I am aiming to make here is whether the candidate had any social ties that helped him/her obtain the job, which would not be the case for a cold walk-in.

[2] Going a step further, Stupnytska and Zaharieva (2015) find it worthwhile to distinguish professional ties from non-professional ties because of the greater favoritism that is likely to occur after hiring though non-professional ties.

to hone a catchy resume, write a persuasive cover letter, answer self-assessments and open-ended questions, etc.; the hiring manager may strive to create an appealing job description, develop good information-session materials and settle on a useful keyword search combinations. In contrast, regarding social contacts, both the job seeker and hiring manager could decide whether to pursue weak vs. strong ties (i.e., more versus deeper connections), whether to proactively seek new contacts vs. just maintain one's natural social network, which kinds of contacts to seek, whether to socialize more (or less) in places where the local economy booming or where the population is dense, whether to socialize more (or less) in boom economic times, etc. And many other practices could be common across the traditional job market and social contacts, such as practicing their presentations, looking up applicant or company information, dressing well, and using proper etiquette in communications and meetings.

The technology available for finding jobs has changed a lot over the past twenty years, especially related to the rise of the Internet (Stevenson, 2009), and this could ostensibly affect the return to job search job-contact networks relative to. Up-to-date job advice is now 'freely' available through news-sites, blogs and widely-distributed newsletters, and people can obtain differentiated advice for their particular situations and according to their particular preferences. There are major private-sector jobs bank sites that constantly post job vacancy information to individuals and offer individual information to firms, some for a fee and some for free. Furthermore, company websites provide basic information about companies and sometimes about types of positions. Video and video series, including university lectures, are now widely available on the

Internet regarding training / retraining even for very targeted jobs and careers. Electronic correspondence, or email, has lowered the cost of communicating with acquaintances, as well as documenting conversations, in searchable format, for years to come. Social media platforms, like Facebook, WhatsApp, and LinkedIn, allow for easy, frequent sharing with friends and family about jobs and careers in general or about one's personal career goals and/or job search efforts. Even most physical employment agencies have an online presence as well nowadays, which can help both job seekers and employers find them, access their services, and stay in constant communication.

Moreover, due to the Internet medium of distribution, the costs of implementing government policy actions, such as worker training/re-training programs, distribution of outreach basic job-preparation information, and hosting central jobs database(s), are, potentially orders of magnitude cheaper (per person reached) than in earlier decades. For instance, pamphlets no longer need to be printed and distributed, phone lines can be reduced, and physical office hours can be curtailed, and yet the reach of government material can potentially penetrate further with just the electronic media. Other non-government jobs-related services, such as newspaper job advertisements, physical flyers, and in-person job fairs, have likely also been reduced. On net, with so many privately available jobs-related resources on the Internet, nowadays, it may be easier than 'ever before' to access relevant job information and converse with peers about jobs. If this is true, then, currently, there may be less 'need' for government help with job-worker matching nowadays than in the past, which would allow for a reduction in government

job-finding services, potentially saving taxpayers money. Things can always change

further though in ways that might necessitate more government action.[3]

Given many ways that social networking can be effective for job finding, it is

worthwhile to consider the workings behind them in depth.

1.2 Social Ties Often Facilitate Hiring

Job referrals could conceivably come from family members, work colleagues,

former classmates, religious groups, hobby groups, friends, etc. For a firm,

organizational ties (like among vendors, regulators, competitors, trade groups) are also

prevalent. The collection of people that might bear such referrals can be referred to as a

"job-contact network" or a "referral network." And the connections or links that a person

has can be termed "social ties." Of course, contacts may be formed through people one

comes across by chance in everyday life, or they can be sought after proactively for job

reasons or for non-job reasons. To 'invest' in job referrals, one might build up their

social network. For professional contacts, he/she might directly contact people from

particular employers, indirectly contact 'people who know people' from particular

employers, attend career fairs or information events, join online jobs forums. For familial

contacts, he/she may socialize more at family gatherings and send holiday cards. For

friend contacts and acquaintances, he/she may generally increase his social footprint,

attending happy hours, group yoga, church, or talk more with the neighbors, or join

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[3] Although some may fear that trends in online purchasing (i.e., the rise of Amazon.com), automation of
work, and artificial intelligence could ultimately lower the demand for workers, making jobs harder to find,
it is worth noting that, in the face of many prior technological shocks, it has always the case that new
ways for workers to add value have been discovered, and workers have continued to be hired, even it is
difficult to see the next phase of job opportunities currently.

online 'meetup' groups, etc. They could also visit an employment agency and 'borrow' from the employment agency's job-contact network, though that's a stretch of the concept.

There is a large volume of data and research documenting that both job seekers and employers often use social contacts as a means for finding jobs or candidates and that a large share of existing employment is attributable to such contacts. Starting with results from the U.S., Bewley (1999) finds that 60 percent of the 161 businesses surveyed indicated that personal connections (including friends, relatives and professional contacts) were important for their hiring. Holzer (1987) finds that 87 percent of employed youth and young adults ages 16 to 23 relied upon friends and/or relatives for securing employment. Corcoran, Thatcher and Duncan (1980) cites that 56.6 percent of white men knew someone at the entity of their current job beforehand, using 1977 Panel Study of Income Dynamics (PSID) data. Granovetter (1973) cites that 55.7 percent of men that found a new job attributed it to personal contacts, among his sample of professional, technical and managerial workers near Boston, MA. Rees and Schulz (1970) reports that over 50 percent of four types of white-collar workers, and over 80 percent of eight types of blue-collar workers, were hired from informal sources. And, even many decades earlier, De Schweinitz (1932) reports that 45 percent of blue-collar workers in the hosiery industry in Philadelphia, PA attributed their employment to friends or family.

Much more recently, Schmutte (2015), using employer-employed linked microdata over 1990-2003, finds that people who live in areas with stronger social

networks tend to switch jobs more often, enter hiring paying jobs, and join at the same

firm with others they know. Topa (2001), using 1980 and 1990 census tract data in

Chicago, IL, finds evidence of local information spillovers in the spatial distribution of

unemployment, especially for younger workers, low-skilled jobs, less educated workers

and minorities, and the spillovers across tracts are smaller between tracts with very

different ethnic compositions and across neighborhood lines. Bayer, Ross, and Topa

(2008), using 1990 census data from the U.S., finds that social ties amongst people living

on the same block vs. different but close blocks increases the chance that they work at the

same entity. Even among currently *unemployed* people that are seeking jobs, a

substantial portion, roughly 26 percent, in the U.S., claim to be in contact with friends or

family as a means to find work in recent years (BLS, 2017e). Moreover, Hellerstein,

McInerney and Neumark (2011), using their 2000 Decennial Employer- Employee

Database (DEED), find that labor-market networks are often contoured along race and

tend to be more significant for those in minority groups and/or who may have lower job

skills. Topa (2011) provides a systematic review of the many other studies regarding the

extent of referral-based hiring over the decades.

Outside of the U.S., Beaman and Magruder (2012) find, in Kolkata, India, that 45

percent of workers assisted a friend or family member in obtaining work at same

employer. Comola and Mendola (2015) reports about migrant networks utilized for job-

finding, among other uses, in Milan, Italy, via survey data. Cingano and Rosolia (2012),

using administrative data from two Italian provinces, document that someone who loses

his/her job due to a firm closure will have an easier time getting rehired the lower is the

unemployment rate of his former (i.e., predisplacement) coworkers. Bian, Huang and Zhang (2015) documents the use of social ties to find jobs in five cities in China via household survey data. By way of census data from Beijing, China and local interviews, Hasmath (2011) documents that social networks (via word-of-mouth about job openings and facilitated introductions) are valuable for job search, though they attribute that partly to limitations of local institutions. Munshi (2003) shows a greater likelihood for employment and higher wages amongst Mexican migrants to the U.S. with larger U.S. social networks, using panel survey data from the 1980s and 1990s. Singerman (1995) documents the use of networks to find jobs, among other uses, in Cairo, Egypt around 1990 in response to missing (disallowed) formal markets and in order to reach government services and obtain favors. Overall, across countries, cultures, urbanicity, and different phases of the business cycle, as evidenced by these myriad studies and many others, social ties are an important factor in job searching and in employment.

1.3   Assortative Matching, Homophily and Network Effects

The use of social ties to share information and give preference to candidates is often connected with assortative matching. As per Li (2008), assortative matching can be thought of as connecting in ways that correlate with observable characteristics; this phenomenon is also sometimes referred to as 'inbreeding bias.' Becker (1973) provided an early economic analysis of assortative matching in marriage markets. Positive assortative matching in the labor market could connote high-quality people or entities tending to associate with high-quality others. This may be one reason for occupational segregation between social groups (van der Leij and Buhai, 2014wp). There may even be

9

assortative matching among industries (Shimer, 2005a; Abowd, Kramarz, Perez-Duarte and Schmutte, forthcoming).

Homophily also likely has a large effect on the observed structure of networks. As per Pin and Rogers (2015), homophily can be thought of as tendency of agents with similar characteristics to link with each other. For example, see Dev (2016), which develops a model through which communities are built up from links, and see Yavas and Yucel (2014), which presents agent-based simulations in which homophily is self-reinforcing in the way it encourages connectivity within groups especially. It also may have an effect on the utility of a network – if the unemployed are more predominantly in contact with the unemployed, then their social ties may be less productive for finding jobs (Bramoulle and Saint-Paul, 2010). Gender homophily could also aid the persistence of a gap in wages and job success for men relative to women (Zochert, 2014).[4]

Job-contact formation may be partly motivated by 'network effects,' or positive externalities, through which additional contacts add value to a network overall and for the existing people in the network (Shapiro and Varian, 1999), either through direct or indirect links. A person can be said to have an indirect link, or a second-order social contact, with the people whom their social ties are connected to. On the one hand, this could mean that a person is indirectly connected to a lot of people and thus could potentially share in broad information coming across any of those many links. But networks can also have negative externalities. If attention is scarce and/or information is

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[4] Interestingly, a genetic basis for homophily may have been identified (Christakis and Fowler, 2014), and, moreover, homophily may influence a population's distribution of genotypes (Fowler, Settle and Christakis, 2011).

rival, then additional indirect links could mean that one's direct links are less likely to share information with the person since they may only be able to share with a small, limited number of people. Looking globally at the network then, there may be a tradeoff between the extra information that may appear within reach of so many indirect links and the extra congestion that those many indirect links induce. Idiosyncratic factors may be important in determining the value of the network for and from individuals (Ioannides and Loury, 2004).

1.4 Incentives for Job-Contact Networking

In a purely formal job market, without any third-party social ties, workers offer certain skills for a job, and they have preferences about the job climate and benefits, but they have only limited information about the situation offered by any particular job. At the same time, firms seek certain skills and proclivities for workers and are ready to provide a specific work environment, but they have only limited information about what the employee can produce for the firm. First, neither side is even aware of each others' existence and/or whereabouts, so, there is a matching problem for the employers and employees to find an acceptable quality (grade) in a worker or acceptable office conditions of a firm. Second, each side can only guess about what the likely match quality would be, so, there is a basic assignment problem for aligning the needed and provided technical skill sets and characteristics of employers and employees,

11

respectively. Overall, informal job contacts can adeptly help to address these two major issues that arise with the formal job market.[5]

As suggested, social ties are used so widely for finding jobs likely because of the special information they convey. Per Rees (1966), there is great heterogeneity across jobs in a way that there is not across products like new cars. This heterogeneity may incentivize people to spend material time examining the 'intensive margin' by obtaining additional information about a given job opportunity, as well as the 'extensive margin' by obtaining basic information about more jobs. Existing social ties may greatly aid the job seeker at intensive margin by providing non-public or 'insider' information about jobs that other job seekers may not have access to or realize exists. Per Granovetter (1973), the social tie may be able to boil down the job description in a more intuitive way and may have greater honesty about the real climate of the job. For example, the job seeker could learn details about the nature of work, core projects and plans, industry trends, etc., that could come in handy during an interview. Or he/she could learn more about the quality of the employer, the working environment, the benefits, etc., which could inform the job seeker about whether a good fit may be had. Somewhat related to this, Section 2.3 discusses how using social contacts for jobs can reduce asymmetric information.

Among other possibilities, the social tie may confer some favoritism for the job seeker, by facilitating preferential consideration for the job seeker's application materials in the first round, or in one or more levels of the interview process. Or they may even

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[5] There is extensive research in search theory and assignment theory that cover these and many other kinds of issues. Rogerson, Shimer and Wright (2005) and Sattinger (1993) provide good overviews, and Sections 2.5.1 and 2.5.2 look into these issues to some degree.

enable the job seeker to be 'tapped' for the job without any competition among others, or with only the semblance of such competition. This favoritism could end once the employee is hired. However, it could also just be the first act of a chain of favoritism in the future. Such on-the-job favoritism for the worker could include lower work standards, pleasant work assignments, preferred work schedule, nicer work area, special access to decision-makers, etc. Nepotistic hires of family members are probably most likely to ever fall into this category. Finally, over and above the job-instrumental reasons for networking, the mere act of job-contact networking could be pleasant, confer meaningful friendship, and/or or enable the excitement of knowing lots of people.

Since the social tie's information can flows in both directions, conversely, for the hiring manager, the social tie's evaluation of the job candidate can be trusted when the hiring manager and the social tie know each other personally, as opposed to merely what a job seeker will say on their resume or in interviews when he/she is on his/her best behavior. Per Rees (1966), the referring workers tend to recommend people like themselves, and may feel that their reputation is on the line. Also, having an additional 'friend' at the job may constitute a 'fringe benefit' from the employer to the social tie without costing the employer financially. The mere association with a person successfully employed and in good standing with the company may indicate quality through homophily. If the social tie goes a step further and vouches for the job seeker, putting in a good word for him/her, this could provide the hiring manager with additional, though possibly biased, information. The hiring manager can also learn additional private factors about the job seeker that other employers might not be privy to, such as

working style, intelligence, resourcefulness, temper, etc., all of which could inform the hiring manager about the likelihood of good fit.[6] Regarding the possibility of favoritism, post-hiring, the firm may gain access to special databases, elite clients, custom software, etc., that the job seeker has privileged access to. In this, the social tie intermediary may have been the key to finding people with such a custom benefit to the employer.

As discussed in Section 2.4, 'trust' may be another reason for networking in that the social tie intermediary has the confidence of both the job seeker and the hiring manager. This is especially the case if the social tie works at the same firm for which the referral is being given. There may be a history of cooperation and reliance between the social tie and the hiring manager, and between the social tie and the job seeker. The social tie may have detailed and personal knowledge about the other party that the job seeker and the employer lack. The act of delivering the job-contact information may represent the latest phase of iterative trusting and trustworthy behavior within their relationship(s). Knowing how strongly betrayal can hurt feelings and harm relationships, the social tie might feel doubly responsible for the poor match that he/she orchestrate. He/she likely strongly wants to continue the beneficial quid pro quo aspect of their relationship(s). With the social tie having so much to lose should the job ultimately go badly, both the job seeker and the hiring manager may naturally feel that they can trust in the social tie to be trustworthy and make a mutually good worker-job match.

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[6] The social tie may have strong incentives not to lie about the quality of the job seeker because his/her reputation is also on the line, both with his/her peer and with his/her employer. If the eventual job placement were not to work out well, then he/she might feel doubly responsible and at fault.

14

It is worth noting that most social networks are not built specifically for finding jobs – one may have good friends that like the same music, attend the same church, play together in a amateur sports league, are parents of kids in their kids' classes, family, etc. This could limit the utility. Moreover, the people in one's personal portfolio likely vary widely in their potential as job contacts, and the overall values of peoples' portfolios of social contacts likely vary greatly across people.

In summary, on the plus side, hiring through social ties via job-contact networks can greatly lower matching costs (i.e., searching frictions), remove some of the information asymmetry on each side, and increase the likelihood of solid worker-employer matching. It can also facilitate employee on-the-job monitoring and moderate turnover (Beaman, 2016). Some of these benefits will be discussed in Sections 1.5 and 1.6. If successful, hiring managers can somewhat outsource their recruiting to current employees, and job seekers can somewhat outsource their job search to their peers.

On the other hand, it is worth bearing in mind that the effect(s) of hiring through social ties can also be associated with significant downsides either during the hiring or after the employee comes on board. For instance, employee or employer motivation could suffer under some social settings (Bandiera, Barankay and Rasul, 2010). There is also the risk of opportunism and conflicting incentives, to the detriment of match productivity (Bandiera, Barankay and Rasul, 2009; Beaman and Magruder, 2012; Fafchamps and Moradi, 2015). A mismatch between workers' comparative advantage and their occupations can develop (Bentolila, Michelacci and Suarez, 2010). Good matching candidates could be crowded out by the use of close friend or family ties by

hiring managers to fill vacancies. Ponzo and Scoppa (2010) develop a model operationalizing favoritism and using Bank of Italy data to show a possibly negative effect on wages from informal hiring, due to the preponderance of low-skill workers using such networks. So, the source of the social ties and the expectations regarding the future social relationship can be a major factor in the overall benefits from job-contact networking.

Moreover, while it may be individually optimal for one to expand his/her social network to include more referral-generating contacts (since it could raise the likelihood that he/she will find a job), there could also be a hidden downside. If the job-contact information (and/or jobs) are rival, as in Calvó-Armengol (2004)'s job-contact model, then additional social network investment may harm the prospects of others for finding a job in the short-term. There are negative network externalities. However, in the longer term, as in Calvo-Armengol and Jackson (2004; 2007), when one's social tie him/herself has more social ties that raises his/her employment prospects on average, and this can have a positive effects, overcoming the short-term negative externalities, as long as the costs for link creation are not too high. Collectively, in a situation of zero or low-cost linking, a group of nodes would have the highest welfare if it were fully connected. However, if the costs are sufficiently high, the social marginal returns for creating additional links can be negative even the individual marginal returns for creating additional links is positive. There could be an 'arms race' in which most people may overexert themselves in networking without sufficiently improving the overall outcomes, leading to inefficiency and loss of overall welfare.

1.5 Effects on Wages

There has also been much study of the impact of job-contact networks on the level and variance of wages. However, in analyzing this question, it is important to remember that people who use job-contact networks may have other important personal differences relative to people who do not use job-contact networks (Topa, 2011; Montgomery, 1992). For example, they could be more or less educated, more or less technology savvy, more or less sociable, more or less adventurous, etc. So, there is likely a self-selection bias at hand. Also, per Manski (1993) there is a major challenge in trying to estimate the impact of a group average behavior on individuals that comprise the group,, which he terms as 'the reflection problem.' Since most group members and any individuals likely experience similar conditions and shocks, it may be very difficult to disentangle the unique effect of the group on the individual. Angrist (2014) harks back to Manski and cites examples of works for which the authors may not have sufficiently identified the group effect that they claim to capture in their data. With this in mind, any studies that do not take this selection effect into account should be discounted accordingly.

Early on, Stigler (1962) argued that paying high wages is often a substitute for expensing large search costs (such as newspaper advertisements and employment agencies). Rees (1966) stated that an implication of this is that the wage effects of informal hiring would then be positive. Three key theory papers in the early 1990s helped frame the main issues more formally. Montgomery (1991) builds an adverse-selection model with social structure, in which employees found through referrals have higher labor productivity, suggesting that greater network density and greater propensity

to hire those with similar characteristics to existing workers tends to widen the wage distribution. Montgomery (1992) develops a model in which the direction for impact of social ties on wages depends on the network structure, including the configuration of weak and strong ties. Simon and Warner (1992) argues that referrals from existing employees provide special information about the job seekers' future productivity due to homophily. Using the core turnover model from Jovanovic (1979a), the authors predict higher starting wages and lower turnover, though with lower wage growth. As an example of more recent theory, Ioannides and Soetevent (2006) develops a model that predicts that well-connected workers would have a small positive wage premium over others, as well as lower unemployment rates. In contrast, Bentolila, Michelacci and Suarez (2010) develop a model with search that predicts a negative wage premium from use of the job-contact network, and they also confirm their model predictions via analyses of U.S. and European survey data.

Empirical evidence on the wage effects of job referrals has been mixed. Regarding evidence in support of positive wage effects, Ullman (1968) finds wages were higher for people hired through informal means, among female clerical workers (typists and keypunch operators) in Chicago, IL. Similarly, Granovetter (1973) finds higher wages among male professional workers near Boston, MA who found their jobs through a social tie. Simon and Warner (1992), in testing their own model using data from the 1972 Survey of Natural and Social Scientists and Engineers, find higher starting wages among people hired through job referrals. More recently, Schmutte (2015), using employer-employee Longitudinal Employer-Household Dynamics (LEHD) data, finds

that job referrals play a part in the observed higher wages among people who have higher-wage contacts, but these effects are likely smaller for job referrals of the unemployed. Caliendo, Schmidl and Uhlendorff (2011), using Germany data from the IZA Evaluation Dataset, estimate that network size has a positive effect on reservation wages.[7] Brown, Setren and Topa (2016), using a exclusive firm-level data set, find that wages for employees hired through referrals start somewhat higher, but then taper off in line with those from non-referral employees. Cappellari and Tatsiramos (2015), using British Household Panel Survey data, find that wages are higher for high-skilled workers linking with non-relatives, but wages are numerically lower, but not statistically significant, for low-skilled workers linking with greater numbers of relatives.

Regarding evidence not in support of positive wage effects, Delattre and Sabatier (2007), using France survey data, find a negative effect of job-contact hiring on wages. Yogo (2011), using Cameroon survey data, finds, upon accounting for selection biases, only a minimal wage premium from job-contact hiring. Antoninis (2006), using Egyptian manufacturing firm data, finds positive wage effects only when the social tie has a lot of relevant professional experience and sometimes find negative wage effects. Loury (2006), using data for youth and young adults ages 14-21 estimates positive wage effects only for male employees who were assisted by their father, grandfather and uncle in obtaining their jobs. Berardi (2013) provides evidence from Senegal that using strong social ties results in lower wages, and is more often used to fill low-skilled positions. Kuzubas and Szabo (2017), using survey data from Indonesia, find that earnings of those

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[7] For more information about the IZA Evaluation Dataset, see Caliendo, Falk, Kaiser, Schneider, Uhlendorff, van den Berg and Zimmerman (2011).

who use strong ties among family and friends to find work are about 10 percent lower on average. Pellizzari (2010) describes a 'referrals puzzle,' citing many empirical studies show a positive impact on wages from referrals while many other studies show a negative impact. Pastor, Jr. and Adams (1996) find evidence, in L.A. County, CA, that lower-quality job networks in poverty-stricken areas have an effect of lowering average wages, controlling for various human capital and social variables.

1.6 Other Impacts of Job-Contact Networks

Although it is clear that a lot of jobs are traceable to referrals, it is unclear, a priori, if they are economically important. It is possible that referral-based hiring is just a lower-cost substitute for formal-market hiring, leading to essentially the same matches (Krauth, 2004). So it is worthwhile to study the 'real' effects that are attributable to job-contact networks. The last section regarding wages already touched on one possible effect. In this section, several other effects are discussed, including: inequality, match quality, labor productivity, tenure or turnover. The warning about taking self-selection in the data seriously applies fully here as well.

Regarding the practice of hiring through social contacts, it is worth considering not just the employment status and wages, but the variance of future employment status and wages (considering job security and worker commitment). And then there is the question of worker-job fit, in terms of industry, trade, work style for the employee, etc. Perhaps nowadays, workers desires and firms desires can be better met and/or perhaps the range of career choice open to people is wider than otherwise. Overall, it could be instructive to study the present discounted value of work under a world 'prohibiting'

hiring through social ties versus allowing it, and both monetary factors and non-monetary factors (such as the joy of work and the pain of the job application process) should be considered. Similar considerations apply from the employer's side as well. Then it could be worth trying to isolate and measure any subtle changes to macroeconomic aggregates data, for example, any effects on industry composition, firm size, overall economic growth, poverty, and income inequality, that could be due to higher levels of social networking. Below I cite a few studies that provide evidence related to one or more of these above questions.

One major consideration is the effect of job-contact networks on labor productivity. Regarding manual labor and managers of manual labor, two important studies are Bandiera, Barankay and Rasul (2009; 2010). First, Bandiera, Barankay and Rasul (2009), using an exclusive data set from a firm that picks fruit, finds that the configuration of the workers matters for the productivity effects. In particular, workers tend to be more productive in the field when the workers nearby them in the field are friends who are more capable than they are, and less productive in the field when they the workers nearby them in the field are friends who are less capable than they are. Overall, they find the net effect, on the firm's overall productivity, of workers having friends in the field is positive, and that firms can enhance their output by stationing workers of varying capability carefully. Second, Bandiera, Barankay and Rasul (2010), using that same exclusive data set from a firm that picks fruit, finds that under fixed wages to managers, managers tend to ignore prospective workers' likely productivity and choose workers with whom they have social ties. In contrast, under paid performance bonuses to

managers, managers tend to take into account prospective workers' likely productivity and not necessarily choose workers with whom they have social ties. Overall, they find the impact, on the firm's productivity, of managers having prior social connections with the workers they hire is negative. Ashraf and Bandiera (2017) provide a survey across the literature regarding the effect of social incentives on productivity, finding roughly a 10 percent effect, on average, either up or down, depending on how situations are arranged, and also that they can either support or cut against explicit financial incentives.

Another major consideration could be the effect on economic stratification. Job-contact networks are generally theorized to increase wage dispersion and income or wealth inequality, and one likely reason is homophily, since the people in one's social network on average have more in common with them than people not in their social network. For instance, those with high professional success themselves are likely disproportionally connected to others with high professional success, and the same for those with low professional success. As a result, the use of job-contact networks may further accentuate differences that exist from job seeker to job seeker. For instance, the theoretical models of Calvó-Armengol and Jackson (2004; 2007) predict that initial disparities in job endowments and wage levels can have material and enduring effects on the time path of future employment and wages. Partly because some agents with low career prospects drop out of the labor force, there is a strong persistence between starting low wages and continued low wages in the future. In Fontaine (2008b)'s matching model, job-contact networks allow for search externalities, given that some people have more contacts than others, and this tends to raise wage dispersions, but also this also

increases the time required for the economy to converge to the equilibrium unemployment rate. Dawid and Gemkow (2013) study the impact of job-contact networks on wage inequality using a macroeconomic agent-based simulation model and find separation among classes of firms, and rising within-skill wage spreads but not cross-skill wage spreads. Gagnon and Goyal (2017) develop a model in which hiring through social ties lowers inequality when the formal market and job-contact networks are substitutes, but raise inequality when the formal market and job-contact networks are complements.

There is a large range of other effects from job-contact networks worth studying. Of note, Burks, Cowgill, Hoffman and Housman (2015), using proprietary data from nine firms across three industries, find that referred applicants accept job offers at a higher rate, are hired at a higher rate, have generally similar productivity, have lower quit rates, and earn slightly more. Moreover, the lower turnover and hiring transaction costs tend to raise firm profits. Another study, Bentolila, Michelacci and Suarez (2010), using survey data from the U.S. and Europe, find that social ties can lower the duration of unemployment, on average, by one to three months, however, they may often come along with some degree of wage discounts. Schmutte (2016a) suggests that, within the firm, job referrals can help enable solid and useful work relationship and can facilitate information flow to cut against information problems that would otherwise exist with solely the formal labor market. Another dimension of network benefit is the likely reduction in the amount of time needed to find and switch to a new job. For instance, Henly (2002) suggests that networks are especially important for people in the 'secondary

labor market' of typically high-turnover, low-paid jobs. Moreover, it is possible that the use of social ties in hiring leads to a slight reduction in the unemployment rate. However, even if that were not the case, social ties could improve the job market outcomes by improving the fit of the job-worker pairing and thus raise productivity and utility.

Afridi, Dhillon and Sharma (2015) reviews a number of papers regarding the use of social contacts to find jobs and their impact on labor productivity once on the job. Also, Topa (2011) undertakes a survey of the literature of networks and employee outcomes, and lays out several other ways that job-contact networks could matter beyond just the mere finding of jobs.

1.7   The Importance of Social Tie Strength

Regarding social contacts and employment, there is a debate regarding whether strong versus weak ties are most helpful for finding jobs. Granovetter (1973, 1983) began a new consideration of social ties in sociology, arguing, based on survey data, that weak ties are the most important for obtaining jobs. By 'weak,' one could mean the ties are mere acquaintances, friends of friends, or old friends that we do not keep up with as regularly nowadays. This is in contrast to 'strong' ties, such as current close friends, family and work colleagues. Granovettor suggested that the "strength" of a tie between people is a "(probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie." [As a simple way to categorize things, strong ties could simply be friends and family, while weak ties could be professional contacts.] Montgomery (1992) points out that two valid interpretations of 'weak ties' could be, first, that job offers are more frequently

received through weak ties than through strong ties, and, second, that the job offers which come from weak ties come from a superior distribution.[8] Overall the author finds that the impact of social ties on wages depends on the network structure, including the configuration of weak and strong ties.

Granovetter later substantiated his work via analyses of large national surveys in the United States, Japan, Germany, Britain, and the Netherlands, and he mostly found confirmation of his earlier finding (Granovetter 1983; 1995). Granovetter's findings would be at first surprising, given the apparent reliance on formal labor markets in the United States, and given the economics field's focus on centralized and anonymous interactions and common, market-clearing prices (Goyal, 2007, Chap. 1). Granovetter's findings were a surprise even to his participants, in that they reported feeling that although they found their jobs through social contacts, most others surely did not find their jobs that way (Boorman, 1975).

Boorman (1975) is the first economics work to model strong and weak ties for jobs in the sense of Granovetter (1973); it combines game theory analysis and notation with empirically-grounded notions from White (1963). The model depicts strong ties as preferentially receiving information over weak ties, and as having larger maintenance costs than weak ties. The results are that, when the chance of losing one's job is low, in equilibrium, individuals will seek to maximize their sheer number of social ties. However, when the chance of losing one's job is very high, in equilibrium, individuals will prefer to have only strong ties. Assuming that in reality the chance of given

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[8] The first interpretation is more in line with Granovetter (1973), while the second interpretation is more in line with Lin (1982).

individuals losing their jobs is typically low, this work seems mostly supportive of Granovetter's hypothesis about the strength of weak ties. More recently, Montgomery (1994) employment-transitions model, under fixed social networks, exhibits the property that weak ties are associated with lower unemployment, as long as homophily is not too strong. Krauth (2004)'s job-contact theoretical model predicts that the higher the share of a group's average social ties that are weak, the lower the long-term unemployment rate.

Over the years, there has been a lot of additional published research, both theoretical and empirical, regarding the importance of weak versus strong ties for finding work, with widely differing or mixed results. For example, Yakubovich (2005) finds support for the value of weak ties using employee and employer survey data in a large industrial Russian city, though strong ties are also important. Van der Leij and Goyal (2011) finds mixed support for implications of Granovetter's theory, in a study of co-authorship of academic papers among economists. Namely, they find support for strong link transitivity, but they do not find support for weak ties being more important than strong ties. Shirado, Fu, Fowler and Christakis (2013) explores the tradeoffs among different relationship quality (or tie strength) levels of contacts in an online experiment, finding that cooperation is optimal when there is a middle amount of quality in relationships (as measured by duration of the ties). Bian, Huang and Zhang (2015) finds, in 5 Chinese cities, that weak ties are better for receiving job information while strong ties are better for facilitating favoritism.

A recent treatment of this question is in Gee (2017a, 2017b), which studies Facebook data of 6 million people, and makes an important distinction between

individual weak ties and the bulk of weak ties taken together. Although weak ties are valuable collectively, that is primarily because they are so prevalent relative to strong ties. In contrast, the marginal value of any given strong tie is much higher than that of a given weak tie. Another recent work, Buettner (2016) finds a negative relationship between the success of job search and the number of social contacts via survey data of working professionals who were also students. Kuzubas and Szabo (2017), using survey data from Indonesia, find a U-shaped relationship between the size of the local ethnic network and the use of strong ties for job search.

2   Network and Labor Market Concepts

In this section I discuss literature related to networks, asymmetric information, search and trust. I start with the basic idea and representation of networks, and their role(s) in economics. I then discuss asymmetric information and trust motivations for networking, and, finally, an in-depth review of several labor market paradigms, especially searching and matching.

2.1   Conceptualizing Networks and Their Role

Some social media nowadays, including Facebook, Google+, and LinkedIn create and maintain online profiles, webbed together, that make explicit the social networking that has always been taking place. They, further, allow for easy, ongoing digital interactions among connected 'friends.' Social media's effect on actual connections to people is likely substantial, though some suggest it allows for the creation and

maintenance of weak ties at the expense of stronger ties, while others suggest social media enable weak ties to become stronger.

As per Wasserman and Faust (1994), networks can be modeled with graphs in which a person is a node and a link, social tie or connection, is a line connecting nodes. This representation is common in the economics of networks. Undirected graphs connote that social ties or access exist in both directions, whereas, directed graphs (with arrows on some lines) could connote one-way relationships or situations in which information flows in only one direction. A broad network approach to describing nature is provided in Boccaletti, Latora, Moreno, Chavez and Hwang (2006). Graph representations can be traced back even as far as to Leonhard Euler's Mechanica (1736). As early as the 1850s, physicist, J. Clerk Maxwell, used some networking notations and concepts in order to describe molecule structure and flexibility properties (Thorpe, 2009).

An important role of networks is to facilitate information sharing and the trading of goods and services, in a distinct way from trading through markets. Kranton (1996) depicts informal exchange as personal and based on reciprocity, in contrast to market exchange, which is impersonal and associated with low search costs. Kranton and Minehart (2001) explains that networks provide a valuable paradigm from which to study self-organized exchange, in both personal and group-based contexts. Their model, which matches key features of many industries, suggests that "buyers and sellers, acting strategically in their own self-interests, can form the network structures that maximize

overall welfare," (Kranton and Minehart, 2001, p. 485).[9] Zschaler (2012) ascribes

collective dynamics to adaptive networks at work on small-level interactions, harking

back to Thomas Schelling's micro-macro paradigm (Schelling, 1978) and segregation

models (Schelling, 1969; 1971).

An Austrian perspective on social network theory emphasizes the uneven

dispersion of valuable information that is spread among contacts on social networks and

which people seek to obtain among one another (Chamlee-Wright, 2009). It also

highlights the broader benefits obtained by the system that even the individual actors do

not desire or envision. Chamlee-Wright and Myers (2008) argue that networks can

somewhat emulate some key aspects of market prices and can "generate widespread

unintended social cooperation among people unknown to one another." They claim that

the economics of literature underappreciates the "discovery process" that guides network

formation by individuals in the face of "radical uncertainty." Related to this, they state

that it is unclear whether "social learning" processes can take place in non-priced

environments. Overall, although non-price information feedback mechanisms, such as

status and reputation are helpful, networks alone would likely be unable to replace the

bulk of market coordination.

Social networks have been a popular topic of research in sociology since at least

the 1970s, with the *Connections* journal launching in 1977 and the *Social Networks*

quarterly journal launching in 1979. Wellman and Berkowitz (1988) provide a broad

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[9] Charness, Corominas-Bosch and Fréchette (2007) study an arrangement right at the juncture of markets and networks, in which laboratory subjects can buy and sell only with the other subjects to whom they are directly connected.

look at the sociology literature on networks through the late 1980s. Watts (1999) brings

together a range of network theory to discuss small-world forces behind large-world

phenomena. Dodds and Watts (2011) provide a more recent discussion of network

dynamics from a sociological perspective. Knoke (2012) brings together an economic

sociology viewpoint of social networks.

Somewhat associated with sociology, an early precursor to study of social

networks can be found in the area of "sociometry," developed in the 1930s and 1940s by

Jacob L. Moreno, a psychiatrist. Moreno wanted to study social relations from the

bottom up, i.e., from the interpersonal connections and group affiliations made among

individuals, and he felt these associations had important effects on peoples' choice and

psychological health.[10] In Moreno (1934), he represented person-to-person relations

using "sociograms," which resemble the node and link diagrams used in the economics of

networks today. He focused on the specific criteria individuals used in making their

associations, and this, arguably, is proximate to the focus on individual incentives as part

of the economics of networks.

Many political topics have been studied from a social network angle, and the

following are some related results. Political fundraising networks may be cultivated and

leveraged in order to raise contributions for campaigns for political office (Robbins and

Tsvetovat, 2009; Herrnson and Kirkland, 2016). Peer networks can have an effect on

individual political behavior (Levine, 2005; Gimpel, Lee and Kaminski, 2006; Lim,

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[10] In order to correctly represent social phenomena, Moreno felt it important to go beyond formal relations
and communications to uncover informal, possibly even secret relations and sharing. However, Moreno
did not originally intend for his work to make scholarly contributions. In contrast, Moreno felt that his
methods could be used to help people make better decisions and live better lives.

2008; Heaney and McClurg, 2009; Sinclair, 2012; Quintelier, Stolle and Harell, 2012; Parsons, 2015). If 'informational cascades' occur, then the source and quality of politics-related information can become de-emphasized, thus allowing for unchecked diffusion to connected others (Bikhchandani, Hirshleifer and Welch, 1992, 1998, 2008; Velasquez, 2012). The connectedness of legislators to other legislators may be shown to affect their voting in Congress (Fowler, 2006). Social networks could have an important role for explaining political influence and domination (Knoke, 1990; Knoke and Kostiuchenko, 2016). The networks of political lawyers also may be consequence to political party power and priorities (Paik, Heinz and Southworth, 2011). A broader discussion of network theory in politics is provided in Patty and Penn (2016).

Although many fields have brought their analyses to bear on social networks, what is unique about the study of economics of networks is its central focus on incentives. Beneath that, the economics of networks is distinguished by the formal modeling of rational agents making individual choices and the formal analysis of efficiency and social desirability of outcomes (Goyal, 2007).

2.2 Networks Versus Markets

It is possible to locate various goods and services through formal markets, social networks, or a mix of the two. But it is an open question whether the market and networks are substitutes or complements, and this can make a big difference in the predictions from theoretical models (Gagnon and Goyal, 2017). For instance, to find a good European history textbook, one could go to the market, searching through online booksellers, amongst books in the history section of local book stores or university book

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stores. Or one could consult my social network, asking friends of mine, especially those who studied history in depth or related fields, for their suggestions. Or he/she could do a little of both and then decide. Moreover, the results from using just one or the other approach might not be the same. For example, if he/she happen to have a friend with strong socialist leanings, then he/she might get a strong recommendation for a history book that has a more favorable perspective on European history. Or if there is already a 'liberal' bias amongst history books, then if he/she has a libertarian and/or conservative friend, then that friend's advice could help to balance out the market information that he/she receives. Overall, there are many possibilities, and it may be difficult to attribute a simple substitute or complement role.

Although networks may have important roles in the economy, the most fundamental economic phenomena, such as price and quantity levels and movements, industry concentration, economic mobility, etc., have been productively examined from a market-based point of view among anonymous agents or bilateral partners (Jackson, Rogers and Zenou, 2017). In contrast, decentralized networks may, themselves, not be able to explain the steering and clearing of supply and demand on a wide scale. Some limitations for networks include externalities and free rider issues that are familiar from public goods problems, coordination problems in network formation, costs and related implicit bargaining, and payoff asymmetry (Callander and Plott, 2005). However, networks may still play an important role at the periphery of markets, facilitating a large volume of small-scale exchange and specialization, and perhaps enabling small actors to

set up markets in the first place.[11] Choi, Galeotti and Goyal (2017) develop a model

featuring posted prices in networks which produces analogs for standard market concepts.

A wide range of empirical work continues to show that social interactions

transmit valuable information and significantly impact individual behavior and thus

large-scale economic phenomena (Goyal, 2007). After all, sales by firms, purchases by

consumers, international trade, legislation, lobbying and voting all are transacted by

individual entities who have unique places in a social structure. In recent years, it has

become more common for economic analyses of economic behavior to also consider the

social context in which it takes place (Jackson, Rogers and Zenou, 2017). Informal

interactions clearly supplement formal market interactions, and networks are a

convenient and effective way for researchers to model these individual interactions. An

important aim of the economics of networks is to better explain economic forces and

outcomes by tying together the price and competition features of markets with the linking

and sharing behaviors of individuals in networks (Goyal, 2007). A good start has been

made in this direction, and, of course, much remains to be done.

2.3   Why Network? To Handle Asymmetric Information

Pissarides (1979) describes the asymmetric information problem that exists

between job seekers and employers and vice versa. When employees apply to a job with

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[11] Kirman (2016), however, would go much farther, proposing a paradigm shift in today's thinking about economics. To Kirman, much aggregate economic activity can be traced back to basic individual and group interactions supported by just limited information, rather than attributed to anything like competitive markets. Furthermore, some of the most meaningful "exogenous" shocks to the economy, such as the mortgage-backed securities strife in the late 2000s, could be fundamentally grounded in small-scale transactions amongst boundedly rational and modestly informed people, and they need not, and should not, be taken as exogenous.

a firm, they typically know themselves way better than the firm can know them. Conversely, the hiring managers at the firm are likely keenly aware about the characteristics of the firm (pro's and con's), including many aspects that would be unobservable to the job applicant. Akerlof (1970) illustrated some of the major implications for asymmetric information in his basic 'lemons' model in which the market can even fully unravel.

One important way to break through the limited information that one side may have about the other is to allow for communication via a costly signal in the sense of Spence (1973), as per (Perri, 2016). The classic example is how enduring the rigors of schooling, aside from offering any educational benefit, could allow one to signal otherwise unrecognizable talent to employers. Slightly more generally, the key is to arrange an institution that allows agents with hidden types to credibly reveal their type, thus reducing the asymmetric information, while at the same time ensuring that the costs to so does not exceed the 'high' type's (i.e., desirable agent's) expected gains from the resulting separating equilibrium. In that case, typically the 'high' type would find it worthwhile to bear the cost to distinguish him/herself, while the 'low' type would not.

Having a social tie in common with an employer or prospective employee could reduce the asymmetric information at hand at least two main ways. Under one interpretation, the social tie could directly raise the expected mean or reduce the variance of the candidate's unknown productivity distribution, perhaps due to the third-party liaison's direct claims about the candidate's talents or merely by homophily i.e., the likely correspondence between liaison and candidate characteristics. Under a second

interpretation, the social tie between the liaison and the candidate could be a costly signal of quality sent proactively by the candidate to the decider. For instance, the candidate may have either 'courted' this specific liaison hoping to make an impression on him/her that could someday be relayed to the decider. Or the candidate may have intentionally been more gregarious in general, perhaps attending more social or career-related events and talking with others, hoping that someone would notice and relay positive thoughts about the candidate to the decider. [In contrast, if the candidate just happened to know the liaison and made a good impression by chance, then the candidate would not have proactively borne any additional cost, and the signaling interpretation could be a bit unclear.]

2.4   Why Network? Trust May Be Another Reason

Alfani and Gourdon (2012) provide evidence from medieval Europe that costly investment in social ties among business partners might have signaled a commitment to working in good faith together. These investments may have enabled trust, that could endure even across vast physical distance and long time intervals, to form among parties. Trust may be fundamental and essential for allowing for larger scale coordination and industry among humans, and in many cases trust is built up incrementally through exchanges back-and-forth with social ties that may ultimately rise in expense and commitment.

At first blush, it is clear that social ties enable a low-cost way to reduce the information asymmetry of both the hiring manager and the prospective employee.[12] Specifically, the social tie, as a middleman, may have a lot of solid information about both the employer and the prospective employee. He/she can tell whether the two are aligned, while in contrast, the employer does not know about the job searcher, and the job searcher does not know about the employer. If the social tie gives a 'thumbs-up,' then the employer and job seeker can feel somewhat assured that they are not selecting from a low part of the talent or job-condition distribution, respectively. Another positive factor for the use of social ties is that he/she likely has traits that correlate with those of the prospective employee and with the skills being sought by the employer. Assuming the social tie has a good match with the employer, then, by even just the hemophilic tendency for one to select people like themselves, the social tie may naturally produce a good match for both the employer and the job searcher.

However, another reason why social ties are so productive for finding jobs may be a matter of trust. Past friendships may have a strong influence on peoples' future willingness to look out for each other and to give preference. Granovetter (2005) argues that trust is an important reason why social structure, as conceived of in networks, is important for determining economic outcomes; strong ties may entail greater trust and thus have high value for cooperation. Laboratory experiments offer one way to isolating and exposing trust phenomena. Consider the 'trust game,' in which one laboratory

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[12] Although the signal from the social tie may feel like a low-cost signal to the candidate once he/she already happens to know the middleman contact, it is really a *costly* and exclusive signal in the sense that in order to give that signal to the employer, he/she had to acquire that middleman contact, and do so in good standing, which not everyone could possibly do.

subject can either take a monetary payout up front or give some amount if that opportunity to another subject, who will now face a larger pie, but could share back a large portion of the gains, or could take all of this expanded amount for him/herself (Berg, Dickhaut and McCabe, 1995). Of note, the authors (Berg, et al., 1995) were considering the idea of "keeping trust" in the sense of Coleman (1990, Chapter 5). The first mover really puts him/herself out on the line if he/she proposes a significant amount for the second mover to work with. In their laboratory experiment, which was the first test of a trust game, the authors found a great amount of trusting and trustworthy (trust-keeping) behavior, and even a social history treatment did not eliminate this effect In the first laboratory trust game (see Berg, et al., 1995).[13] In a networked version of the Berg, et al. (1995) design, Cassar and Rigdon (2011) operationalize trust in a networked environment among triads, and they find further evidence of trust.[14] Johnson and Mislin (2011)'s trust-game meta-analysis catalogues results from 162 experimental tests of the trust game.

Why trust is so fundamental in humans, whether for finding employment or for other circumstances, is not easy to ascertain. Perhaps it is useful to consider what it means, physiologically, for people to trust. From the field of neuroeconomics, Krueger, McCabe, Moll, Kriegeskorte, Zahn, Strenziok, Heinecke and Grafman (2007) first documented neural correlates of trust, including distinctions between conditional and

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[13] In the 'social history' treatment of Berg, Dickhaut and McCabe (1995), subjects were shown the distribution of offers from stage 1 and replies from stage 2, so they could recognize there were some instances in which trust in the first stage was not kept in the second stage (although often the trust was kept). However, the subjects even in this social history treated were trusting to a similar extent as those from the ordinary, no social history case.

[14] Specifically, the laboratory subjects exhibit comparative or relative trust, and they strategically use this trust to raise levels of cooperation, consistent with the use of trust in the earlier Berg, et al. (1995) work.

unconditional trust. Many studies have indicated that trust could be related to "betrayal aversion," or the "desire to avoid negative emotions that arise from learning one's trust was betrayed" (Aimone, Houser and Weber (2014). For instance, Aimone and Houser (2012) find that when people understand they have been betrayed, as opposed to having just merely lost out, they may choose to invest up to one third less, on average. In a follow-up neuro-imaging study, Aimone, Houser and Weber (2014) provide evidence that betrayal aversion may typically involve the brain's anterior insula.[15]

Market transactions commonly involve the risk of loss. For instance, the quality of a good may not be as high as one expected, one may be unlucky to have received a defective product, or the price of a good may drop right after one makes a purchase. Houser, Schunk and Winter (2010) point out that risk typically involves some uncertainty that we face against anonymous and random occurrences; it is impersonal. Trust, also, inherently, involves some exposure to the chance of negative consequences. However, in contrast, trust is typically personal (Houser, Schunk and Winter, 2010). It involves the faith one must put in another person that has agency to control or determine future outcomes that are of importance to the trustee.

This 'trust game' example, stylized though it is, has parallelism in a wide range of settings, including for hiring to fill a job using social ties. In particular, jobs are high-stake situations both due to the duration and the stakes. There may be a huge range in productivity from the first to the worst performers or job conditions for a given employer

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[15] In a similar vein, regarding reciprocity (i.e., people responding to positive behavior with positive behavior), some regions of the prefrontal cortex appear to be involved in reciprocity-inducing situations (McCabe, Houser, Ryan, Smith and Trouard, 2001). Going yet one step further, Cáceda, Prendes-Alvarez, Hsu, Tripathi, Kilts, James (2017), finds that, "the neural correlates of reciprocity are sensitive to prior experience of reciprocity."

or job seeker. Consider that, in a typical hiring situation, both the hiring manager and the prospective employee will need to feel good about each other in order to go forward with a hiring transaction. However, since there exists no social history between the two parties, this initial transaction may be a situation more of risk than one of trust. That is, if the job arrangement does not work out, it is more likely perceived as just a bad draw from nature that, while regrettable, is impersonal; it is not because either party's trust has been betrayed, or that they were let them down from an earlier transaction.[16]

However, with the middleman as a social tie, in contrast, there exist social histories both with the hiring manager and the prospective employee. If the job arrangement does not work out, it is more likely perceived that the middleman betrayed the employer and/or the job seeker's trust, which is not only regrettable, but personal too, and is thus felt strongly. It is not just a bad draw from nature that is random; it feels more like a directed transgression. And if both the prospective hiring manager and the prospective employee simultaneously feel betrayed, that could be especially painful for the middleman. Therefore, the middleman has strong incentives to not allow either party to be betrayed.

Knowing the pain that the middleman would feel if the hiring deal does not go well, both the hiring manager and prospective employee may be willing to trust the middleman (Munshi, 2014). Thus, if the middleman pushes for a particular hiring

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[16] After the initial hiring transaction, most jobs likely involve trust for the very many subsequent task assignments or transaction that will transpire over the life of that employer-employee relationship. Over time, there will be cycling back and forth between person A trusting person B, and person B trusting person A. An extensive social history will emerge, with ongoing chances for betrayal, and things become personal. It is only the initial hiring transaction that I argue is more a situation of risk than of trust because there had not yet been a social history or chance of betrayal from prior actions.

arrangement, then this signals a high likelihood of a truly good match, and, in that case, each party can easily partake in the hiring transaction willingly. Moreover, the two parties can transact with low cost, i.e., even if they have not spent a huge amount of time researching the details of the other party. They can do so comfortably because they can trust in the middleman to have had both of their interests at heart, so as to avoid being blamed doubly for a bad outcome.

More generally, there is evidence that sharing a positive social history with someone can help encourage future cooperation or magnanimity. For example, Pan and Houser (2013), in a controlled laboratory experiment with modified 'trust games,' finds that in-group favoritism and out-group discrimination may be attenuated when there have been initial cooperation socialization and/or collaboration activities prior to the modified trust games. Castillo, Petrie and Wardell (2014), in a field experiment of charity donation solicitations on Facebook, finds evidence that people were more likely to give money if the request came from a Facebook friend than from a stranger. Meer (2011), utilizing a university alumni donor database, finds that students were more likely to give money to people that they knew formerly in college, even though many years had passed since that time, and they were also more likely to give money to people that seemed to be similar to them. Karlan, Mobius, Rosenblat and Szeidl (2009) build a theory of trust and, using field survey data from Peru, find that informal borrowing was more likely to occur among pairs that had spent more time together, and thus likely had more trust for one another. Buchan, Croson, and Dawes (2002), across four countries, finds a positive correspondence between social distance and cooperation in the context of extended trust

games (i.e., investment games). Ashraf and Bandiera (2017), in a review article, suggests that social incentives are a major force that interacts with organizational design and rules. People may be willing to trade off some money in order to fulfill personal friendship expectations and adhere to social norms.

2.5 Job-Matching Models

The task of aligning workers with given skill sets to firms looking for particular skill sets, with geographic mobility constraints for many agents, is not a simple or quick one. Academic economic work on worker-job alignment go back a long time, and there has been a large amount of work in recent decades regarding searching and matching. In this section, I review those areas, as well as a quick look at some sequential design ideas.

2.5.1 Job Assignment. Job assignment focuses on aligning the workers and firms productively, and pure assignment models typically do not consider asymmetric information or transition/adjustment time to arrive at the assignment distributions. However, they are included here briefly as a benchmark case to help illustrate the major consequences of asymmetric information.

The level of total output in an economy of course critically depends on which workers work at which jobs (Sattinger, 1993). The earnings a worker will receive depends not only on his/her individual skill set, but also on his/her choice of job. Of course firm output and profit also will vary depending on the specific characteristics fill the jobs. Tinbergen (1951, 1956) discussed people sorting into occupations given their individuals abilities and the possible resulting level of inequality in the economy. Roy (1950) pondered the distribution of earnings across people, asking why this distribution is

much wider than the distribution of adult height or weight, and theorized that the distribution of earnings would likely log-normal, as opposed to normal, if all people were employed at a common task.

For handling discrete worker types and a discrete number of occupations, in a now-famous thought experiment of a primitive community with hunting and fishing occupations, Roy (1951) found that the distribution of earnings depends on the skills and technology available in the population across occupations, as long as the distribution of human skill is log-normal. Battalio, Kagel, Reynolds (1978) exploited a special dataset that closely matched the Roy hypothetical idea of many people working in the same job, and found results consistent with Roy's model. Heckman and Honore (1990) wrote out the Roy model analytically, scrutinized the assumptions under which certain results could be expected to hold, and drew new conclusions from it. A vast number of theoretical extensions and empirical tests of the Heckman and Honore work have been done over the years (Eisenhauer, Heckman and Vytlacil, 2015). Heckman and Sattinger (2015) provides some perspective on the legacy of A.D. Roy's work.

For handling discrete worker types but with many occupations, Koopmans and Beckmann (1957) used a linear programming approach. A similar approach has also been applied to multi-object auctions, for example, in Demange and Gale (1985). For handling a situation of continuous worker types and many occupations, one approach, illustrated in Sattinger (1979, 1980), is to use a differential rents model. A detailed review of assignment models is provided in chapters 8 and 9 of Roth and Sotomayor (1990). Some more recent extensions of worker-firm assignment models include

hierarchical assignment by Costrell and Loury (2004), and coordination frictions by Shimer (2005a).

Although pure assignment models typically abstract from information or matching problems, research in this area has also incorporated asymmetric information as well, creating some hybrid work.

2.5.2   Searching and Matching.   Of course, worker-job matching is not immediate, and there is typically some amount of unemployment. 'Search frictions,' related to imperfect information about where are peoples' best job opportunities, may be an important reason why (Andolfatto, 2008). One-sided search models, such as in McCall (1970), typically focus on the supply side of the labor market. In the basic framework, prospective employees are looking for jobs, and wage offers (whose level could be related to match quality) are drawn from statistical distribution. The prospective workers accept offers whose present discounted value over time would at least meet their reservation wage. The models describe flows of workers transitioning between employment and unemployment due to job creation and job destruction, and there is a steady-state level of unemployment in equilibrium. Related to work in this area, Blanchard and Diamond (1989) presents a model of the relationship between job vacancies and unemployment that fit with the 'Beveridge curve,' an empirical relation between job vacancies and unemployment data.

In two-sided searching and matching models, the optimizing processes of both the demand and supply sides of the labor market are modeled simultaneously. The most well-known variant is the "DMP" framework, for which, in 2010, Peter Diamond, Dale

Mortensen and Christopher Pissarides were awarded the Nobel Memorial Prize Award. In the DMP framework, a 'matching function' describes the meeting processes of prospective workers and job openings, and, for a given match, wages are determined under bilateral bargaining. The matching rate is determined endogenously. There is a natural rate of unemployment, which is mostly attributable to the demand side of the labor market (Albrecht, 2011). Typically, there are negative intra-group externalities and positive inter-group externalities that offset each other to some degree, but typically result in some degree of inefficiency (Calvo-Armengol and Zenou, 2005).

An alternative paradigm is presented in Jovanovic (1979a, 1979b), two papers which develop a theory of permanent labor turnover in which the quality of the match is revealed incrementally over time, focusing on idiosyncratic matching between workers and jobs and incorporating worker-job-specific human capital. A follow-up work, Jovanovic (1984) incorporates periodic job-to-job transfers as well as voluntary unemployment. Barron, Black and Loewenstein (1989) explore the role of on-the-job training for a worker to eventually realize his/her potential as a match. Finally, it is fairly straightforward to model social ties within the search-theoretic framework. In a related concept, Section 2.5.3 cites a few models that implement a 'middleman' between the buyers and the sellers in order to help reduce the search frictions at hand and thus facilitate matches.

Empirical support for the DMP framework has been mixed. As one example, earnings heterogeneity do not seem to be well explained by search frictions alone (Hornstein, Krusell and Violante, 2011); worker and firm heterogeneity seem to have

more to do with it (Postel-Vinay and Robin, 2002).[17] As another example, Shimer (2005b) argues that the standard search and matching models fall short in their ability to explain the frequency of business cycles and the variation in unemployment and vacancies as responses to exogenous shocks. Also, Shimer (2012), using data on job finding and exiting in the United States from 1948 to 2010 from the Current Population Survey, finds that the rate of job finding is a larger factor, and job exiting is a smaller factor, in explaining sectoral unemployment than is predicted in the DMP framework. Shimer (2012) attributes most of the trouble to the high flexibility of wages in the bilateral bargaining, and Shimer (2005) also. In contrast, Pissarides (2009) suggests that the issue is more about variation in the costs of posting vacancies. There have been innumerable extensions to the basic DMP framework over the years, modeling heterogenous jobs (Acemoglu, 1997), including endogenizing the search frictions (Lagos, 2000), and deriving microfoundations for the matching function (Stevens, 2007). Rogerson, Shimer and Wright (2005) provide a helpful reader for work in this area through 2005.

Although there are many benefits to the searching and matching models, the use of a black-box matching function in the DMP framework could be limiting. For instance, Guerrero and Lopez (2015), using linked employer-employee microdata, find evidence that aggregate matching functions, even at submarket levels, do not gibe with observed real firm-to-firm labor flows, suggesting the need for a richer modeling of labor market frictions. In follow-up work, Guerrero and coauthors try to model the matching directly.

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[17] I attribute these two citations to points made and references given in Arbex, O'Dea and Wiczer (2016wp).

In particular, Guerrero and Axtell (2013) describe 'labor-flow networks' that emerge through firm-worker interactions in decentralized labor markets of heterogeneous adaptive agents. Guerrero and Lopez (2016) presents a model that handles unemployment dynamics with agent-based simulations and actual microdata in a rigorous way and that shows not only macro- level validation but micro-level validation as well.[18] Calvo-Armengol and Zenou (2005) develops a model incorporating job-contact networking into the matching function, which induces a non-monotonic relationship between social network size and the job-finding probability and thus the unemployment rate. Neugart (2004) runs an agent-based-computational simulation of an endogenous matching function within a labor market model with endogenous job creation and search, presenting results that suggest important limitations from models that utilize exogenous matching functions.

Of note, over the years, economists have been involved in devising institutions to facilitate real-world markets for matching, including for medical labor markets (for new doctors and for gastroenterologists), electricity, FCC spectrum auctions, kidney transplantation, school choice, economists and lawyers. For instance, in designing a centralized clearinghouse for new doctors, one issue to handle was the markets unraveling via appointment dates (Roth and Xing, 1994). The clearinghouse had to appeal broadly enough that its market would be thick, in the sense that a large portion of the medical school graduates would want to participate in it (Roth and Peranson, 1999).

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[18] Given the apparent importance of micro-foundations for modeling labor flows and worker-job matching, it is worth pointing out that *LaborSim*, from (Guerrero, 2017), is a free online application that runs computational simulations of individual workers and firms interacting in a complex setting, with customizable constraints and capabilities.

It was important to establish rules about when it was acceptable for offers to be made, accepted, and rejected (Niederle and Roth; 2005, 2009). Roth (2002) catalogs some of the additional work that had been done to date and makes a case for the economist as a market 'engineer.' Signaling options have been implemented in order to handle congestion in decentralized markets with vast heterogeneity amongst people and placement entities. Roth (2008) provides some more recent updates, including application to new types of markets. Olson, Rassenti, Smith and Rigdon (2003) discuss experiments conducted to explore ways to effectively implement energy trading.

2.5.3 'Middleman' Models. Middlemen in markets can come between buyers and sellers to lower transaction costs compared to direct exchange. They may be well-positioned to meet a higher volume of buyers and sellers continuously, and they can obviate the mutual and simultaneous double coincidence of wants. In the face of mutually asymmetric information, middlemen may reduce initial search costs so that buyers and sellers can indirectly meet, and/or they may affirm the quality of the goods or services that flow between them (Wright and Wong, 2014).
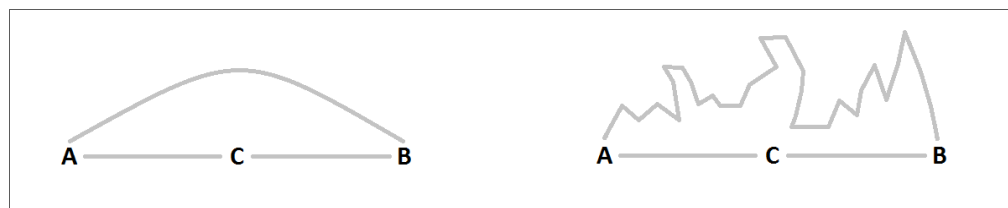
Figure 2. Middleman example
The left panel depicts a smooth path between A and B, while the right panel depicts a less direct path between A and B.

As shown in Figure 2, if hypothetical persons A and B desired to exchange, then person C might be able to reduce the distance or difficult terrain that needs to be crossed. The left panel depicts a fairly direct and smooth path from A to B, while the right panel depicts. The viability of using the middleman depends on the costs that he/she charges relative to benefits conferred. The path need not represent distance, but could instead represent the information needed to complete a transaction. If it is already straightforward for A to find B or to communicate information to B, then C may not be needed. But otherwise there could be relative value in C.

One can think of hiring through social ties as a transaction of indirect exchange, in which the social tie is the middleman, helping the job seeker and the hiring manager meet and ensuring that they are a good match before they begin a costly transaction. The conditional expectation of the candidate's productivity, given the social tie's message, may be higher than the average expected productivity of the more general pool of workers or firms, which motivates them to take action. And the middleman social tie has incentives to arrange a good match; otherwise, the social tie would eventually be scorned by either the job seeker or hiring manager or both. Overall, social ties can be thought to provide an intermediation role in job-market transactions.

Rubinstein and Wolinsky (1987) derives a search-theoretic model with three types of agents: buyers, sellers and middlemen, and they predict the endogenous distribution of these types, as well as the bargaining behavior that would take place among them. Shevchenko (2004) builds upon this earlier work by expanding the choice range of the middlemen to include quantity stored/displayed. Wright and Wong (2014) developed an

offshoot that allowed for chains of middlemen to develop, including the possibility of

what they term 'intermediation bubbles.' Vesala (2008) develops a model, in a setting of

asymmetric information and adverse selection, that explains how two separate markets,

one centralized and one informal, can exist simultaneously and mediated by the presence

of arbitraging middlemen. An important consideration, from Iverson and Torsvik (2010),

is that, while middleman can be connectors, they can also act as constraints, since they

are gatekeepers with their own sets of preferences and incentives that may have to be

traversed in order for other agents to execute a deal at reasonable cost. Finally, in

somewhat related work, Condorelli, Galeotti and Renou (2016) study the flow of goods,

under asymmetric information, from initial producers to final customers that go through

various intermediaries, and it includes a dynamic model of bargaining in networks.

Yavas (1994) and Kubler (1999) are two other papers of relevance to 'middleman'

models that have great import.

2.5.4 Sequential Design. Another, more unconventional, approach for

matching people to jobs could involve ideas from 'sequential analysis.' This application

would relate to the longer-term prospect of settling on a career match, as opposed to find

a job on the margin. Imagine a single employee trying to find the right job option

amongst many possibilities, each with a very uncertain future, but the employee is unable

to quantify these differences and optimize without having any actual experience in the

labor market. Only through sequentially trying many options would the employee start to

know the properties of the job-experience distribution that they face.[19] Consider that, at the end of each work day, employees have an 'exploitation versus exploration' decision to make. That is, they could stick with their current employment, or they could seek out different employment. In this setting, it is important to consider the broad range of factors, outside of just wage and formal benefits, that could make a job feel like a good fit for an employee.[20] Consider that prospective employees might 'sample' jobs over time by first trying to work at one entity, for some chosen length of time, and then switching to another entity if they felt they could do a little better, and so forth. Of course, depending on how the next opportunity worked out they may regret their earlier shift, but they might still learn about the distribution of opportunities in the meantime, and that, in itself, could have value for their future exploitation-exploration decisions. Conversely, from the employer's perspective, the sequential decision could be related to filling a job vacancy with one among many possible candidates. A similar idea had been discussed in Gardner (1960) as the 'secretary problem.'

Sometimes sequential decision problems are illustrated with idea of a multi-armed bandit (i.e., slot machine) in which one can sequentially draws from one of multiple distributions, aiming to maximize the present discounted value of the resulting value stream. A protocol for sequential design of experiments is discussed in Thompson (1933,

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[19] The reason for uncertainty about the returns from one's options could be due to external factors, such as the range of possibilities in the environment. However, it could just as well be due to self-uncertainty about one's own aptitudes, limitations, and proclivities. Or the exploration process could be both self-introspective and externally-probing simultaneously.

[20] For instance, relevant factors could include the rigor of work assignments, the dynamics with one's supervisor(s), the location of his/her personal cube or office, the company by-laws, the types of peers that they find at the organization, the pressure to work overtime, the opportunity to take training or to travel, etc.

1935) for drug research and development choice. A sequential experimentation paradigm is developed in Wald (1945, 1947); Wald and Wolfowitz (1948). Bellman (1956, 1957) proposed a Bayesian formulation and used dynamic programming with Markov decision processes. One would monitor data as they arrive per draw, and choose the sample-size selection on the fly. There is a trade-off between "speed" of convergence versus "accuracy." Typically, agents would use an optimal stopping rule, and they would implement this rule based on sequential hypothesis testing, for instance, by using a sequential probability ratio test (SPRT), which is similar to Likelihood Ratio Test, being most powerful under the Neyman-Pearson Lemma. Overall, the sequential decision problem was thought to be a very challenging mathematical problem for decades. Finally, Gittins and Jones (1974) found the Bayes rule for the discounted multi-armed bandit problem, and, thus found a solution to the sequential decision problem. The authors proposed basing decisions on the value of an index, termed the "Gittins Index," to be computed for each option. Weitzman (1979) also made a similar contribution.

Sequential design problems exist all around us, and adaptive design (Bayesian) approaches have been frequently to handle them effectively. For instance, adaptive design has been utilized in clinical medical trials (Pong and Chow, 2010), as well as in survey data collection (Schouten, Calinescu and Luiten, 2013). In those settings, material resources can be saved in deviating from the planned data sampling based on direction of results obtained so far, and re-optimizing the next phase of data collection accordingly. Sequential analysis has been used for studying stopping time of Brownian motion (Hubert and Pyke, 1997).

Allowing the use of social ties might help to expedite a worker or firm find a good work option by reducing the asymmetric information that workers and firms might have about the other side through the information that the social tie can provide.

3   Economics of Networks: Theory and Some Experiments

In this section I trace through some main developments in economics of networks literature, focusing on strategic network formation theory, in which individuals choose to form links for their own expected benefit. I start with a discussion of key theoretical findings, and devote significant attention to the assumptions and predictions from several job-contact network related models. I then close by reviewing some network empirical results, focusing on laboratory experiments.

Another range of work, sometimes referred to as 'games on networks[21],' typically takes the network structure as given (i.e., exogenous), but explores the ramifications of linking individual game players in various structures, including studying the use of the network and the sharing or diffusion of information on it. This section's review will not cover this latter area of research.

3.1   Network Formation: Cooperative Setting

Myerson (1977) introduced concepts regarding connected and communicating game players to cooperative game theory, though without using the word "network," and these are often termed "communication games." The logical topology, i.e., network structure, was *exogenously* stipulated in advance. He presented an allocation rule (i.e., a mapping between endowments and final holdings across agents) to distribute the value of

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[21] See Jackson and Zenou (2013) for some examples and some key papers in the 'games on networks' area.

52

a game's grand coalition of all linked or communicating players. In this context, the Shapley value is denoted the Myerson value (Caulier, 2009). Of note, under communication games, if the players were connected at all, that was good enough. The particular arrangement of links connecting them was of no consequence (Jackson, 2004). Myerson (1980) generalized the communication opportunities by modeling them via "conference structures" (van den Nouweland, Borm and Tijs, 1992), and, later on, Myerson (1986) developed a multi-stage version of this.

This communication-game or network paradigm benefited cooperative game theory by helping delineate the scope of possible coalition formation (i.e., groups of cooperating players) in cooperative games (Jackson and Wolinsky, 1996). These ideas also assisted with handling transferable-utility (TU) games (Caulier, Mauleon and Vannetelbosch, 2015). Some related work on the endogenous formation of economic coalitions is overviewed in Carraro (2003), and note this is under exogenous-link topology. Qin (1996) discusses a cooperation-formation game and shows that the Myerson value is the imposed solution of this game if and only if this game has a potential, i.e., has a learning property.[22]

Jackson and Wolinsky (1996) started off the economics of networks with their study of individual strategic linking in their "connections model." In their framework, link formation was bilateral, in the sense that it required pairwise incentive compatability, i.e., mutual consent, so the links were undirected, and it was a situation of *cooperation*.

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[22] Furthermore, Qin (1996) shows that players will discover how to form cooperation structures that are payoff-equivalent to the full cooperation structure, if it is the case that players' payoff agree with the Myerson Value.

The authors studied the network topologies that develop under endogenous network formation. They examined properties of network stability and efficiency, introducing the notion of "pairwise stability," and they probed the impact of positive versus negative network externalities. The model assumed homogenous agents that are myopic, i.e., not able to foresee beyond the current moment or round. Their work contrasts with Myerson's communication games in which the connections were exogenous.

A few years later on, Watts (2001) showed that, despite the efficiency of star configurations under the baseline connections model, star configurations are actually unlikely to emerge in this setting due to strong individual incentives not to be the central node in the star. Jackson and Watts (2002a) built further upon the basic connections model, studying it in a dynamic context, now allowing agents to add or delete links over time, but also introducing the chance of accidental consent or deletion. They characterize some statistically stable networks and cycles, and they apply their model to matching problems. Jackson and Watts (2002b), continuing the study of dynamic connections models, set up coordination games to take place among pairs of linked players, and they found that inefficient and risk-dominated equilibria can occur in the coordination games, depending on the overall payoffs and link costs that apply.

Jackson and van den Nouweland (2005) studies the conditions needed for the formation of 'strong' networks in the sense that they are durable in the face of link changes by any coalitions that may form. Jackson and Rogers (2007) develops an endogenous network model that is able to replicate key features of naturally-occurring network structures and that suggests how the patterns of network use are determined by

the way a network is initially formed. Krishnan and Sciubba (2009) refines part of the Jackson and Wolinsky (1996) framework for heterogenous agents and finds different results from the homogeneous-agent case. This work finds that, not only the number of links matters, but the symmetry (or not) of the network structure matters too. It also finds support for its model using data from rural Ethiopia. Page, Wooders and Kamat (2005) introduces the notion of a "supernetwork" under a setting of farsighted consistent networks. Page and Wooders (2009) provides an illustration of the effects of certain assumptions among models of homogeneous networks.

3.2   Network Formation: Non-Cooperative Setting, Individual Linking

Network formation in a *noncooperative* setting, i.e., under unilateral links and pre-specified allocation values, was possibly first studied, in economics, in Goyal (1993), an early discussion paper. Later on, Bala and Goyal (2000a) developed a model of unilateral linking, as compared to the Jackson and Wolinsky (1996) bilateral linking model. Under unilateral links, i.e., directed links, any agent can link to another if they wish, regardless of the incentives of the other to link to them. In this setting, an agent that links to another receives some part of the benefits that the other agent has access to, and this engenders externalities, which plays importantly into measures of network efficiency. The authors assume all agents face homogeneous costs and values, and they are naïve and myopic. The links formed are assumed to fully reliable, and so this is a deterministic setting.

In applying the notion of Nash equilibrium to network formation, Bala and Goyal (2000a) demonstrate the notion of "Nash networks." Both one-way and two-way

information-flow assumptions are explored. The authors also probe the effects of different link costs and different geometric decay factors on resulting network formation and structure, including stars, wheel, etc. Whereas in the cooperative setting the star configuration would be efficient, in the noncooperative setting, the star configuration is both efficient also a strict Nash equilibrium. Finally, the authors also explore the evolution of the network(s) in a repeated-game context, but with some degree of prior-choice inertia.

Bala and Goyal (2000b), using much of the Bala and Goyal (2000a) framework, develops a model that can handle network (un)reliability, in which links can fail at a certain rate, and this failure rate is common among all links. Perhaps surprisingly, the predictions are very different under this setup than under the simpler assumption of information decay by distance. However, following up on this work, Haller and Sarangi (2005) develop a model in which the probability of link failure can vary link by link, instead of with just one common failure rate. Their results are much closer to the results from the deterministic setting from the benchmark Bala and Goyal (2000a) model.

In other related work, Goyal (2005) makes an appeal for developing models with variable link strength and feels the economics of networks framework should be able to reasonably accommodate this. Bloch and Dutta (2009) develop a model with formation of networks under variable link strength, generalizing Jackson and Wolinsky (1996)'s weighted link concept, and generalizing Bala and Goyal (2000a)'s one-sided, two-way flows model. This was an important first step, but since it was just with homogeneous agents, its application is somewhat limited. Galeotti, Goyal and Kamphorst (2006)

studies network formation with heterogeneous agents and finds a fair degree of robustness with original results under homogenous agents.

Galeotti and Goyal (2012) shows how in order to reach a target audience, sometimes it is necessary to target their neighbor (i.e., try to create a path of links to their neighbor), rather than with that audience directly. Somewhat similarly, Baumann (2017 wp) describes a model in which agents differ regarding the quality (in terms of the extent and utility of links that this individual can provide) of who they link with, and they seek to link with the higher-quality agents. Given scarcity of time, connecting to one well-connected person could be much better than connecting individually with a lot of those indirect nodes.

Kannan, Ray and Sarangi (2007) discusses the impact on network structure when information is gained through the network under costs that increase or decrease by distance (i.e., number of edges between nodes). Galeotti and Goyal (2010) develop a model to fit 'the law of the few,' namely, the stylized fact that people tend to get a lot of information from only a few core social contacts who are very similar to them. Ghiglino and Goyal (2010) develops a model in which affects individual utility varies negatively with the consumption levels of one's neighbors. It finds that network structure, including individuals' "centrality," play an important role in determining overall prices and consumption as well has his/her individual consumption levels.

Overall, noncooperative game theory principles have been used extensively in the economics of networks. Even early on, game theory tools helped authors discover that, in networks, individual incentives and efficiency may often be at odds, and as a result

stable networks may often be inefficient (Callander and Plott, 2005). Jackson, Rogers and Zenou (forthcoming) supplies a review of recent work in the economics of networks literature, including how it builds upon the earlier work. Jackson (2016) gives a rundown of the economics of networks' key areas of progress to date, latest open questions, and likely topics of future work, i.e., the topics for which this paradigm is likely to still shed new light. Vannetelbosch and Mauleon (2016) give a thorough review of recent network formation theoretical literature. As of the early 2000s, Jackson (2004) provides a review of the first wave of endogenous network formation theory from the economics of networks literature. Dutta and Jackson (2003) summarizes the main principles of network formation, and Jackson (2003) summarizes the main principles of stability of networks.

3.3   Network Formation: Non-Cooperative Setting, Mean-Field Approach

Solving models with individual linking with large numbers of players can be very complicated, and this limits the features that can be modeled. Therefore, it may help to consider a "mean-field" approach in which many rational agents with limited information each abstract from the local details and strategize based solely on higher-level conditions and average interactions amongst players (Lasry and Lions, 2007; Vega-Redondo, 2007).

Brueckner (2006) may be the first economics of networks work that models network formation with a mean-field approach. Specifically, here, links were created randomly on the basis of the overall level of resource investment in social networking, instead of by individual choice link by link. The result is a stochastic network that is much easier, analytically, to study. It also has a reasonable economic interpretation – the

more time one spends socializing, the more friends one will likely have. We often do not set out to meet particular people. Part of the joy of socializing could be the element of surprise related to talking with whomever one happens to talk with and seeing if two people hit it off with each other.

Similarly, in Golub and Livne (2010 wp), the authors develop 'random networks' in which socialization is chosen in level, as opposed to in connections to specific individuals, and there is uncertainty regarding which contacts will ultimately become friendships. This model focuses on social benefits, and does so for indirect links as well as for direct links. The authors state that their models predict network structure with characteristics of those that really exist. The strength of the links is proxied for by the likelihood that links emerge between nodes. Christakis, Fowler, Imbens and Kalyanaraman (2010 wp) provides a model similar to Golub and Livne (2010 wp), except with less realistic assumptions about agent rationality.

Currarini, Jackson, and Pin (2009a; 2009b) develop and illustrate a model that allows for mixes of types of friends, with preferences valuing diversity or not, and this allows for predictions regarding exploitation vs. exploration behavior, and thus the emergence of homophily or not. Matching occurs in a weighted random fashion in the sense that if people are biased towards friends of their own type, then the matching rate for people of that type will be higher them. Durieu, Haller and Solal (2011) provides a model of 'nonspecific networking' to match the reality that people typically encounter and inadvertently network with wide range of people, some of which may even constitute undesired connections.

Looking forward, it could be useful to have a combination of the Golub and Livne (2010 wp) model with the Galeotti and Merlino (2014) model (see Section 3.4) since then the model would account for both the social benefits of the network, as well as the instrumental job-providing benefits of the network. For instance, perhaps time spent job-contact networking is less enjoyable than time spent naturally socializing. Cabrales, Calvó-Armengol and Zenou (2011), which models productive and socialization efforts explicitly, is a step in that direction, but is somewhat different because the socialization only provides an instrumental benefit.

3.4   Job-Contact Network Models

Many job-contact models utilize strategic network formation of the sort discussed in Bala and Goyal (2000a) in combination with a matching function from the search-theoretic literature. However, once the initial links are in place, some models leave the network as fixed from there on out. Other job-contact models utilize exogenous networks, which allows them to model other aspects more richly. In some models, referrals are used in order to inform job seekers about the existence of jobs, and in other models, the referrals are used to find employees that will be a good match and/or have superior productivity.

Mortenson and Vishwanath (1994) proposed a model in which even identical agents may have different equilibrium wages due solely to the share of job-offer information they receive from the informal versus formal job markets. The model also incorporates job-to-job transitions when agents are presented with job offers that would pay higher wages. Importantly, network linkages are not explicitly modeled across the

60

agents; the network structure is not specified or computed. Instead, agents' connections are summarized by simply the share of job-offer information arriving to them from the informal job market versus from the formal job market. Specifically, job-offer information arrives to agents at some Poisson rate from either informal or formal sources, and the share of information from two sources varies across agents. The distribution of job-offer information from personal contacts statistically dominates the distribution of job-offer information directly from employers because those who are currently employed have wages at least as high as those offered directly by employers, and the job-offer information they share always at least matches their current wage. This model's predictions are consistent with prior findings that people from differentially-connected groups, such as men and women, high-skilled and low-skilled workers, etc., can have different equilibrium wages even while they have the same worker productivity.

Calvo-Armengol (2004) develops a job-contact model in which job offers can be forwarded from neighbors one or two levels away in a social network. Wages are exogenous, and all agents are homogeneous. Agents begin employed, but a share (exogenous) loses their jobs and a share (exogenous) of both employed and unemployed agents receives job offers from the formal labor market. Before the possible job losses and offers, as a kind of insurance, agents can choose to create links to other individual agents at a cost. The job search can be construed as having either an intensive or extensive margin or both. Assuming low-cost links, it may be individually beneficial for one to expand his/her social network to include more referral-generating contacts (since it could raise the likelihood that he/she will find a job). However, unlike in Bala and Goyal

61

(2000a), job-contact information is rival, and so there is a hidden downside to denser network structures. Agents can only forward job information to one of their direct connections. Thus, the more links that a job seeker's neighbor has, the lower the chance that that job information would be forwarded to that job seeker. There are negative network externalities taking place, and a congestion can sets in as more and more people generate social contacts, to the detriment of net overall welfare.

Calvo-Armengol and Jackson (2004) apply the Calvo-Armengol (2004) job-contact model in a multi-period setting. Of note, the network structure is created based on individual strategic linking only at the start, and thereafter it is stable, i.e., fixed. Importantly, there is a small recurring cost to stay in the labor market, and not everyone will start the game employed. Agents have the choice to permanently drop out of the labor force if the present discounted value of their future costs is too high. Technically, when they drop out, their node still remains part of the network structure, but they will no longer bear the recurring cost of staying in the market, and they no longer will have a chance to receive a job. Of note, in the one-shot setting of Calvo-Armengol (2004), there is a negative correlation between one's employment and his two-levels out neighbor's employment status, due to the rivalry discussed above. In contrast in this multi-period setting, longer term, if people are connected to people with stronger or weaker employment histories, there is a contagion effect whereby those peers' employment histories rub off on them. Even with the same network configurations and probabilities of gaining and losing jobs, if there are differences in the initial job endowments, either in terms of both the existence or quality of jobs, then these have persistent effects on the

others future unemployment and wage prospects. The phenomena of 'duration dependence' is predicted.

The Calvo-Armengol and Jackson (2007) work is a generalization of the Calvo-Armengol and Jackson (2004) work, allowing for heterogeneous workers and wages, allowing for the study of wage dynamics as well as employment dynamics. Calvo-Armengol and Zenou (2005) is another search-theoretic model that takes the job-sharing aspects of Calvo-Armengol (2004) and Calvo-Armengol and Jackson (2004), but sets the network exogenously in order to give attention two other aspects, congestion and unemployment rate. The Pissarides (2000) framework is used. In particular, the authors find that some unemployed agents receive redundant job which are thus effectively lost. This congestion limits the optimal network size and density, and there is a non-monotonic relationship between network size and the job-matching rate, which also caused the matching function to not be homogeneous of degree zero. Related to this, the authors show that the equilibrium unemployment rate likewise moves non-monotonically, first increasing in the range of sparse networks and then decreasing in the range of dense networks. Also, due to both search and network externalities, the decentralized market equilibrium is inefficient.

Krauth (2004) also develops a job-contact model, which has so far received less attention. The most fundamental differences are that worker-firm productivity is heterogeneous and idiosyncratic and that the social network evolves based on a stochastic Markov process, without any feedback from the labor market. The main benefits from networking come through the revelation about the worker-firm match, as opposed to the

63

discovery of job vacancies. The model also incorporates exogenous human capital and labor-leisure choice. But the main drawback is the exogenous specification of the network structure, i.e., the lack of strategic link creation. As a result, the model can show only comparative-statics results regarding differences in network structure.

Another job-contact model is provided by Arrow and Borzekowski (2004), who also model heterogeneous and idiosyncratic worker-firm productivity. The authors likewise take the connections among individuals as exogenously fixed beforehand, so the network is neither strategic nor dynamic; the number of social links are assumed to follow a Poisson distribution. Through a simulation exercise of their model, the authors find that 13 percent to 15 percent of variation in log wages could be attributable to variation in the number of social ties that people have. Also, because of competition among employers, the wage may be increasing in the number of offers an agent receives (Calvo-Armengol and Jackson, 2007).

Schmutte (2016b) presents another job-contact model in a search-theoretic framework, with a focus similar to Calvo-Armengol (2004), in that the network structure is endogenously created. Formally, Schmutte (2016b) is an extension of Calvo-Armengol and Zenou (2005), incorporating endogenous job-contact network density. Following a mean-field approach, like is used in Galeotti and Merlino (2014), in Schmutte (2016b)'s model, search for jobs is undirected, i.e., without earmarked links. Agents choose their levels of search effort (i.e., network investment) by picking the mean of the Poisson distribution that will determine the expected number of referrals they will receive, and they pay a unit cost on this expected number of referrals. Like Galeotti and

Merlino (2014), this model does not handle 'on-the-job' search, and so only unemployed people would be seeking job.[23] However, unlike Galeotti and Merlino (2014), where network investments are made in advance, with a chance that they could provide some insurance against the chance of being job-separated, Schmutte (2016b) allows for investment in job search only among the currently unemployed, and so there is only a self-help aspect to their network investment, not an aspect of insurance beforehand.

Continuing, under Schmutte (2016b), at the beginning of each period a share of workers is initially unemployed, but all agents are otherwise homogeneous.[24] Then firms announce a number of vacancies, for which job offers are distributed at random among all agents, employed or not. Agents who are unemployed immediately take such job offers, while agents who are already employed forward the job offers out among unemployed people who request them. As in Galeotti and Merlino (2014), there is rivalry for job offers, and the number of people competing for job offers is also Poisson based on all the job-search decisions. The greater the link intensity of the other agents, the lower the chance of that particular agent receiving a forwarded job on the network. The wage level is determined via Nash bargaining between the worker and the firms over the surplus that comes with the worker-firm match. One advantage of this approach are that the model predicts that higher amounts of referral use will lower the referral productivity (i.e., the network matching rate), which is empirically supported. The model is agnostic about the relationship between network density and the phase of the business cycle. A

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[23] A few models with on-the-job search are Mortenson and Vishwanath (1994), Zaharieva (2015), and Schmutte (2016b).
[24] Although heterogeneous treatment of workers have been incorporated by Fontaine (2008b) and Igarashi (2016), the tradeoff is that they then used exogenous networks.

recession caused by a decline in productivity would be associated with increased referral density, while, in contrast, a recession caused by "structural changes in the rate of job matching."

In Calvo-Armengol (2004), duration dependence (i.e., the phenomena that the unemployed are more likely to be hired the longer they have been unemployed) occurs because the unemployed are also likely to have fewer employed friends which, as a spillover effect, hurts their job prospects even further. However, Bramoulle and Saint-Paul (2010) suggests that while Calvo-Armengol (2004)'s model has the right direction, the magnitude of additional inequality that could be generated by such unequal distribution of employed friends is likely too small to match the empirical data. However, the Calvo-Armengol (2004) model is stuck there because after the initial network formation stage, the network remains fixed over time.

Instead, Bramoulle and Saint-Paul (2010), first, introduce a model of network formation that is not only endogenous, but also dynamic, in that the network structure evolves over the time as new links are formed and deleted. Second, Bramoulle and Saint-Paul (2010) make key assumption, namely, that it is more likely for a social tie to form between two employed persons than between and employed and an unemployed person. The social ties are considered to be a form of depreciable social capital. And this relative decline in unemployed-to-employed links causes a stronger second-round effect on the unemployed that exacerbates their duration dependence, to bring its magnitude more in line with empirical data. However, one limitation of this Bramoulle and Saint-Paul (2010) model is that the links are formed and evolve over time randomly, and thus are not

the product of individual choice. A second limitation is that there is no formal labor market, only an informal labor market; in other words, the only way for the unemployed to receive a job is through the job-contact network. In contrast, strategic link creation is a relative strength of the Calvo-Armengol (2004) model, as well as the presence of both formal and informal labor markets simultaneously.

Fontaine (2007) offers a simple job-contact model in which prospective employees come with the additional benefit of producing referrals, which is explicitly added to the matching function, which remains homogenous of degree one. This is in contrast to Calvo-Armengol and Zenou (2005), which has a matching function that is not homogeneous of degree one. While it is great that to be able to somewhat realistically handle the formation of networks and the resulting structure, a significant downside to the works of Calvo-Armengol and Jackson (2004), Carlvo-Armengol and Zenou (2005), and Bramoulle and Saint-Paul (2010) is that they are fairly complex in order to do so, and as a result, they have to assume that wages and vacancies are exogenous, and hence this framework is not amenable to macroeconomic policy analysis.

Cabrales, Calvo-Armengol and Zenou (2011) develop a model of information sharing, as opposed to job sharing, however, the brunt of this work is still applicable to a job-contact setting. Unique to this model is a major simplification to the network-creation process. In particular, the authors apply a mean-field approach, in which network links are created randomly based on the level of network investment, rather than created individually. The interpretation could be, simply, that links are created on the basis of the amount of time spent socializing overall. For example, one might attend a

career fair or parents night at school, not know exactly who they might meet. This generic linking pays off tremendously in allowing for simple analytical solutions to richer economic environments, with little of importance lost.

Galeotti and Merlino (2014) build a model that combines the Calvo-Armengol (2004) job-contact framework with the Cabrales, Calvo-Armengol and Zenou (2011) mean-field approach to link creation in order to study the effects of job market conditions on the optimal degree of social networking. As in Calvo-Armengol (2004), this is a one-shot setting, and the information is rival, and so while direct links can help agents, indirect links can hurt them because the more links their direct contacts have, the lower the chance that any job information would get forwarded to them. In this setting, agents' only choice variable is the level of network investment, and they pay an associated cost per unit of social network investment. And, again, networking brings only the instrumental value of possible future jobs, no direct joy from socializing. All agents start employed, and then there is an exogenous rate of job loss and job offer. Agents that already have a job and receive a job offer can forward on the redundant job offer to someone in their network.

In an exercise of comparative statics, Galeotti and Merlino (2014) show that when the job separation is low or job offer rate is high, the network matching rate would be low, and thus the optimal network investment and resulting network density should be low. At the other extreme, when the job separation is high or job offer rate is low, the network matching rate would, again, be low, and thus the optimal network investment and resulting network density should be low. It is only in middle ranges of job separation

or job offer rates that it pays off to invest in the social network, and the exact optimal

investment levels can be determined in closed form. The intuition is that when the

economy is very strong, almost no one will be unemployed and so it does not pay off to

invest very much in social networking. When the economy is very weak, again, although

many agents will be unemployed, any scarce job offers that are found are likely absorbed

by these unemployed persons, rather than being forwarded on in the network. So, the

network would be like a tree bearing no fruit, and it does not pay off to invest very much

in social networking. Only when the economy is in the middle range of strength are

conditions tenuous enough that agents are worried about losing their jobs, but not so

tenuous that all job offers are absorbed by the unemployed, that there is a material benefit

from the network, such that it pays off to invest in social network links.

Cahuc and Fontaine (2009) assume a fixed-network version of Calvo-Armengol

and Zenou (2005), and this enables them to explore a wider range of search strategies

which result in multiple possible equilibria. Galenianos (2013) develops a model

handling multiple firm types and variation in match quality between workers and

employers. Firms use referrals in order to receive more accurate information about the

prospective matches. Referral use is costly, but is generic, and there is no network

structure. Galenianos (2014) develops a model of referral use seeking to match stylized

facts about cross-industry variation. Agents can find jobs either through the formal

market (i.e., with search frictions) or referrals, and the referral network is given

exogenously. The author finds the speed of job matching to vary by hypothetical

industry depending on the industry's reliance on referrals, and higher formal market

efficiency is associated with reduced use of referrals. Arbex, O'Dea and Wiczer (2016 wp), develops a model with heterogeneous employees and exogenous networks. Their model predicts that employees who find work through job-contact networks have higher wages with less turnover, mostly due to the correlation between high-quality employees and their high-quality referrals. Use of the mean-field approach is important for their solving their model and obtaining results.

Duran and Morales (2014) builds on Bramoullé and Goyal (2009)'s model of favoritism or personal discrimination when making job offers, allowing an informal job market to emerge alongside a formal job market. For the sake of tractability, the authors assume a fully-connected, exogenous network, however, agents can choose to join social cliques, and these cliques can ultimately facilitate employment. The authors determine equilibrium social clique size(s), note that the cliques engender some degree of efficiency losses, and find a non-monotonic relation between unemployment and the extent of favoritism taking place. Stupnytska and Zaharieva (2015) present a model with endogenous search intensity and heterogeneous workers (which is key because it allows for the presence of homophily). They propose that the informal channel to jobs really should be split between professional contacts and familial contacts. By allowing this bifurcation of referrals, while simultaneously having the option of formal job market search, the authors are able to predict higher wages for professional contacts than for familial contacts and thus possibly explain the referrals puzzle. They find a U-shape in the referral-hiring across worker productivity, and they find lower unemployment rates for more productive workers because their networks contain lower shares of unemployed

contacts. Finally, Ekinci (2016) develops a 'career-concerns' model (Harris and Holmström, 1992; Holmström, 1999) in which reference-based hiring can provide a screening role and thus help to control employees even if employee productivity is not always observable during their time as an employee.

Running agent-based simulations, Gemkow and Neugart (2011) explore the workings of an endogenous job-contact network in which agents choose to divert some amount of time to job-contact networking as insurance in the case of job loss, similar to what is done in Galeotti and Merlino (2014). The authors predict that one way to reduce inequality is for firms to exhibit greater variability in their labor demand, which in turn reduces the level of social network investment among workers.

3.5   Other Employment-Related Models

The results of a number of employment-related models have already been discussed in Sections 1.2, 1.5, 1.6, 1.7 and 3.4 above. In this section, I briefly discuss a few additional studies.

Bandiera and Rasul (2006), using household survey data from villages in Mozambique, find an inverse-U shape pattern between farmers' proclivity to plant a new crop and their social ties (of friends and relatives)'s decisions to plant this same new crop. In other words, farmers seem to interested in trying out the new crop when few of their social ties have yet adopted the new crop so far or when the great extent of their social ties have already adopted that crop. However, in the middle range, when a large but not overriding share of their social ties have adopted the crop, the farmers appear to

be most compelled to shift. The authors also note greater correlation with friends and relatives' actions than with the actions of people that have the same religion.

Falk, Hammermann, Mohnen and Werner (2013) provide a valuable example of measuring the impact of asymmetric information on labor-market outcomes. In particular, using survey data from German firms, they study the impact of having prior social ties which could reduce job candidates' asymmetric information about firms. They find that qualitative information about job conditions (that would normally be unobservable) has greater impact on firms' recruiting success for candidates that have social ties to the firm(s), but, in contrast, monetary concerns (such as wage and benefits) have a greater impact on firms' recruiting success for candidates that lack social ties to the firm(s).

Hellerstein, Kutzbach and Neumark (2014), using employer-employee matched data from the U.S. Census Bureau's Longitudinal Empoyer-Household Dynamics (LEHD) program, finds evidence that job turnover is lower among workers that have neighbors as fellow employees at the same employer. In Glitz (2017), the author quantifies the effect of job contacts, specifically, co-workers, on employment outcomes. In particular, he finds a 7.5 percentage-point rise in re-employment rate associated with a 10 percentage-point higher employment rate of a person's social network; however, he finds no statistically-significant difference in wages.

Brown, Setren and Topa (2016) summarizes and tests a group of predictions from the referral-based hiring literature using a rich data set from a specific firm that employed between 2,000 and 5,000 employees. Their findings include the following: "referred

candidates are more likely to be hired; experience an initial wage advantage, which dissipates over time; and have longer tenure in the firm. Further, the variances of the referred and non-referred wage distributions converge over time. The observed referral effects appear to be stronger at lower skill levels. The data also permit analysis of the role of referrer-referee pair characteristics." (Brown, Setren and Topa, 2016)

Falk and Fehr (2003), in a review of labor-related laboratory experiments up through the early 2000s, emphasize the most important reason to run laboratory labor-related experiments, even despite how different the lab environment is from one's normal day-to-day life experiences, is for the control that they offer. Their utility for replication is also a major asset. Many common criticisms of laboratory experiments can be overcome, and if interpreted properly, lab data can provide insights that are not possible elsewhere. Overall, laboratory experiments typically have a complementary role with field and other empirical studies. Ioannides and Loury (2004) provided an early look at the literature related to using networks to share job information, covering both network theory and experiments. Beaman (2016) gives a more recent review of social networks and the labor market, also covering both theory and experiments.

Pellizzari (2011) suggests, using U.K. public employment agency data, that part of the reason for high turnover among low-skilled workers is attributable to firms' lower investment in searching for highly matching low-skilled workers because of the low measured financial return in doing so. Jackson and Schneider (2011) provides an interesting discussion of whether the use of social connections could mitigate moral hazard, with empirical findings from New York city taxi data. They found evidence of

reduced moral hazard among taxi drivers who lease their medallions from people with which they share community connections.[25] This finding, if replicated, is substantial because it suggests that social ties can be used not only for handling asymmetric information, but also for reducing moral hazard issues. Using economic journal co-authorship data, van der Leij and Goyal (2011) finds support for transitive links among triads, however, it does not find support for weak links being more productive than strong links. They find the reason for the strength of strong ties depends on the property of lopsided connectivity among individuals and the property of stronger ties tending to exist among people with many connections.

Finally, the following few studies are not employment-related per se, but the some of the principles that come up are relevant for job-contact networks. Kossinets and Watts (2006) shows how social networks develop and evolve using university email system data. Halberstam and Knight (2016) finds that politically-engaged Twitter users tend to receive high shares of information from like-minded people fast and repeatedly over long periods of time. Studying the Add Health longitudinal data set of young people (Carolina Population Center, 2017), Christakis, Fowler, Imbens and Kalyanaraman (2010wp) develop and fit an empirical model to the existing networks and use and then predict what the network structure would be like under counterfactual personal characteristics in that same environment. If such predictions are shown to be reliable, this approach could represent a data-driven way to make policy decisions. Using cell phone call and text data, Onnela, Arbesman, Gonzalez, Barabasi and Christakis (2011) compare the observed

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[25] However, in my view, mere homophily could be the reason they authors find reduced moral hazard since the community connections may be fully aligned with country of origin.

network linkage and usage patterns relative to the geographic arrangements, finding the spatial constraints are not binding, and so would not prevent spreading.

3.6   Economics of Networks Experiments

There have been several empirical tests of economics of network theory to date, but they are still sparse overall relative to the volume of economics of network theory. Throughout this chapter, I have thus far provided many examples of empirical studies regarding networks in general and job-contact networks. In this section, I focus on results from controlled laboratory experiments.

Kosfeld (2004) reviews the early laboratory tests on the economics of networks theory, including games on networks (both coordination and cooperation), buyer-seller networks, and network formation. Among the network formation research, Deck and Johnson (2004) was one of the first strategic link creation experiments, and it tested out strategic link formation by having subjects bid for link creation under three institutions: cooperation (Qin, 1996), non-cooperation (Bala and Goyal, 2000a), and pairwise stability (Jackson and Wolinsky, 1996). The authors find average efficiency of 85 percent, and the figures are fairly close across each of the three institutions. The authors also emphasize the unique benefits of laboratory testing, including complete information and full control of the environment and/or institutions.

Falk and Kosfeld (2012) reports on results from a laboratory implementation of the Bala and Goyal (2000a) one-way and two-way information flow models. While the strict Nash equilibrium predictions were mostly upheld in the one-way flow models, with subjects forming the circle or null network, the strict Nash, and sometimes even the plain

Nash equilibrium predictions, were not upheld, with subjects not forming the start or null network. The authors mostly attribute the results in the two-way flow models to the fact that the subject at the would-be central node in the star would then receive relatively low, unfair payoffs, which could potentially be avoided by some kind of rotation policy.

Callander and Plott (2005) is a prominent example which studied network formation, in particular, testing for Nash equilibrium, best responses and predictions from two models from Bala and Goyal (2000a), with one-way links. They find that links are created and networks converge, often to the Nash equilibria, and often to efficient nodes. Efficiency and strict Nash equilibrium are not necessary for stability, but Nash equilibrium is necessary. However, at odds with the macro- results, the individual-link formation by subjects often appear to represent 'simple-strategy' choices (which could be seen in line with bounded rationality) rather than best responses, which is a bit of a paradox. So it appears the mechanism between the micro- to macro- behavior remains unknown. Finally, two patterns of the subjects are interesting. First, some subjects exhibit commitment decisions that the authors believe may be attempts to "teach" other subjects how to play. Second, sparsely-connected networks often follow especially densely-connected, and vice versa, indicating that the groups of subjects tends to try to correct the macro- behavior they had just observed.

Callander and Plott (2005) suggests that laboratory experiments of networks may be have high value since naturally-occurring networks are sufficiently complex and decentralized that field data are not as useful. Lab environments have the advantage of allowing individual incentives and the network evolution to be carefully controlled.

Callendar and Plott (2005) state that game theory principles have not been sufficiently predictive in describing what actual people will do when faced with many of the situations about which they postulate, with one prime example being public goods, in which lab subjects tend to contribute at higher rates than expected. Thus, network scenarios might actually share a lot of characteristics with public goods scenarios.

Charness and Jackson (2007) reports on a laboratory setting of endogenous link formation in a stag-hunt game, and presents the concept of 'robust-belief' equilibrium. The results of this work suggest that social concerns can be very important relative to monetary playoffs in determining individual choice behavior. In Corbae and Duffy (2008), the authors create a laboratory environment in which groups of four agents at a time can form trading networks, in which agents first link through a proposal game and then play repeated coordination games with their chosen link partners. Among four structures (bilateral, local interaction, star and uniform matching), the bilateral structure occurs with the most frequency and stability, and payoff efficiency is approximately 90 percent of the predicted optima.

I review the next two experimental examples in greater detail in order to give a flavor for how network theory can be tested in the lab, and I then cite other studies more generally.

Goeree, Riedl and Ule (2009) provide results from testing the Bala and Goyal (2000a) two-way flow framework in a laboratory setting. Linking decisions were made simultaneously each round, for 30 rounds played sequentially, holding the group composition constant. In trials with homogenous value and link costs among all subjects,

although the star configuration was the efficient structure, stars rarely emerged from the subject interactions. However, upon introducing heterogeneity in the values among the subjects, star structures reliably emerged. Moreover, as the rounds progressed, the networks tended to grow more efficient, centralized, and stable. Upon introducing heterogeneity in the link costs among the subjects, stars also sometimes emerged. Even when the heterogeneous type information was private, the subjects fairly quickly located the high-value subjects and worked into star formation around him/her. However, when both heterogeneous value and link costs were simultaneously present, and this information was private, the frequency of stars were greatly reduced. The results of Goeree, Riedl an Ule (2009) seem to suggest that differences in personal characteristics are essential for the formation of a network with a central hub. If everyone were the same, there would not be an impetus for any single person to step forward and be focal.

In a revealing follow-up experiment, Rong and Houser (2015a) set up laboratory institutions in a way that may more closely follow arrangements among rural farmers in developing countries in which star-like networks in fact do emerge to share information, even though, often, there is nothing distinguishing or focal about any one farm. In particular, Rong and Houser (2015a) instituted both sequential and simultaneous decisions among subjects, group investment limits, and right-of-first-refusal for information investors to continue in that role in future periods if they so choose. In their laboratory game, Rong and Houser (2015a) implemented the Galeotti and Goyal (2010) framework ('the law of the few'), in which agents have the option to obtain key information from someone already invested in it, or to pay a higher cost an invest in the

information themselves. Under this framework, stars frequently emerge from group interaction, even among ex ante homogeneous agents, both for simultaneous and sequential play. These results suggest that, under some institutions, it is not necessary to have ex ante heterogeneous agents for stars to emerge. The authors also were able to reasonably classify the subjects, based on their observed game-playing behavior, into three particular types, which helps towards understanding the effects that the institutions may have had on individuals.

Brandts and Sola (2010) presents laboratory-based results suggesting that favoritism is observed, in both directions, between managers and employees that know each other, but this does not have an effect on the other employee(s) that lack any social ties. Charness, Feri, Meléndez-Jiménez and Sutter (2014) implements, in a laboratory setting, games of strategic substitutes and strategic complements from Galeotti, Goyal, Jackson, Vega-Redondo and Yariv (2010), under settings of both complete and incomplete information about the network structure. They find a good deal of equilibrium play, even under incomplete information, though they are typically willing to give up some profits as a tradeoff for taking less risk, and coordinating is much more challenging under incomplete information, even for efficient equlibria.

Azmat and Petrongolo (2014) review a number of laboratory and field studies regarding gender and affirm that gender appears to be a personal characteristic that matters for many situations. In particular, the authors report that women fare worse in negotiation, are more risk-averse and more competition-averse than men, and appear to be more reactive to social signals. Gender composition can make a difference in results

and in group dynamics. The question of nature or nurture for these difference remains open.

It is still the case that comparatively little work has been done in empirical testing for endogenous network formation. It is hard to measure the natural phenomenon of link creation in the field due to identification problems. Chandrasekhar (2016) argues that one reason for this could be that there, so far, lack many empirical models of network formation to work with. With this in mind, there is likely an important role for laboratory experiments on network formation, especially for the estimation of preferences.

4   Discussion

Taking together the range of literature reviewed, there are a few ideas that stand out and could be actionable information for further research and individual decision-making. As cited throughout, job-contact networks are used heavily in practice in many different contexts, and this is not new. There is significant evidence that social ties help with finding jobs, and this may be due to easier initial matching, reduced asymmetric information, anticipated higher productivity, and other reasons. The effect on wages appears to be uncertain, and the relative importance of weak versus strong tries is still debated. There are studies showing that hiring through social ties offers lower turnover and better matching, but there are also studies suggesting that hiring of close friends and family can cause incentive problems and be abused. The good news is that, especially with today's technology, social networks are not an exclusive tool, in the sense that almost anyone can proactively make new connections of different sorts that could lend a

hand in future employment. Some people may feel empowered upon realizing the effect that job-contact networks can have on being hired for jobs that are broadly of their liking.

It is tempting to try to recommend and institute policy based off of apparently simple understandings about networks, with the aim of encouraging better job success for more people. For instance, one policy recommendation offered in Calvo-Armengol and Jackson (2004) is that, if the government is going to distribute resources to try to discourage labor market dropout, there may be a higher return if such resources are dispersed in clusters rather than uniformly but sparsely. As another example, in the public health field, Kim, Hwong, Stafford, Hughes, O'Malley, Fowler, and Christakis (2015) report on how they used an information campaign in rural Honduras, targeted at well-connected individuals, in order to raise the overall use of water purification and consumption of multivitamins. As a third example, Batagan and Boha (2015) suggest that directing job seekers to basic information about the power of social networks could help students leaving school find apt employment. Finally, Lavezzi and Meccheri (2011) provide a discussion of the effect of job-contact networks on transitions into and out of employment, suggesting that workers should focus on the symmetry of their social networks, and be very mindful of the firms' recruiting approaches. It is encouraging to see such practical ideas springing up from network-related research in economics.

However, it is also important to think carefully about the complexity of social networks and the labor market, since unintended consequences can often result from policy undertakings. For instance, in the models of Fontaine (2007, 2008a), a policy that seeks to increase the efficiency of the job-contact network amongst 'disadvantaged'

workers might at first lower the unemployment rate. However, there may next be a substitution effect in which firms ultimately reduce their advertising and hiring efforts from the formal job market, thus hurting some job candidates that tend to do better in the formal job market. Second, there is evidence suggesting that hiring through social ties exacerbates income inequality and locks people in place since job-contact networks are typically not an equal-opportunity institution. Not everyone has access to the same 'quality' social ties, and even women may not have the same job-contact prospects as their comparable male colleagues. These two factors, and possibly many others, could be severely limiting for people with endowments that place them at the lower part of the earnings and employment distribution. Given the relative advantages that some groups of people have, doubling down on informal hiring could make it even harder for the disadvantaged to break out into career success.

As discussed by Chandrasekhar (2016), most of the economics of networks literature has been theoretical, and employing field studies in networks can be a real challenge. I tend to agree with Schmutte (2015) that, at this current juncture, it is likely still early to make any strong policy recommendations. It is likely most prudent to continue collecting data on networks and running principled statistical analyses. In doing so, it seems important to be mindful of the 'reflection problem' described in Manski (1993), and emphasized more recently in Angrist (2014), namely, that it is often difficult to attribute the effects of average group behavior on individual group members due to the common settings and experiences that they all share. To avoid spurious or misleading results, of course, one should also be mindful of self-selection bias issues that typically

arise when studying people that choose different major actions. As in medicine, 'do no harm' is likely a first principle, and for that it is important to not let prescriptions get ahead of the real science at work, and there is still much to learn about networks (Jackson, 2016).

The recent announcement of Richard Thaler as the 2017 winner of the Noble memorial prize winner in economics (The Royal Swedish Academy of Sciences, 2017) suggests that, nowadays, behavioral economics is recognized as one, among many other, important perspectives for thinking about economic problems and imagining ways to make improvements. Sometimes a 'nudge' or framing may be all it takes to prime people for individual action and thus collectively make a large difference. However, such nudges ostensibly could be used for the better or for the worse; there is not only potential, but also vulnerability. If aspects of the economy and the workforce are so sensitive, and if social networks are as complex as they seem to be, then economists have even more reason to think carefully and slowly, and to raise any cautions about counter effects, second-round effects, etc., before making networking policy recommendations.

In this spirit, in Chapter 2 I take up a careful laboratory experiment related to a published theoretical work in order to document human behavior in a stylized network setting under carefully controlled conditions. In particular, I implement a version of the Galeotti and Merlino (2014) model in order to study the degree to which lab subjects respond to changing job-market conditions according to the theoretical model, as well as to probe the likely reasons behind what I observe. In the next chapter, I present the experiment design and laboratory procedures, report results from several laboratory

treatments, as well as results from corresponding simulations, and I motivate a few extensions. By contributing these laboratory data and overall findings to the endogenous job-contact literature, I hope to help yield some incremental insight(s) related to some aspect(s) of endogenous job-contact network theory, that could ultimately have some practical beneficial effect.

Rigorous laboratory experiments, combined with expert field studies, linked microdata studies, and other empirical work, taken together, can help economists and others better understand the essential reasons for, patterns of, and impacts from aspects of basic human activity and coordination. This way, if policy action appears to be called for, then such can be done promptly, leveraging actionable data, with decision-makers realistically informed about the most likely effects. Bramoullé, Galeotti, and Rogers (2016) claim that the field of network economics is currently at a 'third phase' in which researchers across disciplines recognize the value of the discipline's approach and seek to apply it widely. If this is true, then the potential reach and impact from continued research in these labor market and related topics could have measurable economic effects, hopefully for the better, and that would, indeed, be rewarding for all involved.

CHAPTER TWO: A LABORATORY TEST OF ENDOGENOUS JOB-CONTACT NETWORKS

In this chapter I motivate and describe a laboratory experiment that tests

predictions from a published theoretical paper, Galeotti and Merlino (2014), to be

referred to henceforth as "G&M." In particular, I set up a mock job market in the

laboratory in which the laboratory subjects, acting as job seekers, can obtain and lose

jobs, and have the option to spend some amount(s) to invest in network links with other

subjects. Those connections to others can pay off if one is jobless and happens to receive

a forwarded job offer from a linked neighbor. I study the extent of network investment,

as well as the share of jobs found through the job-contact network, under varying job-

market conditions, at both individual and aggregate levels. I run an empirical model of

network investment choices in line with the theoretical model, and I statistically test

whether the lab data conforms to benchmark simulations based on the theory. I then

statistically test for an effect from the extent of information provided to subjects

participating in the experiment. In order to rule out alternative explanations of the data, I,

further, test three extensions beyond the benchmark setup. I close with a discussion of

the variation of subject response patterns in the data and unanswered questions, which

leads up to the topic of Chapter 3.

The G&M model is worth testing because, if supported, it offers a fairly

straightforward prescription of what people could do to improve their chances for

employment, e.g., by taking the business cycle into account regarding the extent of their job-contact socializing. Since having a job may be important for life fulfillment, and since a large number of people (as many as 6 million in the U.S. currently (BLS, 2017a)) are looking to change jobs or start new work at any given time, even small gains in employment due to job-contact network could have material overall gains to society. Moreover, jobs found through one's social network have additional benefits, such as increased tenure, reduced hiring/search costs, better employer-employee match, etc.

1   Background

In this section I discuss the role of job-contact networks and related theory development and empirical testing, and I set the stage for my lab design and hypotheses.

1.1   The Role of Job-Contact Networks

As discussed in Chapter 1, a busy hiring manager may see a large number of applicants and interviewees for a given job posting, and a job seeker may have many employment options. Finding the best candidate employees or employers can be a trying process as most candidates, regardless of their actual quality, are on good behavior during the formal interactions of email, application and interview; candidates may take pains to make their official materials compelling (including resumes, cover letters, personal websites, corporate mission statements, job descriptions etc.). Asymmetric information, in which each party knows itself better than the other, is often a major friction for the hiring process. Hiring managers and job seekers can ask thoughtful questions, but they

cannot necessarily fully believe what they hear back in response. Each party may verify the other's available materials, but doing so can take substantial amounts of time.

Job-contact networking provides a way for a job-seeker or employer to stand out amongst the others by sharing a credible private signal based on prior interactions or on known intermediaries. Through the social tie, one can more cheaply assess the quality and fit of a candidate by either prior firsthand experience or with secondhand experience from another trusted contact. If the third-party credibly cares about his/her reputation to both parties, then he/she likely has strong incentives to coordinate a mutually solid match and avoid betrayal of either party which could otherwise harm trust needed for future transactions. All else being equal, hiring through the informal jog market (i.e., via a candidate who is confirmed via firsthand or third-person networking), is sometimes cheaper than hiring through the forma job market, and may further be associated with lower on-boarding costs and lower risks of future misalignment. The safe, already-vetted option may be the lucky 'inside' candidate who happens to have the right connection(s).

Since the Great Recession (2009-2011), the ratio of unemployment to job openings has been persistently higher in the United States (U.S.) and many European economies than it was during the early to mid 2000s. As shown in Figure 3, there has been a rightward shift of the Beveridge curve in the U.S., starting around June of 2009.

Chart 4. The Beveridge Curve (job openings rate vs. unemployment rate)
Seasonally adjusted

Source: Bureau of Labor Statistics, Current Population Survey and Job Openings and Labor Turnover Survey, October 11, 2017.
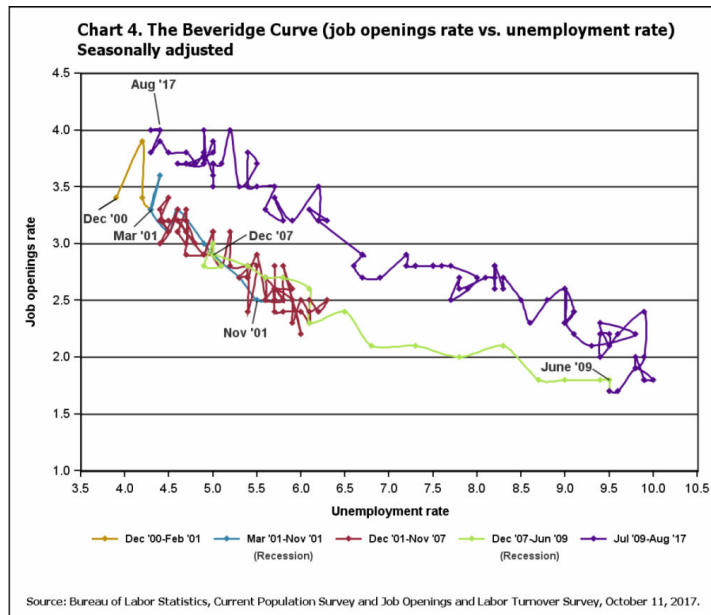
Figure 3. Beveridge curve in the U.S., 2000 through 2017
Source: Bureau of Labor Statistics, https://www.bls.gov/web/jolts/jlt_labstatgraphs.pdf

That is, more job-seekers are vying for a given job opening in the U.S. This has also been the experience in many other developed economies. This may indicate that it is, nowadays, harder to find the best candidate amongst the others, or that candidates are choosing to be more discerning and careful in making their selections. Given the expensive sorting process that job seekers and employers face, and given the larger volume of job seekers for a given opening nowadays, networking may continue to be a productive way for job-seekers to distinguish themselves from the ample others and get hired or switch employers.

Therefore, a candidate job seeker or employer may have strong incentives to network widely. But he/she faces important decisions regarding how much time he/she should spend developing his/her social networks for the informal labor market, seeking work via the formal job market, and enjoying leisure activities. G&M's model of

endogenous job-contact networks helps to answer this resource allocation question in a simplified context. In this chapter, I use the G&M framework to study the way that job-contact networks are formed and are used under varying economic conditions. Specifically, I present results from a controlled laboratory test of G&M's "endogenous job contact networks" model, and I reflect upon this evidence in order to point to further avenues of related research.

1.2 Empirical and Theoretical Studies

Information is abundant, but may be costly. Individually, social ties may play an important role in managing information and thus help people find employment. As described in Chapter 1, many studies indicate that as much as half of all jobs are filled through the use of social networks. One of the most prominent of such studies is Granovetter (1973). Furthermore, these results have been amply generalized across countries, industrial sectors and demographic characteristics. As per Chapter 1, a few examples of such studies include Corcoran, Thatcher and Duncan (1980); Singerman (1995); Bewley (1999); Beaman and Magruder (2012); and Cingano and Rosolia (2012); Bian, Huang and Zhang (2015).

There have been a large number of job-contact network models derived within the economics of networks literature. As reviewed in Chapter 1, these include Boorman (1975); Mortensen and Vishwanath (1994); Calvo-Armengol (2004); Calvo-Armengol and Jackson (2004, 2007); Calvo-Armengol and Zenou (2005); Fontaine (2007, 2008a, 2008b); Bramoulle and Saint-Paul (2010); Duran and Morales (2014); Galenianos (2014); and Schmutte (2016b). Some network models specify distribution of social ties (i.e.,

exogenous), while other models endogenize the social tie creation. Given the complexity in modeling the network-formation process, labor market network theory often models the job-contact networks exogenously, so that attention can be spent on other aspects of referrals and of the informal labor market.

Galeotti and Merlino (2014), hereafter *G&M*, whose work is the focus of the laboratory test described in this chapter, study the impact of labor market conditions on network formation and usage. In particular the authors derive a non-monotonic relation (first increasing, then decreasing) between the job separation rate and levels of social network investment and networking matching rate. They then provide empirical documentation of this relation using United Kingdom (U.K.) Labour Force survey data from 1994 through 2005. The authors' model is described in detail in Section 2.1.

1.3 Laboratory Studies

Laboratory analyses are often complementary to theoretical developments and field studies. By enabling controlled conditions, the laboratory allows for explicit tests of theory, removing environmental factors, ruling out competing explanations, studying selection among multiple equilibria, and attributing causation, not just correlation. Per Charness and Kuhn (2011), laboratory studies can shed light on questions that would be prohibitively expensive to study in the field. In particular, one can do some things that cannot do in real world, such as studying ethical "punishment" and seeing the effects of revealing person-specific private information. One can measure beliefs through the clever use of monetary incentives. One can transcribe peoples' strategies via the "strategy method," and then compare these with actual behavior. Experimental

economics can assist in assessing statistical versus economic significance and the accuracy of structural model predictions.

In addition, the laboratory provides opportunities to test scenarios that are not solved analytically, yielding data that might even motivate future theoretical work. Houser and Xiao (2010) cite examples in which lab results are sometimes quite surprising and would likely not have been predicted by theory alone. Smith (2008) points out the value of both ecological and constructivist rationality paradigms in understanding human phenomena. The interplay between theoretical and experimental economics can be very important to advancing ideas.

The economics of networks field has produced a large volume of network theory papers over recent years, with comparably fewer laboratory tests of these theories. In Chapter 1, Section 3.6, I discussed a few key laboratory experiments regarding hiring through referrals. For instance, Callandar and Plott (2005), Falk and Kosfeld (2012), and Rong and Houser (2015a) are revealing studies. Via my laboratory study, this work seeks to help provide a bit more empirical analysis of job-contact networks predictions that could be considered and leveraged in future theory development. Specifically, the motivation for my laboratory experiment is to bring a controlled human data generation process to the G&M theory and to see if the expectations are still borne out.

2   Theoretical Predictions

In this section, I trace through the assumptions and theoretical predictions from G&M, which are key for implementing the related laboratory experiment of this theory.

2.1 Theory Derived

G&M's endogenous job-contact model is a contribution to economics of network theory related to individual choices of social network investment and network use. There are three building blocks to the G&M model, namely: (1) Labor market turnover (...job separations and offers), (2) Information diffusion within the network, (3) Formation of job contact networks.

Of note, this is a one-shot setting, not a dynamic or repeated-game setting. Regarding (1), labor market turnover, there is a set N containing n risk-neutral workers, enumerated 1.....n (with no spatial dimension). Starting from full employment, a random set $B \subset N$ of workers loses B jobs. There is an exogenous job separation rate, $b = B/n$. A random set $A \subset N$ of workers receive direct job offers; no one receives more than one job offer. There is an exogenous job offer rate, a. The number of job offers $= V = an$, with $a \in (0,1)$ and $b \in (0,1)$. Agents first take any job offers for themselves if they need it. The set U contains the agents who lost their job and did not receive a direct job offer. The number of agents in U equals $U = B - V = b(1-a)n$. The set O contains the agents who receive redundant job offers. By redundant, it is meant that they had not lost their job, and so they do not themselves need the job offer that they receive. The number of agents in O equals $O = a(1-b)n$. The unemployment benefit is normalized to 0, without loss of generality.

Regarding (2), information diffusion within the network, agents can "insure" against the risk of being unemployed by investing in "social connections" in order to access the redundant job offers of others. Information can only flow from those who

receive a redundant job offer to his/her direct neighbors, who had a job separation. When someone who received a redundant offer has more than one neighbor who faced a job separation, he/she chooses *one* of the neighbors randomly to send the information to. The social networks are undirected. Set G' is the collection of all undirected links.

Regarding (3), formation of job contact networks, agents invest s_i (from the real positive number line) generically in social contacts, interpreted either as building social networks or maintaining existing ones. The strategy profile for all agents is represented by $s = (s_1, s_2, s_3, ..., s_n)$. Agents randomly gain some neighbors (via links) to the extent that they generically invest, s, in network contacts. Note agents cannot have any neighbors if they literally invest zero. The unit cost of investing is c per unit of s. The sum of all workers' investment is y(s). There is no benefit from second-order, third-order, etc., neighbors, since job offers can be forwarded only to immediate neighbors. The network is anonymous and generic in terms of both link formation and forwarding of job offers. G&M define $\Psi_i(s)$ = Pr(i receives at least one offer through network), which they call the "*network matching rate.*" Therefore, the probability of not having a job after the separations, offers, and network information have taken place is: Pr(no job) = $b(1-a)(1-\Psi_i(s))$.

Under G&M, the optimization goal is to maximize expected utility, EU$_i$, with respect to s_i:

$$EU_i(s_i, \mathbf{s}_{-i}) = 1 - b(1-a)[1 - \Psi_i(\mathbf{s})] - cs_i$$

There is a pure-strategy equilibrium, at which:

$$EU_i(s_i, \mathbf{s}_{-i}) \geq EU_i(s'_i, \mathbf{s}_{-i}), \forall s'_i \in \mathcal{S}_i$$

The expression for the network matching rate is:

$$\Psi_i(s_i, s) = 1 - e^{-\frac{a(1-b)}{b}\frac{1-e^{-sb}}{s}s_i}$$

G&M makes four propositions that sequentially derive their main findings. First, G&M considers a simpler case, in which the level of s_i is determined exogenously, in particular, with the same level for all agents. "*Proposition 1:* Consider a large labor market and suppose that $s_i = s$ for all i in N. Then, the matching rate and the network matching rate are *decreasing* in separation rate, whereas unemployment rate is increasing in separation rate." But the empirical data do not show such a decreasing trend, at odds with the idea of exogenous levels of s_i. In contrast, with an endogenous determination of s_i, the results are very different, and they match the stylized facts much more closely. So, with the individuals choosing strategically their optimal level of s_i, we have the following three remaining propositions.

Then "*Proposition 2:* Consider a large labor market. An interior equilibrium $s*$ exists if and only if $c < ab(1-a)(1-b)$, and $s*$ is the unique solution to:

$$b(1-a)\left[\frac{a(1-b)}{bs*}\left(1 - e^{-s*b}\right)e^{-\frac{a(1-b)}{b}\left(1-e^{-s*b}\right)}\right] = c$$,"

And "*Proposition 3:* Consider a large labor market and suppose that $c < ab(1-a)(1-b)$. 1. For every a in (0,1), there exists $\bar{b}(a) > 0$ such that if $b < \bar{b}(a)$, then the network investment increases in the separation rate, otherwise it decreases in the separation rate. 2. For every a in (0,1), there exist $\hat{b}(a) > 0$ and $\tilde{b}(a) >= \hat{b}(a)$ such that if $b < \hat{b}(a)$, then the network matching rate increases in the separation rate, while if $b > \tilde{b}(a)$,

then it decreases in the separation rate."

Regarding the impact of rise in b on s, essentially, G&M describes a *complement* and *substitute* effect. A rise in b, i.e., a greater chance of needing a job offer, under the *complement* effect, leads to greater network use and greater network productivity. But, under the *substitute* effect, the rise in b leads to greater competition for existing jobs, decreasing the likelihood that one's neighbors will have a redundant offer to share with him/her, leading to lower network use and lower network productivity. And the expected comparative-static effects apply: At low levels of B (or b), ds/db>0 because the complement effect exceeds the substitute effect. At high levels of B (or b), ds/db<0 because the substitute effect exceeds the complement effect. Thus, s is non-monotonic in b. And it is a similar story for the impact of a fall in a on s, with the trend in the reverse direction. Specifically, at first, as a falls from a high level, this increases s, but then past a certain point, as a decreases yet further, this decreases s, and so there is a peak s level somewhere in the middle of the a domain.

Regarding the predicted density of G&M's job-contact network, when the job loss rate, b, is low (or the job offer rate, a, is high), the optimal network investment level, s, is low, and the resulting network is fairly sparse. When the job loss rate, b, is a bit higher (or the job offer rate, a, is a bit lower), the optimal network investment, s, is a bit higher, and the resulting network is much more connected. Finally, when the job loss rate, b, is high (or the job offer rate, a, is low), the optimal network investment level, s, is again low, and the resulting network is again fairly sparse.

Finally, G&M considers the choice of a social planner trying to achieve a Pareto

optimal arrangement. In particular, the social planner maximizes:

$$SW(s) = 1 - b(1-a)[1 - \Psi(s)] - cs$$

And "*Proposition 4:* Consider a large labor market, and let $\tilde{s}$ be the solution of the planner problem. If $c < ab(1-a)(1-b)$, then $\tilde{s} = 0$. Otherwise, $\tilde{s} < s$, and it is a unique solution to:

$$ab(1-a)(1-b)e^{-\tilde{s}b}[1 - \Psi(\tilde{s})] = c,"$$

Note these results imply a lower level of individual network investment, *s*, under the guidance of the social planner. The catch is that there are congestion effects from workers' connections due to the rival nature of job information in the G&M framework. Since workers do not internalize these congestion effects, the network is overconnected when agents are free to pursue their individual optimizations. In contrast, the social planner fully takes the congestion effects into account in determining the optimal network investment levels, and so ends up choosing lower levels of investment for all agents.

2.2 Main Assumptions

The G&M model is a static, point in time, model. It is not dynamic; transitions are not in scope. People all receive the same rate of job offers even if they are employed. There are exogenous separations and job finding, and there is no feedback in which job matches affect the job separation rate or job offer rate. This model handles only the initial meeting of workers and firms, with no consideration for the quality of the match to be formed, and no asymmetric information to be addressed.

It is assumed that workers are homogeneous, but may select their choice amounts

of job-contact networking and informal job market search. However, given the common

conditions in this environment for all agents, the equilibrium predictions are identical for

all subjects in all cases. Since wages are homogeneous in the G&M model, there is no

incentive to seek a better job, as any job will suffice, and so there is no on-the-job search.

The authors state that the job search can be construed to happen either along the intensive

or extensive margin or both.

Although firms are mostly abstracted from in this model, one could assume the

firms create the exogenous vacancy and job offer rates. The authors suggest that, while

some of the modeling assumptions make the derivations a bit simpler, they do not matter

essentially for G&M's main result. In particular, the authors work out the results from

relaxing two key assumptions, exogenous formal market job offers and no second-round

job forwards, and the resulting model predictions are not substantially altered.

Although G&M's mathematical derivations are made specifically for the case of

large n, the authors state that the results could readily be adapted to situations with finite

n that is sufficiently large.

G&M assumes a linear utility function, implying risk neutrality. Specifically,

they use the form, $U_i = w - cs_i$. That is, individual utility equals the wage, w, minus the

investment costs, which are the unit investment cost, c, times the number of generic

investment units chosen, s_i.

$$U_i \text{ (if job)} = 1 - cs_i$$

$$U_i \text{ (if no job)} = 0 - cs_i$$

However, there is evidence suggesting that most people display at least some

degree of risk aversion, and Rong and Houser (2012 wp) probes the G&M expectation under risk averse agents. The authors run simulations to trace out the relation between job separation rate and network investment under risk-averse agents.
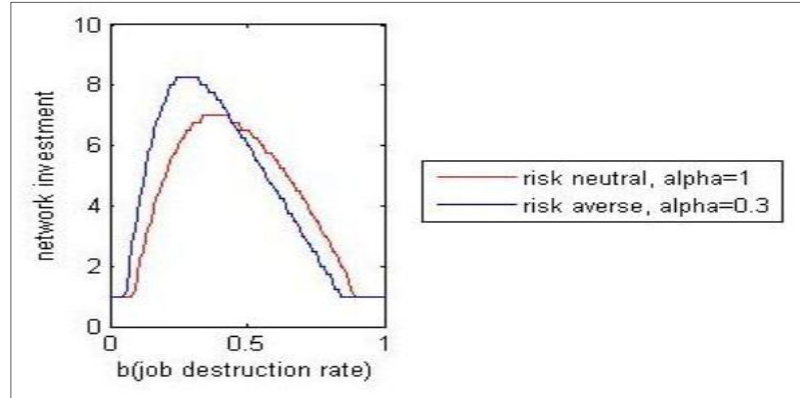
Figure 4. Approximate impact of risk-aversion vs. risk-neutrality
Source: Rong and Houser (2012wp)

Figure 4 visually depicts the approximate impact of modeling with risk-averse agents instead of with risk-neutral agents, based on simulation results from Rong and Houser (2012wp). Overall, with risk aversion, subjects tend to insure more against the bad state of the world, and the overall distribution shifts upward and leftward, so there is a higher peak level of network investment, and this peak occurs at a lower job loss rate.

2.3   Network Formation Process

In G&M, the network investment in Cabrales, et al. (2011), is generic, not "earmarked." As per the mean-field approach discussed in Chapter 1, Section 3.3, the links in this model are created generically and anonymously. While the individual level of networking is chosen strategically, the individual links are not formed strategically,

and so the network is formed quasi-randomly. Given the level of generic network investment choices, assumed to be symmetric in this treatment, the network structure is created probabilistically, and it coincides with a Poisson random graph.

$$\Pr(g_{ij} = 1|\mathbf{s}) = \begin{cases} \min\left\{\frac{s_i s_j}{y(\mathbf{s})}, 1\right\} & \text{if } y(\mathbf{s}) > 0, \\ 0 & \text{otherwise.} \end{cases}$$

This above property holds as long as three conditions hold, namely: there are undirected (as opposed to directed) links, there is aggregate constant returns to scale in s_i, and the link formation is anonymous.

A selection of s is chosen by all participants; then using the above probabilities, a multinomial random graph is created. Note that under the simple scenario of all subjects choosing the *same level* of investment, this setup would imply that the probability that two workers are connected equals min{s/n,1}, the per-capita network investment, and the resulting expected number of neighbors of a node is (n-1)min{s/n,1}. Although the expression would be more complex under heterogeneity in the investment level, this simple expression shows that a simple scale up in the level of s (possibly due to artificial reasons) can raise the level of graph connectivity.

Notably, the model predicts individual overinvestment relative to what a beneficent social planner would choose because there is a negative externality associated with additional indirect links, as discussed earlier. Again, the issue is that, as in Calvo-Armengol (2004), information is rival, and so if a neighbor him or herself has more neighbors, there would be a smaller chance that any particular one of those neighbors would receive the forwarded job offer.

In computing the optimal network investment levels, s^*, it is not the case that agents can just look at a given network structure and decide whether to buy into it or not. First, note his or her investment is made in advance, so he/she would not be able to know the state of the network before choosing. Second, his or her investment in the network itself changes the likely network structures as well as the likely job-information flow for the other agents that he/she would be connected to. However, G&M's solution of the model already takes into account this feedback effect of the agent's investment on the network connectivity with other agents.

2.4 Visualizing the G&M Predictions

Figure 5, Figure 6, and Figure 7 trace out the shapes of the predicted network investment curve, network matching rate, and unemployment rate, respectively, according to G&M's theory. For this illustration, the parameters are set at c=0.01, a=0.5 and b ranging from 0.05 to 0.95.
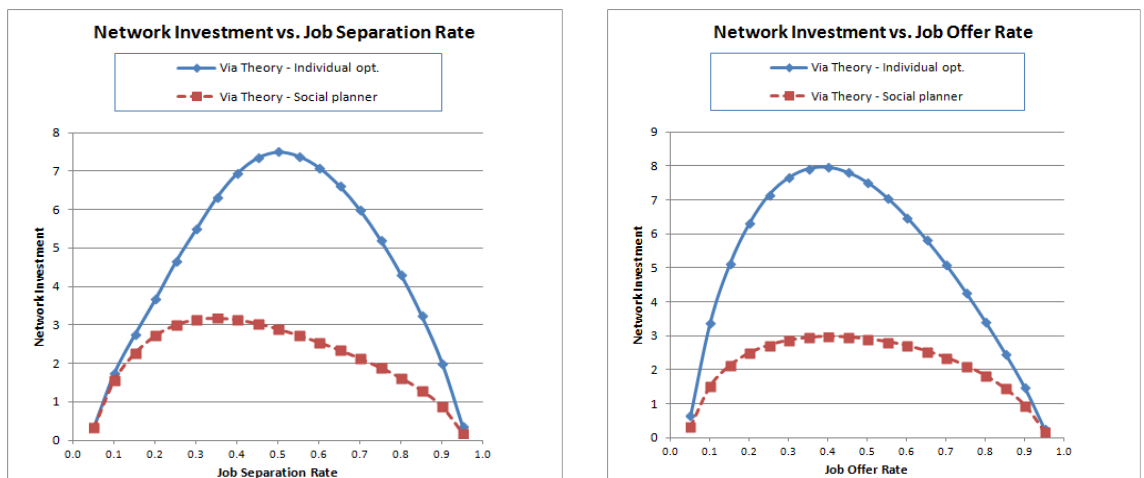
Figure 5. Network investment relative to job loss rate (left panel) and job offer rate (right panel)
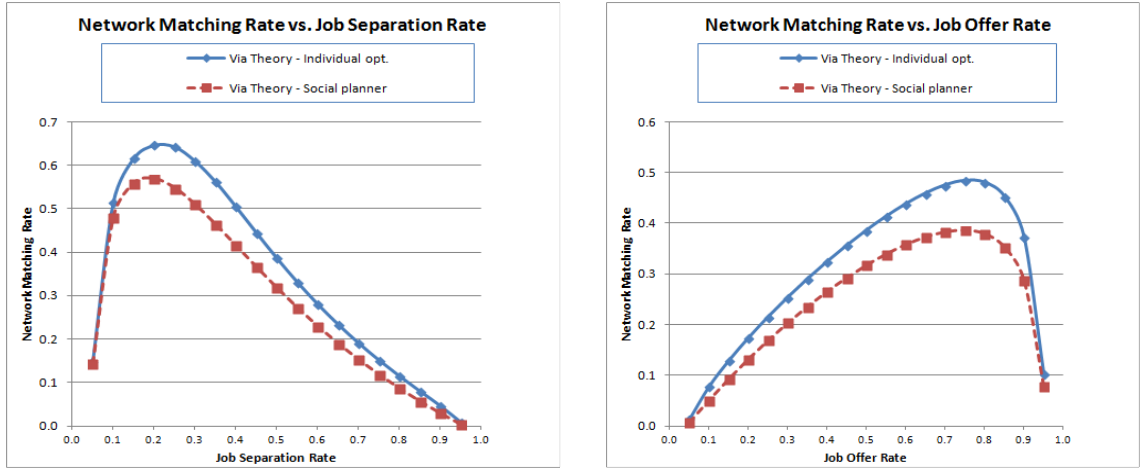
Figure 6. Network matching rate relative to the job loss rate (left panel) and job offer rate (right panel)

Figure 7. Unemployment rate relative to job loss rate (left panel) and job offer rate (right panel)

As shown in Figure 5, the equilibrium levels of network investment first rises and then fall versus the job loss rate, as well as versus the job offer rate. Also, the profile of network investment choices by the social planner is lower than by optimizing individuals. As shown in Figure 6, the network matching rate first rises and then falls with respect to the job loss rate and job offer rate, though the shape the curve relative to job offer rate is somewhat mirrored around the 0.5 value, as compare to the shape of the curve relative to

the job offer rate. Finally, as shown in Figure 7, the unemployment rate is rising against the job loss rate and falling against the job offer rate. Also, the unemployment rate tends to be slightly higher under the social planner choices, due to the lower levels of network investment in that setting.
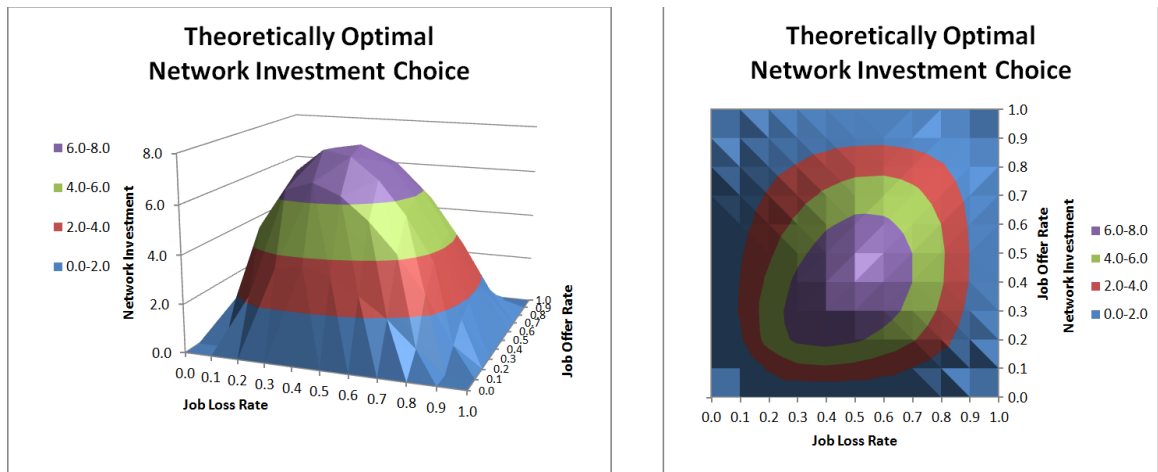
Figure 8. Theoretically optimal network choice.
Left panel is a 3-d display, and right panel is a contour plot.

Figure 8 depicts a 3-d map (left panel) and contour map (right panel) of the equilibrium optimal choices of network investment in the G&M framework, when the cost parameter, c, is set to 0.01, for job loss and job offer rates ranging from 0 to 1, inclusive. The peak equilibrium investment level is about 8.0 with a job offer rate of about 0.4 and a job loss rate of about 0.5; note a coarse grid of only 0.1 intervals was used to approximate the shape and maximum.

2.5   Empirical Exercise and Dynamic Model

G&M also documents a few stylized facts that qualitatively match the predictions

from their theory. The authors' data source is the U.K. Quarterly Labor Force Survey (QLFS), from 1994:Q3 through 2005:Q1 in 20 U.K. regions. They focused just on those male ages 16-64 looking for a job, according to the United Nations' ILO (International Labour Organization)'s unemployment definition: "the proportion of unemployed workers looking for a job or waiting to start a job in the next two weeks over the whole active population" in each period. This amounts to a sample of roughly 1,800 to 4,000 individuals per wave.

G&M's proxy variable for network investment is the share of workers that use the following as a main job search method in each period, by region: "ask friends, relatives, colleagues or trade unions about jobs." G&M's proxy variable for network matching rate is the share of job seekers that found their new job by "hearing from someone who worked there" in each period, by region. G&M's proxy variable for job loss rate is the share of unemployed workers looking for a job or waiting to start a job in the next two weeks relative to the population actively looking for jobs. They estimate this job loss rate as the probability of transitioning from employment to unemployment, computed at regional level. They use the refined methods of Shimer (2012) in computing these transitions. G&M do not include any measure for the job offer rate in their models.

In G&M's first, and simplest, model, the authors regress their network investment proxy variable simply on regional indicators and annual time indicators, as follows:

$$Y_{j,t} = \alpha_0 + \sum_{j=1,19} \alpha_j I_j + \sum_{t=1,10} \beta_t I_t + \epsilon_t,$$

in which the indices are j for region and t for time (annual). The authors find a large amount of variation in the network investment proxy explained by this model, and both

103

the regional and year indicators appear to be important.

In G&M's second model, the authors regress their network investment proxy variable on the job loss rate and job loss rate squared, including year indicators. They also regress their network matching rate proxy variable on the same covariates and year indicators. These models are fit as linear probability models. In G&M's mathematical notation, the models are of the following form:

$$Y_{j,t} = \gamma_0 + \gamma_1 b_{j,t} + \gamma_2 b_{j,t}^2 + \epsilon_{j,t},$$

in which $b_{j,t}$ is their proxy variable for job loss rate and some of the models also include time (annual) indicator variables. For both their network investment and network matching rate models, the authors find significant and positive coefficient estimates for the linear terms and significant and negative coefficient estimates for the quadratic terms. Overall, they find a large amount of variation in the dependent variables explained by this model, though not as high as for their simpler indicator model, which had also included regional indicator variables. The authors associate a 1 percentage point increase in the job loss (separation) rate (around its average value) with a 1.24 percentage-point increase in network usage and a 3.92 percent-point increase in network matching rate.

G&M also run an alternative version of their second model, but separating workers by skills, as low, medium and high, with proxies as educational attainment from the International Standard Classification of Education (ISCED1997). They do in order to account for the fact that labor market conditions may not have a uniform effect on all workers, but, rather may differentially affect workers that have different employment opportunities. Their estimation results from this refinement have less extreme curvature

against the job separation rate proxy variable than do the corresponding results not accounting for educational attainment. The authors associate a 1 percentage point increase in the job loss (separation) rate (around its average value) with a 1.13 percentage-point increase in network usage and a 2.91 percent-point increase in network matching rate. Finally, G&M point out that their results suggest that low-skilled people, who may rely most heavily on social networks, are likely to be more adversely affected by negative shocks than other people, in line with other empirical work.

G&M also run similar models with their proxy variable for network matching rate as the dependent variable (instead of their proxy variable for network investment). In those results, they, likewise, find quadratic curvature in the expected direction against their proxy variable for job loss rate.

Overall, G&M finds empirical support for there being curvature in the network investment and network matching rate data relative to the job loss rate. While these findings are qualitatively in line with the G&M theoretical model, the extent of curvature from the empirical exercise appears to me to be much more pronounced than in the model. So, I, provisionally, would argue that, quantitatively, the empirical findings are not very supportive of the G&M model. However, it is possible the extra sensitivity of the networking and matching to the job loss rate has to do with the coarse proxy variables that are available for their running their analysis or the particular form of model chosen. I would withhold any serious assessment until I confirm a few other points with the study's authors.

Of note, G&M (2014) also present a dynamic form of their model in Section 3.3

of their work. In this setting, although agents lose and gain jobs over time, the network configuration is fixed over time, based upon the initial choice of network investment at time zero (and the related original link probabilities and resulting link formation). Although the authors do not analytically find the unique interior equilibrium or its comparative statics, they present a numerical exercise, grounded with real data from the U.K., which suggests that such a unique equilibrium exists and that it has the expected comparative statics relationships. In my laboratory experiments, I do not test this dynamic form of the G&M model; I test only the purely static form of the G&M model.

2.6   Commentary

In summary, the G&M model predicts that at lower job loss rates or high job offer rates, it is optimal to invest little in network links. At low job loss rates (or high job offer rates), the reason is that one is unlikely to lose his/her jobs; at high job loss rates (or low job offer rates), the reason is that there would be few redundant job offers on the network to go around anyway. In the middle ranges of job loss and offer rates, it is worth investing a bit more in network links (i.e., to insure oneself) because there is enough chance that one will be unemployed and yet also a sufficient number of redundant job offers floating around on the network to make it worthwhile. So, this trend in network investment is non-monotonic, first increasing in the job loss or offer rate, and then, beyond a certain point, decreasing in the job loss or offer rate.

As noted, G&M abstracts from the details of particular links, or earmarked individuals, in network formation by modeling just a generic level of social network investment, as had been done in Cabrales, et al. (2011). By this choice, the authors are

trying to capture the phenomena of random contacts that may form when people venture out into the world searching for contacts, unsure of whom they will actually meet in the process. A few examples of this could be attending job fairs, attending conferences, or attending school functions for ones' children. This stands in contrast to targeted contacts in which people preferentially seek out other people, to the exclusion of others.

There are two main factors that give the 'network matching rate' its lopsided inverse-U shape. First, high job loss rates mean that it is less likely for agents to have spare jobs to forward on to others, even if the network were fully connected. Essentially, when there are few jobs going around, the network is like a tree bearing no fruit. Second, since agents know that the network likely would not provide them with much benefit (even it were fully connected), they are less inclined to invest in social ties. As a result, the network is more sparsely connected. The combination of the few extra jobs going around and the more sparsely connected network together exert downward pressure on the network matching rate for high job loss rates, as depicted graphically. [The network matching rate is the share of the unemployed agents that find a job through the job-contact network.]

The network investment curve is a locus of equilibria. Given G&M's condition that the private marginal benefit equals the private marginal cost in equilibrium, the network investment curve is also equivalent to the 'expected benefit from the network curve,' i.e., it reveals the financial benefit from investing in the job-contact network, at the given wage and cost levels. Since the wage is just a constant in this model, by dividing the expected benefit-from-network, or, equivalently, the network investment, by

the wage, one thus computes the rise in the expected probability of being employed, due to the job-contact network. I elaborate on the above points in the last paragraph of Section 3.4. This computation is a helpful benchmark when considering what optimal investment could look like in the case that the network wage is higher than the non-network wage, as discussed in Chapter 3.

3   Experiment Procedures

In this section I describe the laboratory procedures and sample design undertaken for this experiment.

3.1   Experiment Design

A total of 308 students at George Mason University participated in the experiment, and they signed up using the standard online recruiting tool for the Interdisciplinary Center for Economic Science (ICES). Most of the students were undergraduates, though there were a few graduate student participants as well. The experiments were run between March 2013 and May 2015, with 180 subjects participating between March 2013 and November 2013, 43 subjects participating in March 2014, and the remaining 85 subjects participating in May 2015.

The experiment was run using z-Tree software on computer terminals, one per human subject (Fischbacher, Bendrick and Schmid, 2015). The students are encouraged to remain silent during the experiment and to turn off and/or put away any phones or other electronic devices.

Table 1 depicts the laboratory sample collected for this experiment. The left half

of the table provides information about the base cases of the experiment described in this Chapter. The right half of the table provides information about the augmentations that were run in order to confirm results from the base cases and to explore related questions, and these are reported upon in Chapter 3.

Table 1. Summary of laboratory sample size, by date and treatment

Base Cases					_Augmentations_			
(Total of 308 subjects)	# of Subjects	Min. Infor. Level	Max. Infor. Level		Computer Players	Heterogeneous Rates - Known	Heterogeneous Rates - Unknown	High Network Wage
Mar-13 to Jul-13	60	1	1					
Aug-13 to Oct-13	55	1	2					
Nov-13	65	1	2			30	65	
Mar-14	43	1	2		43			
May-15	85	1	3					85

The first 60 subjects received information level 1 only, while the next 163 subjects eventually received up to information level 2, and the final 85 subjects eventually received information up to level 3. However, all experiments started with informational level 1, and so information level 1 data are available for all subjects.

The laboratory experiments lasted two hours in total, and contained 47 periods of game play. The subjects were paid based on the results from 6 random draws amongst their periods of play, plus the basic show-up and completion fees. All subjects were provided with a post-experiment questionnaire regarding demographic information and prior experience, as well as some open-ended question in which they could write in the gist of the strategy they followed during the game(s). In the base case setting, the job market conditions, i.e., the job loss rate and job offer rate, were common knowledge to all

players, and each player would receive his/her own independent and random draws. Each period, the lab subjects were allotted 30 seconds to review the given job conditions and decide about their network investment choice, but they could submit their entry early if they wish. Their selections were then processed together in the G&M framework, coded in the z-Tree software. The period results were quickly provided, and the lab subjects were allotted 30 seconds to view results, though they could click away earlier if they wish. Between each period, the subjects' full history of choices and results from all prior periods was shown on their screens for 10 seconds.

Each period was entirely separate from all other periods, and there was random re-matching among the selected groups of five each time, so there were no obvious spillover effects across periods. The subjects did not know who in the room they were corresponding with at any time. Thus, I had a repeated game without major concern about reputational effects. Given the Cabrales, et al. (2011) algorithm for link formation, in order to yield a reasonable number of links, I allowed the s_i investment choice to range from 0 to 10, integers only, and the cost was varied between 1 and 6 cents per unit.

Each lab session started with 3 practice periods, and then included 47 real periods. As mentioned earlier, subjects' eventual earnings were based on the results from 6 randomly-drawn periods, drawn later on. For most of the experiment, I administered job-market conditions in trios, with low (10%), medium (50%) or high (50%) rates. Those three levels alone were enough for me to see if the lab subjects' responses (choices of network investment level) bore the expected curvature, i.e., whether the medium-rate observation was higher than the average of the low-rate and high-rate observations. I

would hold the job offer rate fixed at some level while I varied the job loss rate from low (10%) to medium (50%) to high (90%). Also, I repeated each of these trios, so that I got two reads at each level, to help measure the lab subjects' intended choices under each of the conditions. There were also some trios of 0%, 50% and 100%.

Table 2. Sequence of job-market conditions, including theoretical predictions

Period	Job Offer Rate (in percent)	Job Loss Rate (in percent)	*Not* shared with the lab subjects — Theoretical Prediction of Network Investment, when cost = 0.01
Practice	50%	50%	7.50
Practice	10%	90%	0.00
Practice	90%	10%	0.00
1	50%	10%	1.75
2	50%	50%	7.50
3	50%	90%	1.95
4	50%	10%	1.75
5	50%	50%	7.50
6	50%	90%	1.95
7	10%	10%	0.00
8	10%	50%	3.40
9	10%	90%	0.00
10	10%	10%	0.00
11	10%	50%	3.40
12	10%	90%	0.00
13	90%	10%	0.00
14	90%	50%	1.45
15	90%	90%	0.00
16	90%	10%	0.00
17	90%	50%	1.45
18	90%	90%	0.00
19	50%	0%	0.00
20	50%	50%	7.50
21	50%	100%	0.00
22	50%	0%	0.00
23	50%	50%	7.50
24	50%	100%	0.00
25	0%	0%	0.00
26	0%	50%	0.00
27	0%	100%	0.00
28	0%	0%	0.00
29	0%	50%	0.00
30	0%	100%	0.00
31	100%	0%	0.00
32	100%	50%	0.00
33	100%	100%	0.00
34	100%	0%	0.00
35	100%	50%	0.00
36	100%	100%	0.00
37	50%	0%	0.00
38	50%	10%	1.75
39	50%	20%	3.65
40	50%	30%	5.50
41	50%	40%	6.95
42	50%	50%	7.50
43	50%	60%	7.10
44	50%	70%	6.00
45	50%	80%	4.30
46	50%	90%	1.95
47	50%	100%	0.00

More specifically, Table 2 shows the full sequence of periods from the lab experiment, along with G&M's theoretical prediction for each period (which was <u>not</u> shared with the lab subjects) when cost is 1 cent per unit. In particular, I varied the job market conditions (i.e., job loss and job offer rates) from 0 to 1.0, and the lab subjects each selected a network investment level for each period. I started off each laboratory session with trios of low, medium and high job loss rates while holding the job offer rate at a medium level. Then I brought the job offer rate down to a low level and proceeded again with trios of low, medium and high job loss rates. Then I brought the job offer rate up to a high level and proceeded again with trios of low, medium and high job loss rates. In the next phase of the experiment, I repeated this sequence, but now taking the low and high job loss and offer rates to extreme levels (0.0 and 1.0). I closed each lab session with an eleven-period sweep through job loss rates from 0.0 to 1.0 at 0.1 increments while holding the job offer rate steady at 0.5.

Beyond the <u>explicit</u> (i.e., obvious) trios for varying job *loss* rates, there were also <u>implicit</u> (i.e., less obvious) trios for varying job *offer* rates. For example, periods (8, 2, 14) and (11, 5, 17) formed implicit trios of job offer rate when the job loss rate was fixed at 50%. [Similarly, periods (7, 1, 13) and (10, 4, 16) were implicit trios of job offer rate when the job loss rate was fixed at 10%. And periods (9, 3, 15) and (12, 6, 18) were implicit trios of job offer rate when the job loss rate was fixed at 90%. Additionally, (25, 19, 31) and (28, 22, 34) were implicit trios of job offer rate when the job loss rate was fixed 0%; (27, 21, 33) and (30, 24, 36) were implicit trios of job offer rate when the job loss rate was fixed 100%; and, finally, (26, 20, 32) and (29, 23, 35) were implicit trios of

job offer rate when the job loss rate was, again, fixed 50%, but now sandwiched between the more extreme periods of 0% and 100% job loss rate instead of lying between the less extreme periods of 10% and 90% loss rate.]

Overall, this design allowed me to trace out the curvature in the lab subjects' chosen levels of network investment by job loss rate for a given job offer rate, and it also allowed me to trace out the curvature in the lab subjects' chosen levels of network investment by job offer rate for a given job loss rate. Moreover, I obtained higher resolution for the specific case of variation in the job loss rate when the job offer rate is held at 50%, given that I closed the experiment by running separate periods with from 0% to 100% by increments of 10%, holding the job offer rate fixed at 50%.

As mentioned above, I implemented three different information levels across different sessions of this lagboratory experiment, as depicted below.

- Information Level 1: Lab subjects received basic lab instructions only

- Information Level 2: Lab subjects received additional computations sheet with tables provided after initial periods

- Information Level 3: Lab subjects received additional computations sheet with graphs and period-by-period visuals

Specifically, under Information Level 1, only the basic laboratory instructions were distributed, and these are available for viewing in the Appendix to this dissertation. For the Information Levels 2 and 3 treatments, the lab subjects were presented with handouts which plotted the rise in probability of being employed due to the network for the different job loss and job offer rates. The Informational Level 2 version plotted just a

column chart of the information at some discrete conditions, while the Information Level

3 version plotted many more intermediate points and was more visually appealing. For

the Information Level 3 treatment, also, the subjects saw a depiction of the current job

market conditions on his/her screen before the choice box appeared, each period. These

information levels are illustrated in greater detail with the screenshots in Section 3.4.

These kinds of handouts potentially cue the lab subjects to realize the optimal investment

choice, since the lab subjects may recognize that the rise-in-job-probability concept

plotted for them is related to the theoretically optimal investment choices.

I implemented a group size of five persons in my laboratory treatments, with

random re-matching, because that size group seemed small enough that one could really

know everyone in their small neighborhood, and with only ten total links possible among

the five nodes, there could be a feeling that every link mattered. However, a downside to

setting the group size at five is that it exogenously imposed some structure on the group's

network formation processes, and thus may have crowded out some kinds of network

structures that might have emerged more organically from the group. However, early on,

I had run a session with twenty-five subjects in the laboratory and set no limits on

maximum group size. Although the network structures that emerged were, naturally,

more complex, the lab subject choices and the network matching rate was not notably

different from the rest of the cases which used group size of five.[26]

In addition to the set of base case laboratory sessions, I also ran several sessions

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[26] As mentioned in Section 2.2, G&M's results are derived specifically for large n, though they state that
the results could be readily adapted for some finite n. As discussed, the results from the early lab session I
ran with twenty-five subjects were very close to those from the standard group size of five subjects. While
$n=5$ may or may be too small for G&M's derivations to apply, $n=25$ might be sufficient. Still, it is likely
worth confirming how different the G&M predictions might be in this case of small n.

of extension treatments, and these are discussed in Chapter 3, as mentioned earlier.

3.2 Conveying Ideas to Subjects

During the instructions portion of the laboratory session, I provided the subjects with clarifying examples. For example, in Figure 9, I illustrate some of the possible network configurations that could arise among five subjects in a given group.
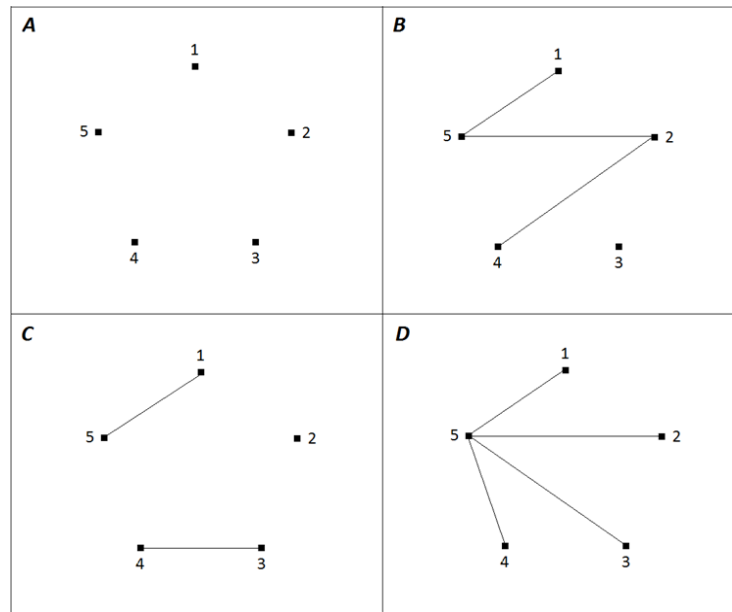
Figure 9. Illustration of some possible network topologies

In panel A (top-left), no subjects are connected; in panel B (top-right), a four subjects are connected, and just one subject is not connected; in panel C, there are two pairs of connected subjects; and in panel D, there is a star configuration, in which subject 5 is at the center.

Moreover, I illustrated the way the game works to the lab subjects by going over the four possible states of employment/unemployment, as shown in Table 3.

Table 3. Employment and referral possibilities for an agent

		Get Direct Job Offer?	
		No	**Yes**
Lose Job?	**No**	(1) *Employed,* Status quo. You have no redundant job offer to forward on network	(2) *Employed,* You forward your redundant job offer on network to someone else (if connected)
	Yes	(3) *Unemployed,* Maybe can receive a forwarded job offer from network	(4) *Employed,* Your loss and offer cancel out. You have no redundant job offer to forward on network

If the subject did not lose his/her job and did not receive a job offer, this situation of status quo corresponds with the upper-left panel in the table. If the subject did not lose his job and received a job offer, this situation of having a redundant job offer corresponds with the upper-right panel. If the subject lost his/her job and did not receive a job offer, this situation of being unemployed (unless he/she received a job offer forwarded through the job-contact network) corresponds with the bottom-left panel. Finally, if the subject lost his/her job but also received a job offer, this situation of the loss and offer canceling each other out corresponds with the bottom-right panel.
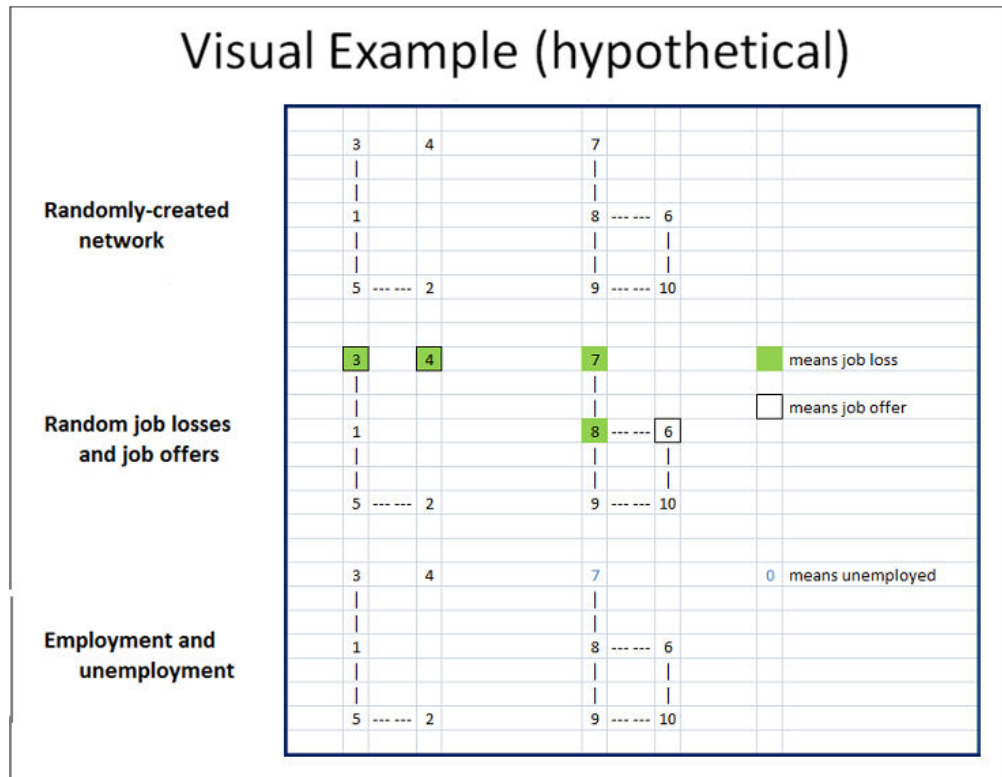
Figure 10. Visual example of network creation and resulting states.

I also walked the laboratory subjects through the hypothetical example shown in Figure 10. This example depicts two groups of five people, or ten people in total. In the top panel, hypothetical random connections (based on presumed choices of network investment) are created for each group of five people. Then, in the middle (vertically) panel, there are random job loss and job offers. Next, any people that had redundant job offers forward them on to connected neighbors in the job-contact network. Finally, the bottom panel depicts the final employment and unemployment status of each person.

In addition, I presented the laboratory subjects with a "neighbors' neighbors" visual, as given in Figure 11, in order to suggest the rival nature of job information provided on the network. This figure is a depiction of the local neighborhood around a

given node in the social network. As implied, when a neighbor has more neighbors, this decreases the likelihood of a job being forwarded on to any particular neighbor.
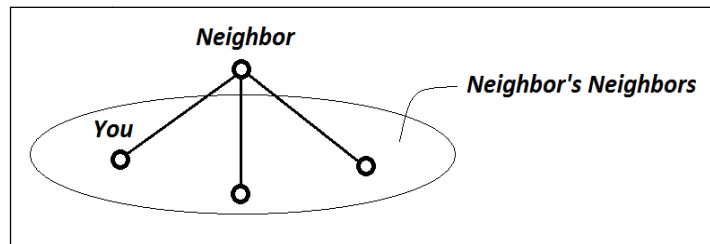
Figure 11. Depiction of neighbor and his/her neighbors

I also presented the link probability computation to the laboratory subjects via the following simple formula:

Prob(link between Person A and B exists, given all participants' level of network investment)

$$= \frac{(\text{A's network investment}) \times (\text{B's network investment})}{\text{sum of all 5 group members' network investment}}$$

This link computation is consistent with the Cabrales, et al. (2011) approach to link formation used within the G&M model.

As a reminder, there are no second-round job forwards in the G&M model, and this spares the lab subjects from having to deal with some complexity. [However, the G&M authors have worked out the analytics for such a case, and the results did not materially differ from those in the case in which there are only first-round job forwards.]

3.3 Details of Link Formation

This subsection contains more detail regarding how link formation took place in the experiment. The goal is to aid in my analysis of the network-based data obtained from the laboratory sessions. These additional concepts were not presented to the

laboratory subjects during the experiment.

Table 4 is a hypothetical example of link formation probabilities, following the approach described in Cabrales, et al. (2011), and used in G&M, in the case of five people. Since person E invested zero, there is zero chance that any links will form with person E. Note that the more that two people invest, the greater the likelihood of a link forming between them, as such mutual investments would tend to raise the product of their investments in the link probability formula, relative to the sum of all investments. As it works out, the investments of person D are a sufficient amount higher than the average level of investment of the others such that the computed link probabilities exceed 100% for the links between persons D and A and persons D and B, and so the maximum of 100% probability restriction is binding in those cases.

Table 4. Example of Link Formation Probabilities

	Investment Choices			Likelihood of Bilateral Link Formation				
Person Label	Investment level	Expected # of Neighbors		A	B	C	D	E
A	4	2.23	A	n/a	92%	31%	100%	0%
B	3	2.15	B		n/a	23%	100%	0%
C	1	0.92	C			n/a	38%	0%
D	5	2.38	D				n/a	0%
E	0	0.00	E					n/a

	Sum of Investment	Total Expected # of Links	Total Possible # of Links	% Connected
A, B, C, D, E	13	3.85	10	38.5%

Table 5 is an example of network link formation under an exogenous link-formation probability of 25 percent for all links, in the case of five people. Note that there are ten total links possible among the five people. In this case, the expected number of neighbors, or links per person is 2.5, and this would represent 25 percent of the ten possible links overall. Again, note this table is not provided to the lab subjects.

Table 5. Example of network link formation under exogenous probabilities
The table is for the case of five people with a 25 percent likelihood of each individual link emerging

Number of people	Number of possible links	Assumed likelihood of each possible pair-wise link existing	Implied likelihood that a given link does not exist	Number of links	Number of non-links	Probability of a given instance of this number of links and non-links	Number of possible combinations	Probability of any instance of this number of links and non-links	Number of links weighted by probability of occurance	
5	10	25.0%	75.0%	0	10	5.6314%	1	5.63%	0.000	
5	10	25.0%	75.0%	1	9	1.8771%	10	18.77%	0.188	
5	10	25.0%	75.0%	2	8	0.6257%	45	28.16%	0.563	
5	10	25.0%	75.0%	3	7	0.2086%	120	25.03%	0.751	
5	10	25.0%	75.0%	4	6	0.0695%	210	14.60%	0.584	
5	10	25.0%	75.0%	5	5	0.0232%	252	5.84%	0.292	
5	10	25.0%	75.0%	6	4	0.0077%	210	1.62%	0.097	
5	10	25.0%	75.0%	7	3	0.0026%	120	0.31%	0.022	
5	10	25.0%	75.0%	8	2	0.0009%	45	0.04%	0.003	
5	10	25.0%	75.0%	9	1	0.0003%	10	0.00%	0.000	
5	10	25.0%	75.0%	10	0	0.0001%	1	0.00%	0.000	
								Sum of probability	Expected number of links per person	As a % of all possible links
								100.00%	2.500	25.0%

Table 6 is an example of the network benefits available in a fully-connected network. The table is for the case of five people; the wage is 1.0 paid to those employed, and 0.0 otherwise; the job loss rate of 50 percent, and a job offer rate of 50 percent. In this case, the expected earnings to be received without the network is 0.75. However, via the links, there is a roughly 5.7 percent increase in the likelihood of receiving a forwarded redundant job through the network. This increases the overall expected earnings to roughly 0.807, which is roughly 7.6 percent higher (=0.807/0.750-1) than in

the case without the network. Importantly, these network benefits would vary depending on how connected or not the five people are to one another. While more direct links provide more channels through to receive forwarded job offers, more indirect links also reduce the chance of receiving a forwarded job because the job information is rival among all neighbors. These forces are balanced out in G&M's analytical optimization, but, overall, because of these two opposing forces, the likelihood of receiving a redundant job offer from a connected neighbor does not vary that much in connected groups of five, four, three or two people.

Table 6. Example of network benefits in a fully-connected network
The table is for the case of five people that are in a fully-connected network

Neighbors' number of neighbors (assuming symmetry among neighbors)	Job separation rate	Job offer rate	Chance each neighbor has redundant job offer	chance that need a job offer	Chance each neighbor forwards said offer to you	Chance of job offer forwarded from any particular neighbor	Chance of not job offer forwarded from any particular neighbor	Number of forwards	Number of non-forwards	Probability of a given instance of this number of forwarded job offers and absence of forwarded job offers	Number of possible combinations	Probability of any instance of this number of forwarded job offers and absence of forwarded job offers	Number of forwards weighted by probabilty of occurrence
4	50.0%	50.0%	25.0%	25.0%	25.0%	6.3%	93.8%	0	4	77.2476%	1	77.2476%	0.0000
4	50.0%	50.0%	25.0%	25.0%	25.0%	6.3%	93.8%	1	3	5.1498%	4	20.5994%	0.2060
4	50.0%	50.0%	25.0%	25.0%	25.0%	6.3%	93.8%	2	2	0.3433%	6	2.0599%	0.0412
4	50.0%	50.0%	25.0%	25.0%	25.0%	6.3%	93.8%	3	1	0.0229%	4	0.0916%	0.0027
4	50.0%	50.0%	25.0%	25.0%	25.0%	6.3%	93.8%	4	0	0.0015%	1	0.0015%	0.0001
prob of having a job independently		Expected number of forwards	prob of receiving 1 or more forwards		prob of being employed	increment from network	(equivalently)	wage if have job	wage if have no job		expected wages without network	expected wages including network	rise in expected wages
75.0%		0.250	22.75%		80.69%	5.69%	5.69%	1	0		0.75	0.81	0.05688

	percent rise in expected wages
	7.58%

There are possibly two separate considerations for a lab subject to make in choosing his/her network investment levels. First, holding the investment decisions of their peer lab subjects constant, there may be an optimal choice for them. However, the subjects also have to form beliefs about how their peers perceive the situation and how much those peers will want to invest. There are different investment strategies depending on whether one assumes his peers are naïve, strategic, disinterested, etc. A key part of

this test of endogenous job-contact networks is what investment amounts the subjects will choose in the face of the complicated, two-level problem of figuring out what others might choose and then self-optimizing within that. Since the mathematical intuition can be hard to absorb quickly, subjects may resort to intuition at first and then to prior experience as the scenarios are repeated across periods in the laboratory. They may find useful heuristics to guide their decisions, even if they do not see the logic the 'optimal' way that as has been laid out here.

The investment choices of one's peers in the experiment matter for one's best-response choice of network investment in two ways: first, with respect to the number of links, and second, with respect to the number of offers forwarded through those links. Regarding the number of links, given our focal individual's investment choice, a higher level of identical investment by the other subjects monotonically raises the expected number of links that the focal individual would have. Moreover, if this focal individual has more links, then he/she has more channels by which a job could potentially be forwarded to him/her. However, the higher the level of networking investment by the other agents also raises *their* expected numbers of neighbors. As a countervailing force, the more linked neighbors that our focal agent's linked neighbors have, the smaller the chance that any individual link will forward a job onto the focal individual. This is the case because job information is rival, as in Calvo-Armengol (2004); it can only go to one node, and is not diffused out to all the neighboring nodes, as would be the case in Bala and Goyal (2000a)'s model. Since these two effects work in opposite directions, even if the subject thinks his/her peers invest 'too much' or 'too little,' the optimal individual

response to this situation is not easily known, and depends on the job market conditions.

3.4   Information Levels

All subjects, regardless of information level, were started out with the basic

instruction pages, of which an excerpt is shown in Figure 12; the full laboratory

instructions are included in the Appendix.

"Laboratory Instructions"

1.   Welcome

Thank you for coming! You've earned $5 for showing up on time, and the instructions explain how you can make decisions and earn more money. You will have **15 minutes** to silently read and review these instructions and to make any notes. The rest of the experiment to follow depends very much on your understanding of these instructions. There should be no talking or cell phone use at any time during this experiment. If you have a question, please raise your hand, and the experimenter will assist you quietly.

2.   Summary

This experiment is an employment game in which you will earn a "wage" each time you "have a job," and you will earn "no wage" each time you "do not have a job." During each Round you will be anonymously and randomly re-grouped with 4 other people (for a total of 5 people per Group) from this room. At any given time, these are the only other people you will interact with.

In each Round, you will be asked to make decisions about the how much you would like

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Figure 12. Excerpt from the first page of the laboratory instructions

However, at the beginning of Period 4, some subjects were then also shown the

following information level 2 handout in Figure 13. This handout depicted the laboratory

conditions and key related variables under scenarios of lower (10 percent), medium (50

percent) and high (90 percent) job loss rate, while holding the job offer rate constant at

the medium (50 percent) level. From Figure 13, one can see that the return to network investment appears to be highest in the middle ranges of job loss rate, and much lower for higher and lower ranges of job loss rate. The experimenter narrated the handout out once upon distributing it out to the lab subjects.
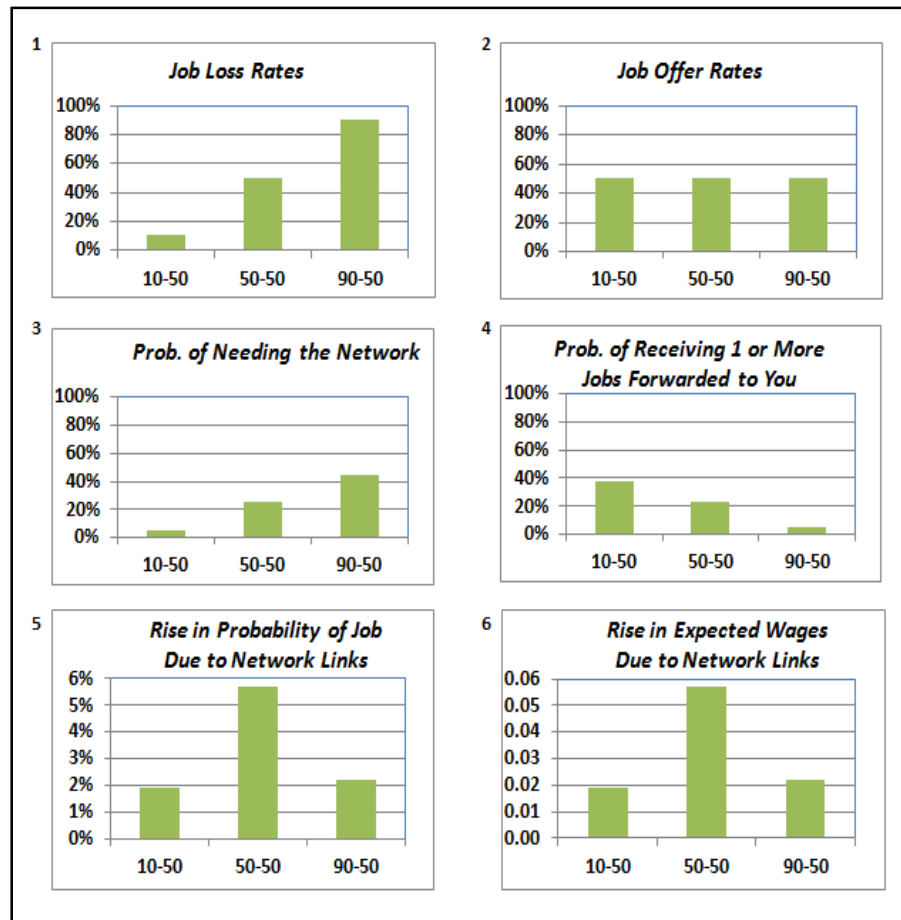
Figure 13. Information level 2 handout, tabular information
For job offer rate of 0.5 or 50 percent

Then, at the start of Period 7, these same lab subjects received a similar sheet depicting information for the three job loss rates when the job offer rate is 10 percent, and the experimenter narrated the handout as well. And, at the start of Period 13, these same

125

lab subjects received a third sheet depicting information for the three job loss rates when the job offer rate is 90 percent, again with the experimenter narrating the handout once.

Return to Period 4, some other subjects were shown the following information level 3 handouts, from Figure 14. This handout depicted the laboratory conditions and key related variables under scenarios of lower (10 percent), medium (50 percent) and high (90 percent) job loss rate, while holding the job offer rate constant at the medium (50 percent) level. From Figure 14, one can see that the return to network investment appears to be highest in the middle ranges of job loss rate. These information level 3 handouts, likewise, were narrated once by the experimenter to the group of subjects.
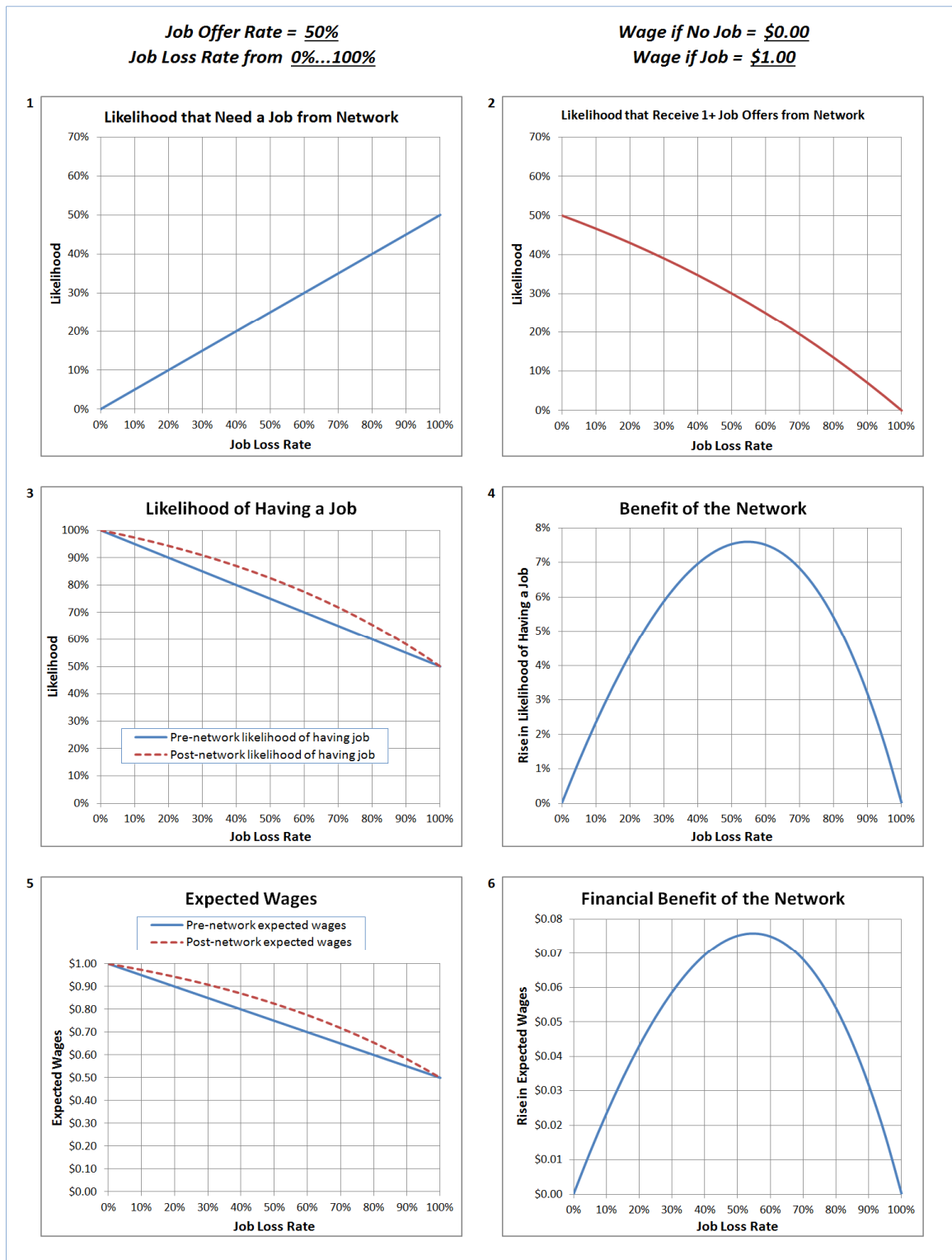
Figure 14. Information level 3 handout, graphical information
For job offer rate of 0.5 or 50 percent

In addition, the information level 3 participants received a period-by-period image on their screens showing the current job-market conditions and the associated other analytical result, as shown in Figure 15. These screen displays, which recurred each period, emphasized how the return to network investment appears to be highest in the middle ranges of job loss rate, though that was for the subjects to notice on their own.
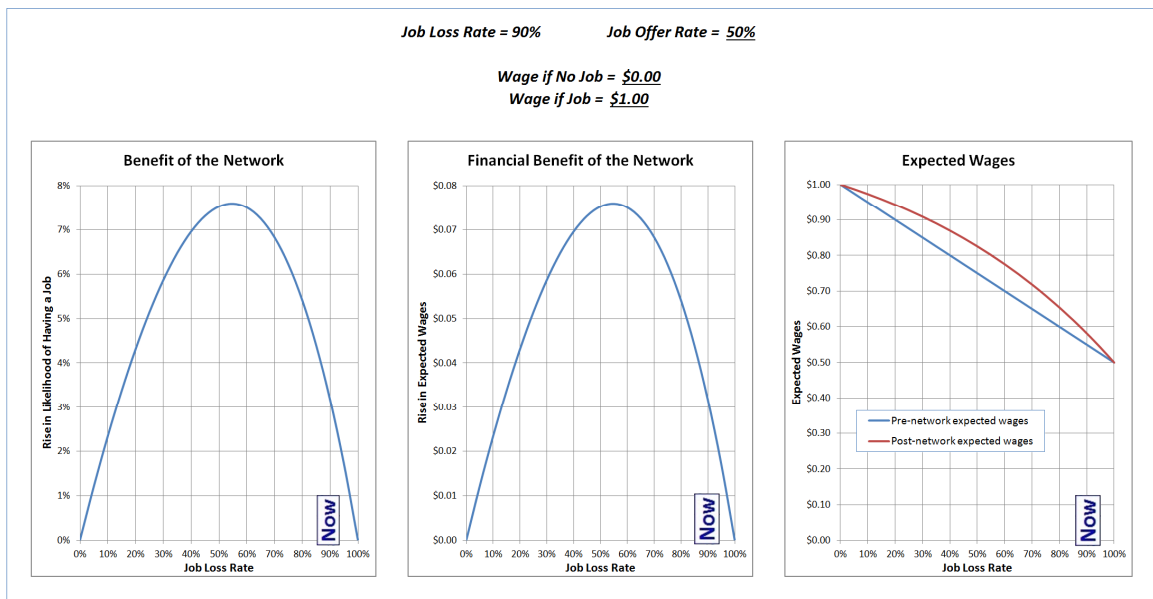
Figure 15. Information level 3 screen display, for job loss rate of 90%
This is what subjects would see before each period under information level 3. The "Now" icon shows the current job-market conditions that apply, which, in this example is for a job loss rate of 90%, while the job offer rate is 50%.

Then, at the start of Period 7, these same lab subjects also received a similar sheet depicting the three job loss rates when the job offer rate is 10 percent. And, at the start of Period 13, these same lab subjects received a third sheet depicting the three job loss rates when the job offer rate is 90 percent.

For reference, I here explain the way the values shown in the Information Level 2 and 3 handouts were created. This discussion elaborates upon ideas from the last

128

paragraph of Section 2.6. In equilibrium, G&M require that the marginal cost of network investing equals the marginal benefit of such investment. For example, if G&M's optimal network investment were 5, and the unit cost was constant and fixed at $0.02, then this amount of network investment would cost $0.10. In equilibrium, the marginal benefit of network investing must also equal this same $0.10. If the wage were $1, then the expected rise in probability from the network must be $0.10 divided by $1, for 0.10. This expected rise in probability from the network is defined as the probability of simultaneously needing a job from the network, and receiving a forwarded job from a connected neighbor. Since these two phenomena are cleanly independent in the G&M setting, the expected rise in probability from the network is merely the product of the probability of needing a job from the network and the likelihood that the network will actually provide such a job. As mentioned, I can easily compute the probability of needing a job from the network, since it is determined solely by the job market conditions. So if I divide the expected rise in probability from the network by the probability that one will need the network, the result is the 'likelihood that at least one contact will forward a job to a given job seeker,' which, otherwise, would be much harder to computer. However, with this likelihood in hand, it is then straightforward to produce the Information Level 2 and 3 handouts and notes. These materials, thus, show the following concepts: the likelihood of needing a job, the likelihood of receiving a forwarded job through the network, the resulting expected benefit of the network (i.e., increased probability of having a job), and the expected financial benefit of the network.

3.5 Categorization of 'Trios' of Choices

As described in Section 3.1, the lab periods often were organized in trios of job loss or job offer rates that varied from low to middle to high values. Often, the job offer rate would be fixed across three sequential periods during which the job loss rate would go sequentially from low to middle to high.[27] There were also implicit trios in which the job loss rate was fixed across three spread-apart periods during which the job offer rate would go from low to middle to high values.

By applying simple rules to the trios of low-med-high rate based choices in the laboratory data, I am able to classify the individual lab responses by trend in their network investment choices. The main trend categories consist of the following:

- Inverse-U: I define this as the case in which the lab subjects' middle observation exceeds the average of the outer two observations. Although, strictly speaking, the inverse-U shape would require the network investment choice to start low, then be higher, and then be lower again, given the low integer values of typical network investment, this criterion appeared to be overly stringent. Additional information is included below.

- Upward-sloping: I define this as the case in which the difference between the lab subjects' outer choices exceed the product of the high choice minus the middle choice and the middle choice minus the low choice. Although, strictly speaking, this shape would require that the network investment

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[27] For instance, often, the job offer rate would be held at 50 percent, and the job loss rate would be varied from 0 percent to 50 percent and then to 100 percent, sequentially, across three separate periods of the experiment. See Section 3.1 for more details.

choice starts low, is then higher, and is then higher again, given the low

integer values of typical network investment, this criterion appeared to be

overly stringent. Additional information is given below.

- Zeros: I define this as the case in which the lab subjects' network

  investment choices are identically zero for all three choices among a

  particular low, medium, high rate trio of data.

Although, clearly, other kinds of trends in the lab-subject response across rate

trios are possible, together they typically amount to only a small share of all lab subject

responses, and so I do not study them in detail.

Regarding the *inverse-U criteria*, as alluded to above, I compute the following

inverse-U curvature index: M - (H+L)/2, in which H=choice at high job loss or offer

rate, L=choice at low job loss or offer rate, and M=choice at the middle job loss or offer

rate. When this index is computed to have a positive value, that typically corresponds

with an inverse-U shape in the three points, and when either the choices at the low or

high offer rate exceed the choice at the middle rate, that lowers the value of the index.

This index is less strict than requiring that the middle value exceed both the lower value

and higher value. It is helpful in handling integer discreteness of choices in the lab

experiment. For example, if a lab subject had the same choice at the lower and middle

values, but a lower choice at the higher value, then this could still count as some degree

of inverse-U curvature, though not as much as if the subject chose both the lower and

higher values to be below the middle value.

Regarding the *upward-sloping criteria*, as alluded to above, I compute the following upward-sloping linearity index: H-L + (H-M) x (M-L), in which H=choice at high job loss or offer rate, L=choice at low job loss or offer rate, and M=choice at the middle job loss or offer rate. When this index is computed to have a positive value, that typically corresponds with an upward-sloping trend in the three points, and any dips that take place in the middle lower the index value. This criterion is less strict than requiring that the network investment choice starts low, is then higher, and is then higher again, given the low integer values of typical network investment. It is helpful in handling integer discreteness of choices in the lab experiment.

Finally, regarding the *all-zeros* criteria, as alluded to above, I simply located the trios in which the lab subjects chose zero network investment in all three choices that made up the trio.

Note these three categorization formulas on rare occasion determine the data to be in more than one category (inverse-U, upward-sloping, all-zeros). As a result, the shares of responses of each trend type do not always exactly sum up to 100 percent.

3.6   Benchmark Simulations

In order to obtain some benchmarks for running my hypothesis tests from Sections 4.3 and 4.5, I first ran a few simple agent-based simulations of the laboratory experiment using automaton agents programmed under a few different assumptions of individual choice behavior, and I then ran these simulated data in the same empirical model that I would next run my actual lab data in.

In the first case, called "optimal," I programmed the agents to select the G&M

theoretically predicted response of perfectly 'rational' actors, according to the prevailing job market conditions. Since only integers are allowed for entry in the lab setting, when the optimal choice under G&M was not an integer, I added and subtracted a uniform random number between 0 and 1 to the theoretical prediction and then rounded the result. This way, the integer that was closer to the optimal value was chosen with a higher frequency, in proportion to its relative distance from the optimal value.

In the second case, called "random," I programmed the agents to just select a random integer investment level over the range of possible choices from 0 to 10 regardless of the prevailing job market conditions. In this case, the lab subjects would be acting like 'zero-intelligence' agents in the sense of Gode and Sunder (1993).

In the third case, called "multi-armed bandit (MAB)," I implement an epsilon-greedy exploration-exploitation algorithm from the approach described in Section 2.2 of Slivkins (2017). In particular, I use an epsilon of 0.2, and the automatons choose among four 'arms' or strategies in response to the low, medium, high trios of rates: Inverse-U shape, Upward sloping, Random and All-zeros. The algorithm is designed to, 1 - epsilon percent of the time, 80 percent in this case, choose the strategy with the the highest average historical net return. Whenever there is a four-way tie in average historical earnings, the algorithm simply picks one of the four strategies with equal probability. And epsilon percent of the time, 20 percent in this case, the algorithm randomly selects among the four arms (strategies). In the first period, the historical earnings are zero for each strategy, and so the algorithm simply randomizes in that case. So, this algorithm has the feature that, even when the algorithm has converged on what appears like a profitable

path, the algorithm, with epsilon 0.2 probability, will again select a random strategy for a given period, and the historical returns will then be updated and checked again in order to choose the strategy for the next period. This allows for *some* exploration, i.e., some chance for discovery of profitable other options, yet without risking major overall losses in that exploration process.

This MAB approach attempts to approximate the choices that some form of boundedly rational agent might make in a complex situation in which the returns across various options are unclear at first. For instance, subjects may start out by tentatively making choices they are unsure of, and then perhaps using some heuristics to decide their preferred choices under particular conditions; they may come to recognize the relative expected returns for each choice upon analyzing their empirical returns over many periods. The four strategies that I implemented in the MAB were based on the main clustering of choices that appeared in the laboratory data. In the spirit of Kimbrough (2011), I had first combed through the lab data in search of patterns. I had then programmed the essence of these few categories of subject behavior into automaton agents (i.e., computer-based players), run the data simulation, and then compared the results relative to what I had observed in the laboratory setting.[28] Some lab subjects even individually appear to follow their own kind of exploration-exploitation algorithm across various strategies that somewhat looks like the particular MAB algorithm which I

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[28] Taking this method a step further, one could next propose changes to the simulation environment, such as altering the rules of exchange, individual preferences or endowments, and then observe outcomes from the new simulation. Differences between the results from the base case and modified simulation environments could serve as a prediction for what real lab subjects might do under similar proposed changes in their environment. One could then observe what the lab subjects actually do, and use this information to refine the simulation programming. And one could do this iteratively, leading to more realistic modeling that is still focused on capturing just the essence of the human behavior.

programmed here.

Finally, I also ran a fourth case, based on pooling the data from all three types of simulations (i.e., the optimal, random and MAB simulations) together in order to create one large mix of different simulation strategies chosen.

With results from these four types of simulations (optimal, random, MAB and pooled) in hand, I had some grounding guidance regarding what the regression results would look like under a few data-generating processes for a subject choice data.

4 Empirical Results

In this section I introduce the empirical approach I use to analyze the lab data, and I review the resulting empirical results.

4.1 Descriptive Data

I here present some descriptive data from the laboratory subjects' choices of network investment relative to the job loss and job offer rates.

4.1.1   Averages, medians and rates. Figure 16, Figure 17, and Figure 18 show the average and median levels of network investment chosen by the lab subjects versus the job loss rate, for Information Levels 1, 2 and 3, respectively. The mean is shown in blue, and the median is shown in green. The job loss rates range from 0.0 through 1.0 at 0.1 increments.
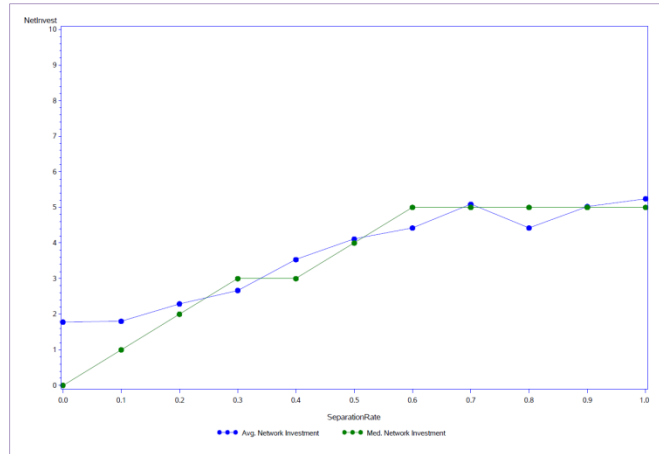
Figure 16. Mean and median network investment, under Information Level 1
Versus the job loss rate
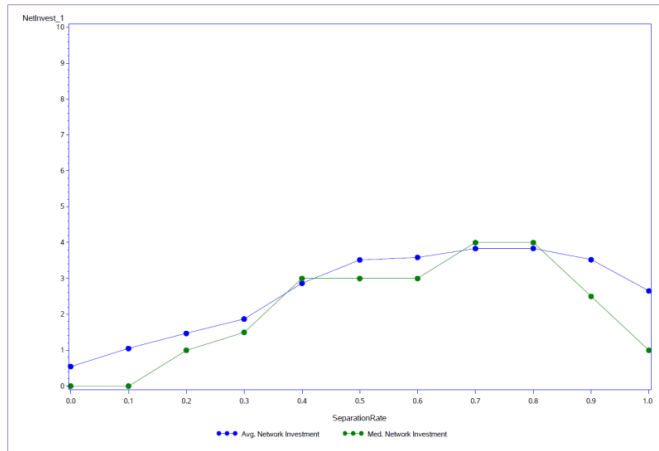
Figure 17. Mean and median network investment, under Information Level 2
Versus the job loss rate
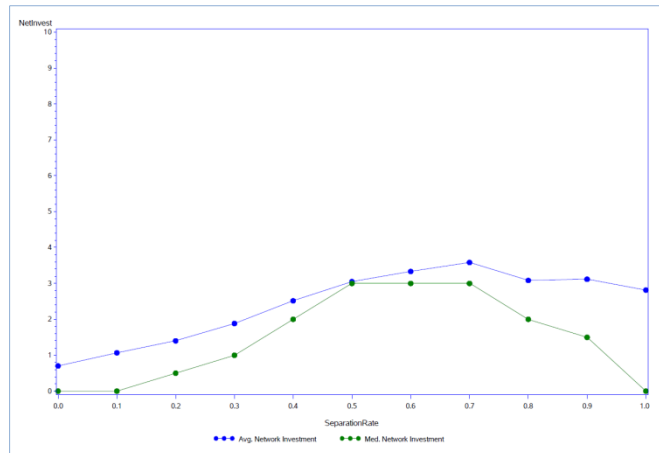
Figure 18. Mean and median network investment, under Information Level 3
Versus the job loss rate

136

Casual inspection suggests a greater degree of inverse-U curvature in the network investment profile under the treatments with higher Information Level. In Figure 16, under Information Level 1, the plot is mostly upward sloping and then flattens out. In Figure 17, under Information Level 2, there is a rising and then falling trend in both the median and mean network investment. In Figure 18, under Information Level 3, the investment level drops off more at high job loss rates. Also, the median network investment curve appears to be more symmetric, relative to the 50 percent job loss rate, than does the mean network investment.

Figure 19 displays a plot of the network investment and number of neighbors versus the job loss rate, under Information Level 3. There is a rising and then falling trend in both the median and mean number of neighbors.
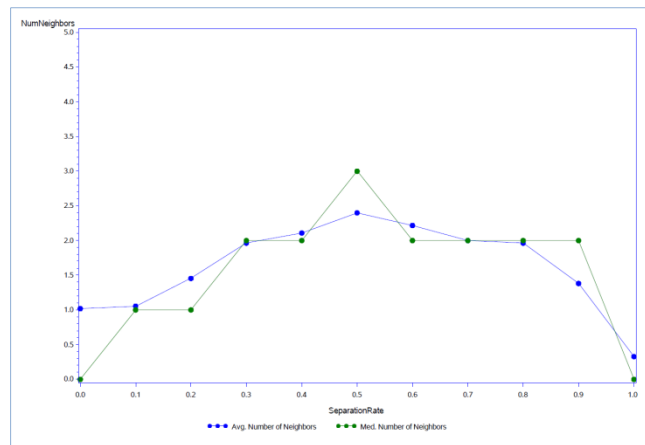
Figure 19. Mean and median number of neighbors, under Information Level 3
Versus the job loss rate

Figure 20 plots the unemployment rate versus the job loss rate, both before and after the network job sharing, under Information Level 3. The unemployment rate rises

monotonically with the job loss rate, and the spread between the pre-network (in blue) and post-network (in green) unemployment widens in the middle ranges of job loss rate. This spread measures the benefit from the job-contact network in terms of reduced final unemployment.
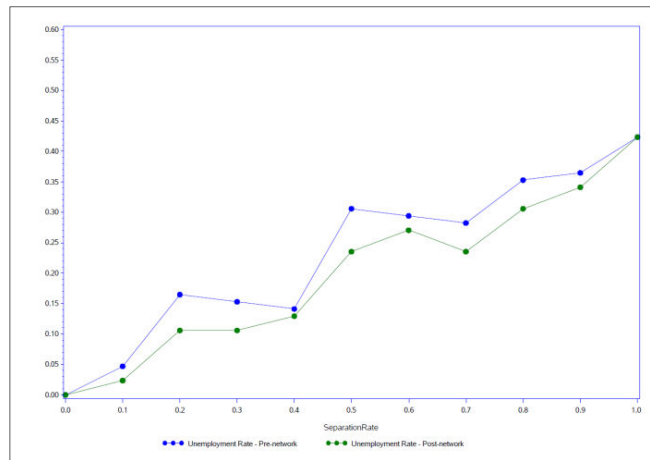
Figure 20. Unemployment rate versus job loss rate, under Information Level 3
Versus the job loss rate

Figure 21 plots the network matching rate, which is the share of the people initially unemployed who find jobs through a network contact. The network matching rate starts at zero, spikes at 0.1, and then falls back to zero. This trend is the product of at least three forces. First, by design, the unemployment rate is rising monotonically against the job loss rate, as was shown in Figure 20. Second, the number of (redundant) job offers that exist to be shared on the network starts high and then monotonically decline with the job loss rate. Third, the inverse-U curvature for the network investment choices shown in Figure 18 means that fewer links being created among the subjects at both the low and high job loss rates, as suggested in the number of neighbors trend from Figure

19, which means that a greater portion of any (redundant) job offers that happened to be shared are lost due to the source person being unconnected.
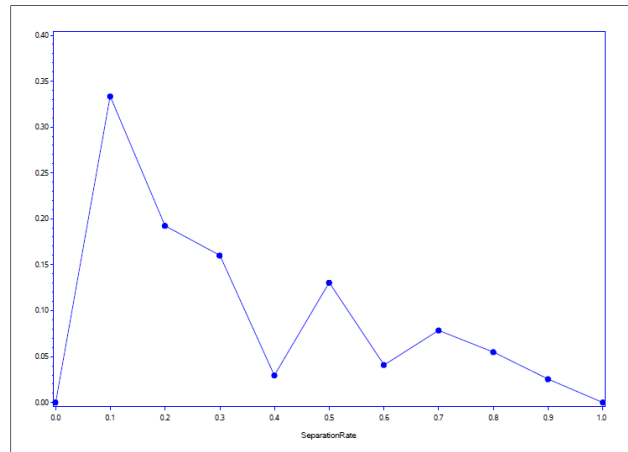
Figure 21. Network matching rate, under Information Level 3
Versus the job loss rate. This is the share of the initially unemployed who find a job through the network.

Figure 22 plots the rate of job sharing under two different measures, with version 1 having the share of employed people in the denominator and with version 2 having the share of all people in the denominator. The rate of job sharing naturally falls as the unemployment rate rises and fewer subjects have redundant job offers to share.
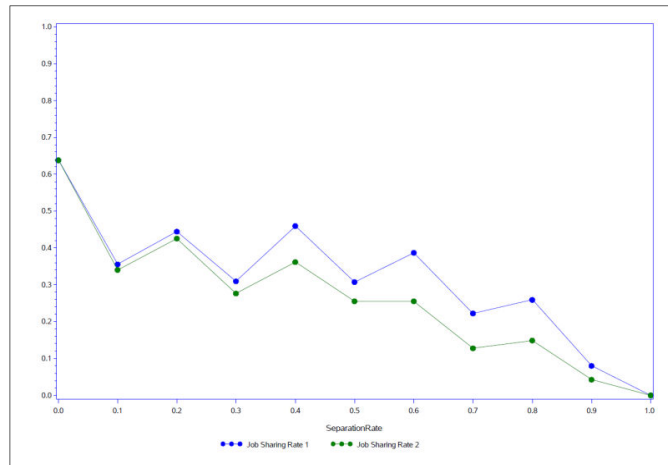
Figure 22. Job sharing rate versus job loss rate, under Information Level 3
Versus the job loss rate

Figure 23, again, plots the average network investment choices, but this time relative to the job offer rate instead of the job loss rate. Since only three levels of job offer rate were tried, namely 0.1, 0.5 and 0.9, the plot has only those three points, as compared to the other network investment plots against job loss rate which have eleven levels between 0.0 and 1.0 by increments of 0.1. The median network investment amounts are slightly higher at the 50 percent job offer rate, and slightly lower, by contrast, at the 10 percent and 90 percent job offer rates. The trend in the mean network investment rate appears to be upward sloping relative to the job offer rate, though with the slope much lower at the higher job offer rate.
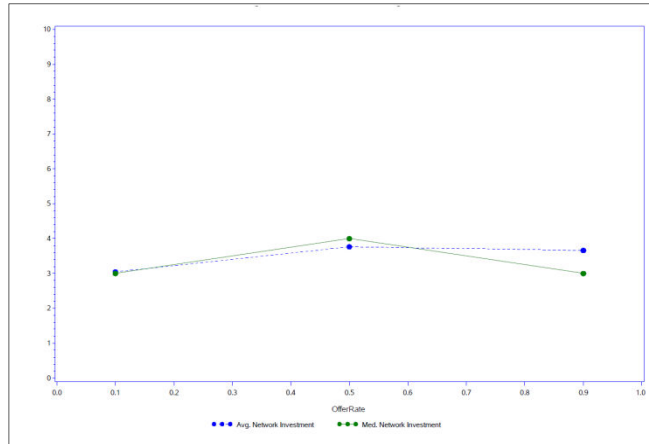
Figure 23. Network investment versus job offer rate, under Information Level 3
Versus the job loss rate

4.1.2 Individual data trends. Figure 24 and Figure 25 are histograms of

network investment choices. Figure 24 shows responses to job loss rate 'extremes,'

corresponding to job loss rates of 0.0 (top-left), 0.5 (bottom-left), 1.0 (top-right), and

combined, i.e., for all job loss rates (bottom-right). Figure 25 shows the responses to the

job loss rate 'non-extremes,' corresponding to job loss rates of 0.1 (top-left), 0.5 (bottom-

left), 0.9 (top-right), and combined (bottom-right).
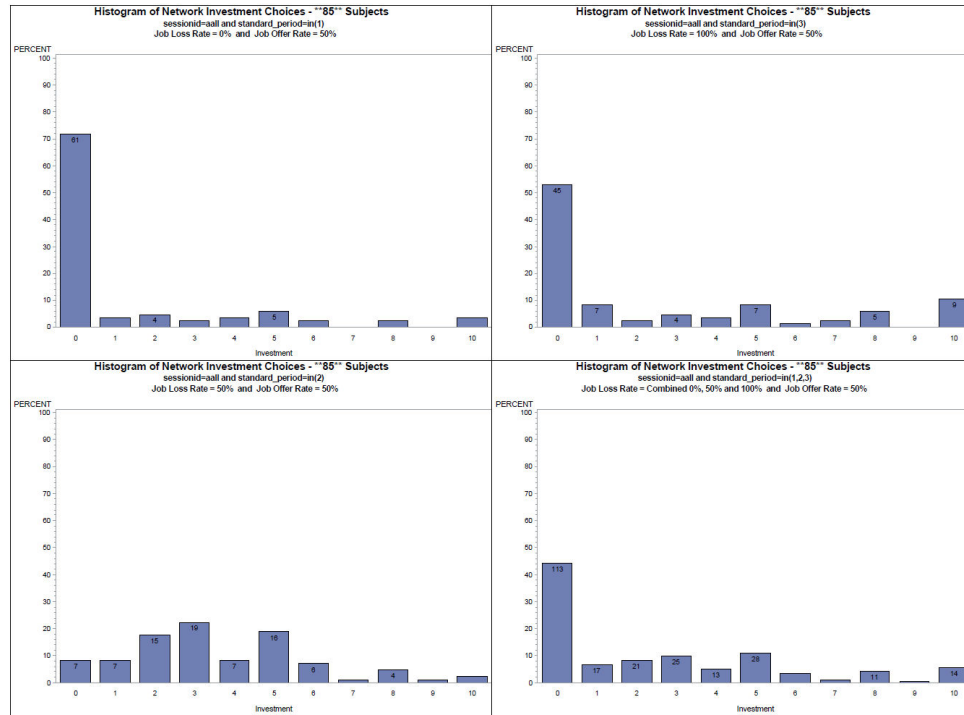
Figure 24. Histogram of network investment choices (Extremes))
For job loss rates of 0.0 (top-left), 0.5 (bottom-left), 1.0 (top-right), and combined (bottom-right)
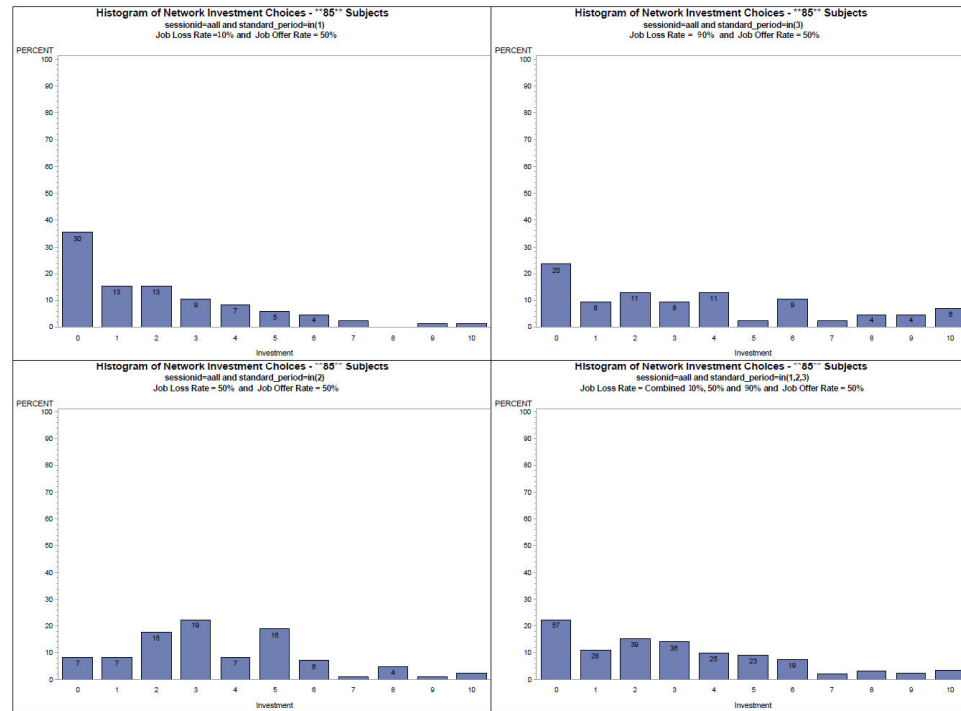
Figure 25. Histogram of network investment choices (Non-extremes)
For job loss rates of 0.1 (top-left), 0.5 (bottom-left), 0.9 (top-right), and combined (bottom-right)

142

In Figure 24, for the job loss rates of 0.0 and 1.0, i.e., for the top-left and top-right panels, there is a large cluster of responses for the choice of zero network investment, and for the job loss rate of 0.5, i.e., for the bottom-left panel, the responses are more spread out, with peaks at three, five and two. In Figure 25, for the job loss rates of 0.1 and 0.9, i.e., for the top-left and top-right panels, there is a small cluster of responses for the choice of zero network investment, and for the job loss rate of 0.5, i.e., for the bottom-left panel, the responses are more spread out, with peaks at three, five and two; these loss rate 0.5 data are, intentionally, literally the same in this and the prior figure. Both sets of results are broadly consistent with the G&M predictions of lower network investment for low or high job loss rates and higher network investment for middle ranges of job loss rates. It appears that the level of clustering in zero choice is greater in the 'extreme' rates case, which includes loss rates of 0, 0.5 and 1.0, from Figure 24, than in the non-'extreme' rates case, which includes loss rates of 0.1, 0.5 and 0.9, from Figure 25.

4.1.3 *Trends by Period.* In this section I present summaries of the lab data across period, often in the form of multi-period averages. The data studied include the spread between network investment choices and the theoretical predictions, trends in trios of subjects' choices across job loss and job offer rates, and the time spent in responding per period.

Figure 26 shows the spread between the network investment lab average choices and the theoretical predictions from G&M. Near the start of the experiment, subjects invest in roughly three additional units of network investment more than predicted by the

theory. As the periods go on, this spread decreases to just 0.5 of an investment unit, on average, with the median difference at around 0 units. Also of note, while the mean and median series generally trend together, the gap between them appears to start out more narrow, then widens during the middle periods and then stays about constant thereafter.
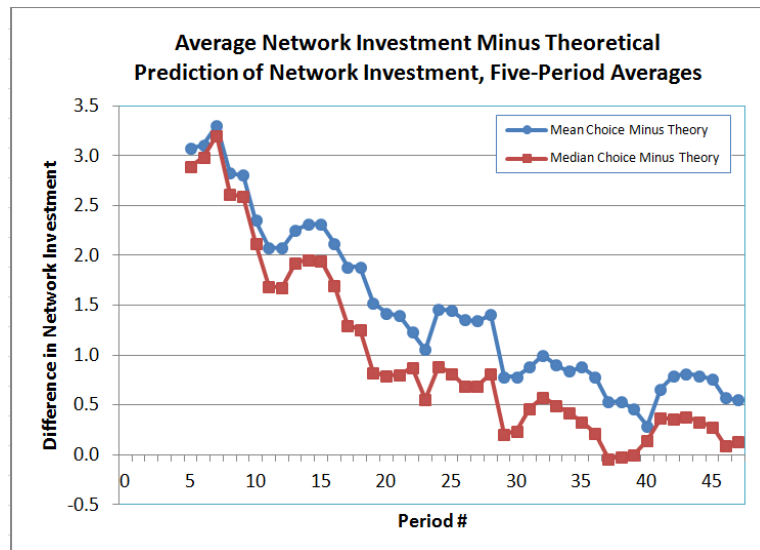
Figure 26. Spread between network investment lab average and theory, by period

Using the categories of trends discussed in Section 3.5, Figure 27 shows the results from grouping the lab subjects' data into trios of job *loss* rates across a fixed job offer rates. The 'trios' concept was described in reference to Table 2 of Section 3.1. Near the start of the experiment, roughly 55 percent of subjects choose an upward-sloping strategy across the three sequential job loss rates. In contrast, less than 10 percent of lab subjects start by playing all zeros, but this share ultimately rises to over 55 percent in the later periods of the experiment. [This high share of zeros is understandable because many of the latter periods have either a 0 percent or 100 percent job offer rate, in

which case the optimal investment, in fact, would be zero.] Finally, the share of subjects

displaying inverse-U curvature in their responses falls from roughly 45 percent to roughly

30 percent over the course of the experiment, largely as more subjects choose to play all

zeros for their strategy. As mentioned at the end of Section 3.5, the sum of the shares

across types of trend will not always equal 100 percent due to some data combinations

that could be classified among more than one type of trend.
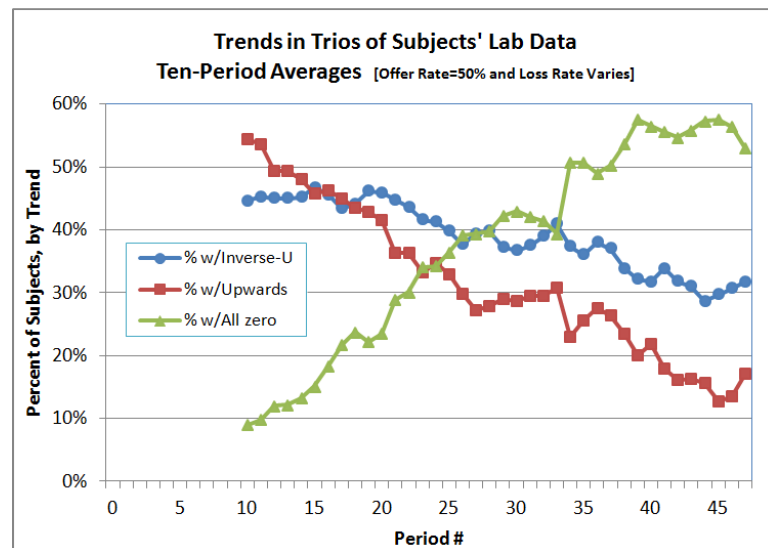
Figure 27. Percent of subjects with trends in their loss-rate trios, by period

Similarly, Figure 28 shows the results from grouping the lab subjects' data into

trios of (implicit) job *offer* rates across a fixed job loss rates, as described regarding Table

2 of Section 3.1. Unlike in the trios of loss-rate data, in these trios of offer-rate data, only

a relatively small share, less than 20 percent start with an upward-sloping trend (as

compared to the roughly 55 percent reported for the trios of loss-rate data). However,

like the trios of loss-rate data, the share of subjects choosing all zeros rises substantially

during the experiment, up to over 60 percent by the end of the experiment. [This high share of zeros is understandable because many of the latter periods have either a 0 percent or 100 percent job offer rate, in which case the optimal investment, in fact, would be zero.] Finally, the share of subjects exhibiting the inverse-U trend over the offer rates declines from roughly 50 percent to 35 percent over the course of the experiment.
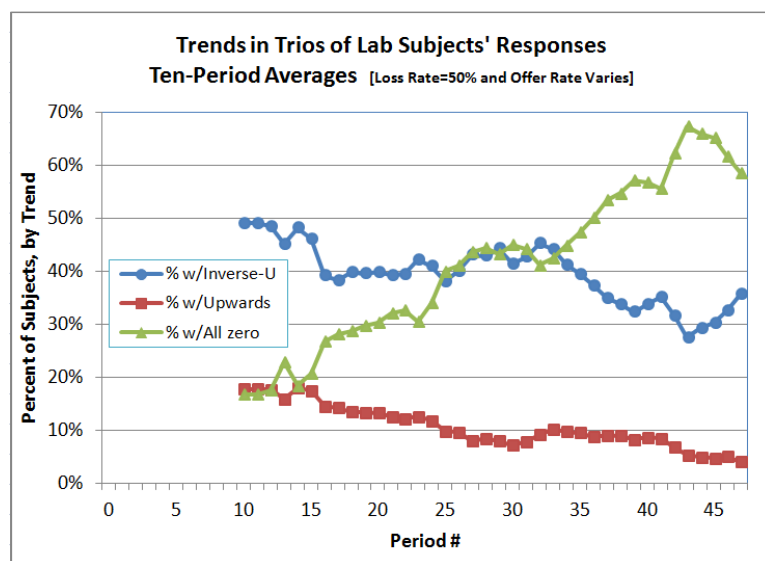
Figure 28. Percent of subjects with trends in their offer-rate trios, by period

Figure 29 shows the average response time of the lab subjects, by period. In the early periods, the average time spent is about 11 seconds, and this incrementally falls to an average time spent of about 5 seconds by the end of the experiment. This is relative to the 30 second time allotment, and so on average subjects leave a large amount of time on the table, when they otherwise could have still been making computations. Thus, the time allotment usually does not appear to be binding in this experiment. But the amount of time spent is systematically about 4 seconds lower amongst subjects who

simply choose zero for all three periods in a given trio, relative to the amount of time spent by subjects whose responses trace out either an inverse-U or upward-sloping trend. This suggests that the zero strategy is easier to quickly compute, or that these lab subjects intentionally pay less attention to the period-specific details that are provided. The decline in response time occurs about equally regardless of the trend in lab subject data, and so the 4-second spread between those playing zero and those not playing zero remains fairly constant across the periods.
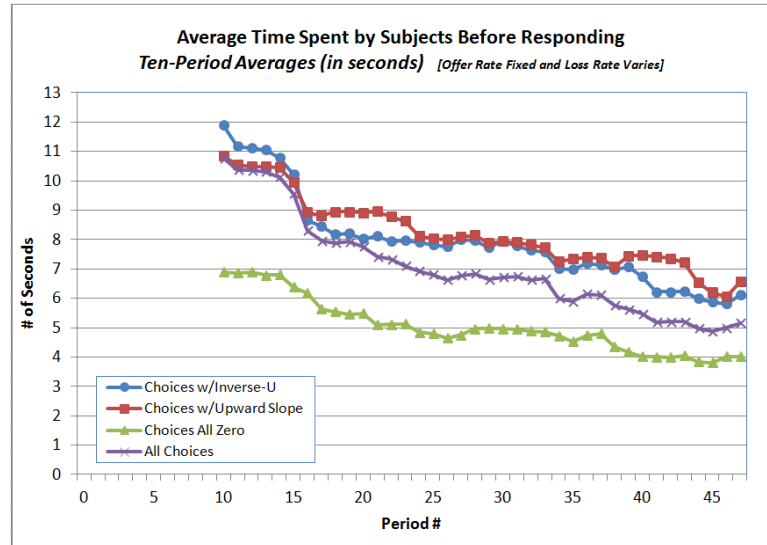
Figure 29. Average time spent by subjects according to trends in their loss-rate trios, by period

4.1.4 Simulation Trends.

In this subsection, I show the overall shapes of the simulation results for each of the four simulation setups: optimal, random, multi-armed bandit (MAB), and pooled. Figure 30 illustrates the average and median network investment against the job loss rate for the *optimal* simulation.

147
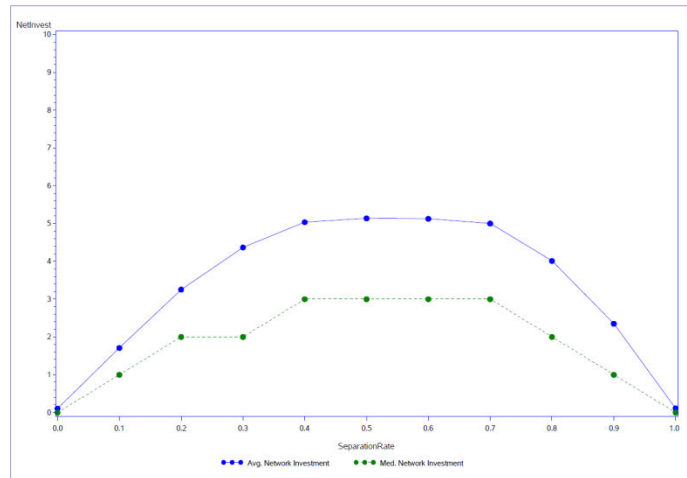
Figure 30. Average and median network investment, under the 'optimal' simulation
Versus the job loss rate

In the blue, upper line, for the average, there is a clear upward sloping and

downward trend in the data, with a peak around 0.5 job loss rate. The blue curve looks

fairly similar in shape to the theoretical predictions plotted in Figure 5. In the lower,

green line, for the median, there is also an upwards and then downwards trend. The

median data appear more staggered due to the discreteness of network investment choices

available to the lab subjects. Of note, the mean values are consistently higher than the

median values. This could be due to there being a large number of zero choices, with a

few high values here and there that naturally are relatively 'overweighted' in the mean

relative to in the median.

Figure 31 illustrates the average and median network investment against the job

loss rate for the *random* simulation.
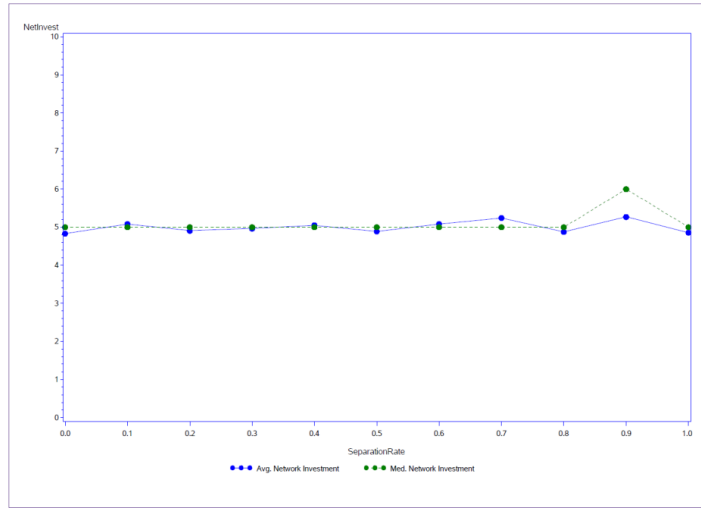
Figure 31. Average and median network investment, under the 'random' simulation
Versus the job loss rate

As expected, there is no clear trend in the data, as individual automaton data were randomly generated between 0 and 10 for each choice.

Figure 32 illustrates the average and median network investment against the job loss rate for the *MAB* simulation.
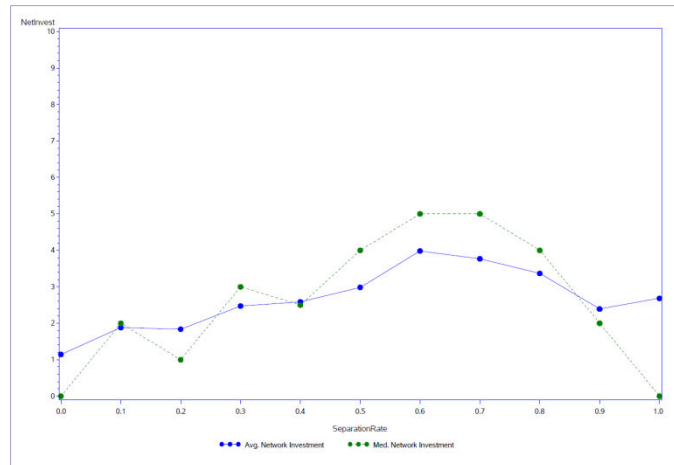
Figure 32. Average and median network investment, under the 'multi-armed bandit' simulation
Versus the job loss rate

149

This figure has some aspects of both the optimal and random simulations, as expected. It also resembles the average and median data created from the human lab subjects data to some degree, which was shown in Section 4.1.1.

I also produced some data analysis from pooling the results from the three simulation types. Figure 33 illustrates the average and median network investment against the job loss rate for the resulting pooled data set.
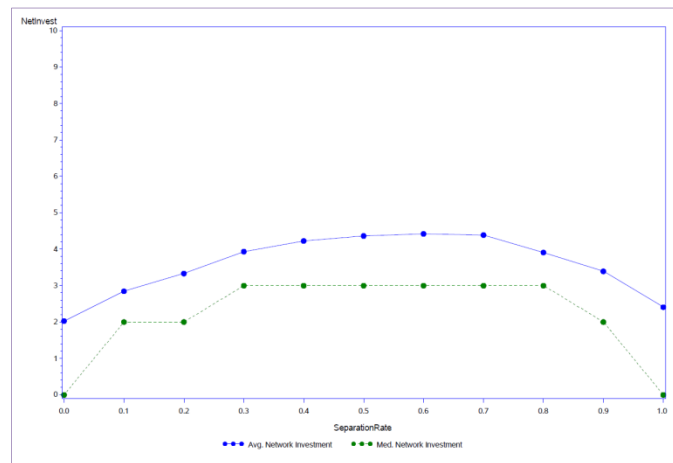
Figure 33. Average and median network investment, pooled data from all three simulations
Versus the job loss rate

Not surprisingly, the results look like somewhat of an average of the other (optimal, random and MAB) simulation results.

4.1.5 Summary of Initial Findings. From the initial review of the lab data without any modeling so far, the averages and medians of the lab data appear to conform to the G&M theoretical predictions to some degree. The levels of overall network investment appear to somewhat rise and then fall when plotted against the job loss rate. Also, empirically, there does appear to be some benefit from the job-contact network, as

evidenced by the slight reduction in unemployment rates due to the network. Other plots, such as of the network matching rate and unemployment rate appear to generally match the shapes predicted in the theory.

Upon studying the individual-subject data, the correspondence with the theory appears to be a bit stronger. In particular, a large share of lab subjects choose zero network investment for the cases of low job loss rate or high job loss rate; a smaller share of subjects choose zero network investment for the case of medium (i.e., 50 percent) job loss rate.

Regarding trends across periods, the subjects, on average, begin by investing a lot more than what is predicted by the theory, but then settle down near the expected network levels, on average. In trios of loss rates (holding the offer rate constant), over the course of the experiment, there is a major drop in the share of lab subjects choosing an upward-sloping strategy, a major rise in the share of lab subjects choosing the all-zeros strategy, and a moderate decline in the share of lab subjects choosing the inverse-U strategy. In trios of offer rates (holding the loss rate constant), the share of subjects choosing an upward-sloping strategy starts at a lower level but also declines; the share of subjects choosing the all-zeros strategies rises substantially; and the share of subjects choosing the inverse-U strategy declines by a moderate amount.[29] Regarding the average amount of time spent per subject response, it always is substantially below the amount of time available to the subjects, and it declines over the course of the experiment. Not

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[29] I do not attribute the sub-optimal lab responses to lack of comprehension or basic reasoning ability among the lab subjects since, in reality, many other issues may be going on. Mere performance relative to the theoretical predictions is often not enough to know the lab subjects' capabilities (Chou, McConnell, Nagel and Plott, 2009).

surprisingly, the lab subjects responding with the all-zeros strategies tend to spend less time per decision.

The median network investment choices may appear to be more sensitive to the job loss and offer rates than are the mean network investment choices. The reason for this may be that those lab subjects who do not reduce their network investment choices at high job loss rates actually choose relatively high levels of network investment for the high job loss scenario, which overweights their responses in the computed averages relative to those choosing lower amounts of network investment closer to the theoretically predicted levels. This conjecture is most supported by the analysis of individual-subject data as shown in histograms of the share of lab subjects investing at each possible integer choice from 0 to 10.

4.2   Empirical Model, Variables and Approach

In this section I present the empirical model I use to test the lab data, describe the covariates I use in fitting the model, explain my estimation methodology, pose my study's hypotheses, and review the results of my hypothesis testing.

4.2.1   Empirical Models. I run the laboratory data through two empirical models that are fairly closely aligned with G&M's theoretical model (see Sections 2.1-2.4) and with G&M's empirical model (see Section 2.5). In G&M's empirical exercise, the authors test their theory using an empirical model with U.K. Labour Force Survey data, in which their proxy variable for network investment varies, at the area level, with linear and quadratic terms of their proxy variable for the job loss rate. Similarly, in my empirical models, I incorporate linear and quadratic terms of the job loss rate, but I

include these for the job offer rate as well. I use individual lab subject observations as

my units of measure, as opposed to area-level data. Also, I include in my models a

covariate for the cost of network investment, and a few other factors that could influence

subjects, which are motivated in the "Covariates" subsection below. Finally, I include

dummy variables for demographic controls, which are based on responses to the post-

experiment survey questionnaire.

Specifically, my empirical models for the network investment level and rate take

the following form:

Empirical Models:

Level Model
$$Y_{i,t} = \delta + \theta_i + \boldsymbol{\alpha}\mathbf{X}_t + \boldsymbol{\beta}\mathbf{M}_{i,t} + \boldsymbol{\gamma}\mathbf{D}_i + \varepsilon_{i,t}$$

Rate Model $\quad Z_{i,t} = \Pr(Y_{i,t}^* > 2 \mid \mathbf{X}, \mathbf{M}, \mathbf{D}) = \rho + \varphi_i + \boldsymbol{\pi}\mathbf{X}_t + \boldsymbol{\kappa}\mathbf{M}_{i,t} + \boldsymbol{\lambda}\mathbf{D}_i + \mu_{i,t} \quad ,$

where i is for individual and t is for period, i.e., time.

The θ_i and φ_i represent random person (subject) effects, and, as will be discussed

in Section 4.2.3 below, I estimate them using the Fuller and Battese (1974) method.

Since the error terms, $\varepsilon_{i,t}$ and $\mu_{i,t}$, in this setting may involve heteroskedasticity and

autocorrelation, I use the Newey-West (1994) estimator to estimate the covariance

structure, as discussed in Section 4.2.3. I then use the resulting variance-covariance

matrix to run a feasible generalized least squares estimation routine. These steps lead to

heteroskedasticity- and autocorrelation-consistent standard errors in the model runs.

The level and rate models are run entirely separately, and they are not considered

as simultaneous equations here. The only difference between these two models is that, in

the level model, the dependent variable is lab subjects' numeric choice of network

investment, while in the rate model, the dependent variable is a binary response of 1 or 0,

corresponding to whether the chosen level of network investment exceeded two in value.

The same covariates are included for both the level and rate versions of the model and

under the same data format or transformations.

The main motivation for running my rate model is to facilitate comparison with

the modeling results from G&M's empirical exercise, though it also provides a small

degree of robustness checking of the level model results. The intuition for the dependent

variable of my rate model is as follows. As discussed in Section 2.5, G&M's empirical

model counted people whose survey responses indicated that they "ask friends, relatives,

colleagues or trade unions about jobs" as having made an investment in their job-contact

network, and G&M coded these data as a binary response. For people to respond

affirmatively to this survey question as such, they likely had a level of job-contact

network investment above a certain cutoff. Analogously, in my lab setting, I needed to

have a particular cutoff at which subjects are considered to have made a material

investment in their job-contact network, and I chose two units to be that cutoff value.

Note the rate model described here is a form of the linear probability model, as is the case

in G&M's empirical exercise. For contrast, I also ran a logisitic regression, logit, version

of the rate model, and the results were qualitatively not very different from what I report

later on for the linear probability model.The α, β, and γ vectors each contain multiple

coefficients, stacked vertically, on the covariates from the level model. Likewise, the π,

κ and λ vectors each contain multiple coefficients, stacked vertically, from the rate

model. The **X** core data, discussed below, are from fixed covariates, and they are unaffected by the network investment choice. For instance, the job loss rate and job offer rate variables are modeled by the G&M authors as exogenous, and I have also kept them fully exogenous in my laboratory experiment design. In addition, the cost per unit of network investment is varied exogenously, as in the G&M model.

The **M** analysis data are included as covariates for some regressions, and they include the subjects' historical weighted average numbers of neighbors, job offers shared or job offers received through the network. I include these subject history variables only provisionally in order to gain a sense of correlation and to consider whether they might have strong effects and be worthwhile to investigate more. However, including such history variables could lead to some endogeneity in the empirical model; the history variables would likely violate the assumption of fixed covariates in the model because the subjects' choice in the dependent variable data can impact these particular covariates. For instance, if network investment were high, this could lead to a greater number of linked neighbors on average, as well as an increased likelihood of sharing and/or receiving a job through the network. With this in mind, for the subset of regressions that include these weighted history variables, the overall regression results, particularly the coefficient estimates, should be discounted accordingly.

The **D** demographic and other data come from subject responses to the post-experiment questionnaire that I administered at the end of each lab session.

4.2.1.1   Network matching rate, etc., models. Since G&M's empirical exercise also provided regression results from models with their network matching rate proxy

variable as the dependent variable, I ran two corresponding models with the laboratory

data, one for the network matching rate and another for the share of subjects who

received jobs through the network per period. To do so, for the network matching rate

concept, I included only records in which the subjects had lost their job in that period.

For the concept regarding the share of subjects who received jobs through the network, in

contrast, I included all records. For both concepts, I coded occurrences of jobs found

through the network with a 1 and the remaining occurrences with a 0. These binary

variables were then included as the dependent variables in models with the same

covariates as from the other regressions previously discussed.

However, I do not view the results from these regressions (of the network

matching regressions and/or of the share of subjects who received a job through the

network) as being indicative of whether the lab subjects behave according to theory, and

so I place little weight on such results. The reason why is that almost any pattern of

network investment will produce an inverse-U curvature in these concepts, as long as the

network investment is not too close to zero. The basic structure of the G&M model alone

ensures that there will be inverse-U curvature for these two concepts, almost regardless of

the pattern in network investment chosen by the individuals.

For instance, simple simulations of the G&M framework show that an inverse-U

curvature (of the network matching rate and/or the share of subjects receiving a job

through the network) will emerge from an entirely flat profile of network investment, and

even from a U-shape curvature of the network investment, i.e., even when the network

investment choices by participants are exactly the opposite from the trend in network

investment predicted by the G&M theory.[30] It seems to be the case that other factors

influencing the network matching rate, such as the unemployment rate, and the share of

workers that have a redundant job offer, greatly outweigh the impact of network

investment choices on the shape of the network matching rate curve, as long as those

investments are not too close to zero.

With these considerations in mind, I do not formally present my network

matching rate models or related regression results in this chapter, though I include a brief

summary of those results in Section 4.4.1 further below.

4.2.2   Variables Included in the Model(s). The following are the specific

variables included in the empirical regression models:

Dependent Variable:

- Level Model: $$Y_{i,t}$$
  Network investment choice from the laboratory subjects

- Rate Model: $$Z_{i,t} = \Pr(Y_{i,t}^* > 2 \mid \mathbf{X}, \mathbf{M}, \mathbf{D})$$
  Binary value (0 or 1) for whether network investment choice exceeds two in value

Covariates:

Core Job-Market Factors (**X**):
  - Loss Rate (X_1), Loss Rate squared ($X_2 = X_1^2$): These variables connote the job loss rate and loss rate squared in the current period.
  - Offer Rate (X_3), Offer Rate squared ($X_4 = X_3^2$): These variables connote the job offer rate and offer rate squared in the current period.
  - Cost (X_5): This variable connotes the monetary cost for investing in one unit of

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[30] Of note, the inverse-U pattern of the network matching rate typically has a left-lopsided inverse-U shape, as depicted in Figure 6, whereas the inverse-U pattern of the share of subjects receiving jobs through the network is more symmetric.

network investment.

Analysis Variables (**M**):

- Period (M_1): The period number, starting with 1 up through the number of periods played
- Time Limit (in seconds) (M_2): The maximum number of seconds allowed for the lab subjects to respond
- Seconds Used / Session Avg (M_3): Number of seconds the lab subjects spent before responding divided by the session average number of seconds spent
- Past Num Neighbors / Session Avg (M_4): Geometric-weighted average of the number of neighbors that a subject had in all prior periods, using a 5 percent discount rate per period
- Past Lost Job Rate (M_5): Geometric-weighted average of the number of job losses from all prior periods, relative to the geometric-weighted number of periods so far, using a 5-percent discount rate per period
- Past Got Job Through Network Rate (M_6): Geometric-weighted average of the number of jobs obtained through the network from all prior periods relative to the geometric-weighted number of periods so far, using a 5-percent discount rate per period
- Past Shared Job Rate (M_7): Geometric-weighted average of the number of jobs shared through the network from all prior periods relative to geometric-weighted number of periods so far, using a 5-percent discount rate per period

Demographic Controls (**D**), (based on post-experiment questionnaire responses):

- Gender (D_1): Responses of male are coded as 0, and responses of female are coded as 1
- Age (D_2): Self-reported age of subjects, by single year of age.
- The following five race and origin variables were self-reported and coded as 1 if that particular race or origin was indicated, or coded as 0 otherwise.

  Race Black (D_3),   Race Asian (D_4),   Origin Hispanic (D_5)

  Of Mixed Race (D_6),   Of Unknown Race (D_7)
- Log Family Income Range (D_8)
- Math Apt and Interest (D_9): The average of self-reported math aptitude and interest subject data were clustered into 'high' (1) or 'low' (0) values per subject
- Sociality / Session Avg (D_{10}): Self-reported subject data on 'how social are you in general,' were clustered into 'high' (1) or 'low' (0) values per subject
- Num Friends / Session Avg (D_{11}): Self-reported subject data on the 'number of

good friends,' were clustered into 'high' (1) or 'low' (0) values per subject

- Work Experience (D_{12}): Self-reported subject data on the extent of prior work experience were clustered into 'high' (1) or 'low' (0) values per subject
- Ever Found Job Through Social Ties (D_{13}): Self-reported data on prior use of social ties for jobs were clustered into 'high' (1) or 'low' (0) values per subject
- U.S. Citizenship (D_{14}) : Self-reported citizenship status in which responses of U.S. citizen were coded as 1, and other responses were coded as 0.
- Risk Loving Preference (D_{15}): Responses of risk-averse were coded as 0, and responses of risk-neutral or risk-loving were coded as 1.
- Previous Lab Experience (D_{16}): Self-reported data on prior use of social ties for jobs were clustered into 'high' (1) or 'low' (0) values per subject
- Clarity of the Instructions (D_{17}): Self-reported data on how clear the instructions appeared to be were clustered into 'high' (1) or 'low' (0) values per subject

As mentioned in Section 4.2.1, the **X** matrix contains the <u>core covariates</u>, whose relationships (to the dependent variable) are key for this chapter's overall statistical results. These core **X** data are the same in both the level and rate models. They vary over the periods, t, but are the same across all individuals, i. The corresponding coefficients on the **X** data are indexed from 1 to 5 in the **α** vector for the <u>Level</u> model and in the **π** vector for the <u>Rate</u> model as follows:

$$
\text{Level model core covariates:} \quad \boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{bmatrix} \qquad \text{Rate model core covariates:} \quad \boldsymbol{\pi} = \begin{bmatrix} \pi_1 \\ \pi_2 \\ \pi_3 \\ \pi_4 \\ \pi_5 \end{bmatrix}
$$

The **M** matrix contains additional <u>analysis variables</u>. These **M** data all vary over the periods, t, and some of them also vary across individuals, i. These **M** data are the same in both the level and rate models. The corresponding coefficients on the **M** data are indexed from 1 to 7 in the **β** vector for the <u>Level</u> model. Likewise, the corresponding coefficients on the **M** data are indexed from 1 to 7 in the **κ** vector for the <u>Rate</u> model,

respectively.

The **D** matrix contains <u>demographic control variables</u> and prior experience variables in order to account for some individual heterogeneity. These **D** data vary across individuals, i, but are constant across periods, t. These **D** data are the same in both the level and rate models. The corresponding coefficients on the **D** data are indexed from 1 to 17 in the γ vector for the <u>Level</u> model. Likewise, the corresponding coefficients on the **D** data are indexed from 1 to 17 in the λ vector for the <u>Rate</u> model, respectively.

4.2.3 Estimation Strategy. In the laboratory experiment, as per Section 3.1, there are 47 periods of data for each laboratory subject. As is common in this type of lab setup, I find some degree of subject-specific clustering in the data. A basic F-test finds that the data are not poolable across subjects. To handle the subject effects, I run a one-way random effects method from Fuller and Battese (1974) in order to estimate the variance-covariance matrix and then use this to run an iterated feasible generalized least squares (GLS) routine. Using Hausman (1978)'s *m*-statistic, I do not reject the null hypothesis that random effects are a more appropriate specification, relative to fixed effects; it appears there is not a material correlation between the random person (subject) intercepts and the covariates. For the sake of comparison, I separately also ran the models using fixed effects, and the results were very much the same as with random effects, so the choice of random versus fixed effects turns out not to be critical here.

As is also common in this type of lab setup, I find autocorrelation in the subject responses across periods. Moreover, I find some amount of heteroskedasticity, even after incorporating the person (subject) effects. To handle the autocorrelation, one approach

could be to create a dynamic model with some form(s) of lagged dependent variable on the right-hand side of the equation. However, in the case of panel data such as with my laboratory data, the random intercepts will often not be independent of the lagged dependent variable, even if they are independent of all the other covariates. Thus, lagging the dependent variable in the presence of person effects would likely involve a material risk of obtaining biased coefficient estimates, and I seek to avoid this.

Instead, I address the serial dependence in the choice data, as well as the heteroskedasticity, by using a form of multivariate kernel density estimation of the covariance structure. In particular, I use the Newey-West (1994) estimator, which uses a Bartlett kernel, and I use a fairly standard bandwidth parameter. I then use the resulting variance-covariance matrix estimate in an iterated feasible GLS routine. These steps together appear to result in heteroskedasticity- and autocorrelation-consistent standard errors in the model runs.

Regarding multicollinearity amongst the regressors, variance inflation factors do not indicate high collinearity except for between the linear and quadratic terms of the job loss rate and the job offer rate. However, given the computation of these squared terms as the **X** data times itself, this finding is not surprising. Still, it may raise the standard errors of the coefficients on these variables and make them overly sensitive to even small changes in the model specification.

I use this same above estimation strategy for both the level and rate regressions.

4.2.4   Information Levels. As discussed in Section 3.4, I run the lab experiment under three information-level treatments. Under each information level, the core $\mathbf{X}_t$ and

161

demographic controls $\mathbf{D}_i$ and are the same. The $\mathbf{M}_{i,t}$ are distinct because some these data vary with specific lab outcomes. In the hypothesis testing, I will refer to the parameter values and equations, by information level, under the following superscript conventions:

Level Models

All Information Levels: $\qquad Y_{i,t} = \delta + \theta_i + \boldsymbol{\alpha}\mathbf{X}_t + \boldsymbol{\beta}\mathbf{M}_{i,t} + \boldsymbol{\gamma}\mathbf{D}_i + \varepsilon_{i,t}$

Infor. Level 1: $\qquad Y_{i,t}^{in1} = \delta^{in1} + \theta_i^{in1} + \boldsymbol{\alpha}^{in1}\mathbf{X}_t + \boldsymbol{\beta}^{in1}\mathbf{M}_{i,t}^{in1} + \boldsymbol{\gamma}^{in1}\mathbf{D}_i + \varepsilon_{i,t}^{in1}$

Infor. Level 2: $\qquad Y_{i,t}^{in2} = \delta^{in2} + \theta_i^{in2} + \boldsymbol{\alpha}^{in2}\mathbf{X}_t + \boldsymbol{\beta}^{in2}\mathbf{M}_{i,t}^{in2} + \boldsymbol{\gamma}^{in2}\mathbf{D}_i + \varepsilon_{i,t}^{in2}$

Infor. Level 3: $\qquad Y_{i,t}^{in3} = \delta^{in3} + \theta_i^{in3} + \boldsymbol{\alpha}^{in3}\mathbf{X}_t + \boldsymbol{\beta}^{in3}\mathbf{M}_{i,t}^{in3} + \boldsymbol{\gamma}^{in3}\mathbf{D}_i + \varepsilon_{i,t}^{in3}$

And the superscripting of 'in1,' 'in2,' and 'in3' is done analogously for the <u>Rate</u> models, with the corresponding superscripts on the $\boldsymbol{\pi}$, $\boldsymbol{\kappa}$ and $\boldsymbol{\lambda}$ vectors, though these rate equations are not explicitly shown here.

4.2.5 Simulation Benchmarks.

As discussed in Section 3.6, I ran a few benchmark simulations which are helpful in assessing the lab experiment results. Specifically, there are the optimal, random, multi-armed bandit (MAB) and pooled versions of the simulations, but I will here generically indicate them with the superscript, "sim," in the below equations.

<u>Level Model:</u> $\qquad Y_{i,t}^{sim} = \delta^{sim} + \theta_i^{sim} + \boldsymbol{\alpha}^{sim}\mathbf{X}_t + \boldsymbol{\beta}^{sim}\mathbf{M}_{i,t}^{sim} + \varepsilon_{i,t}^{sim}$

<u>Rate Model:</u> $\qquad Z_{i,t}^{sim} = \Pr(Y_{i,t}^{sim,*} > 2 \,|\, \mathbf{X}, \mathbf{M}^{sim}) = \rho^{sim} + \varphi_i^{sim} + \boldsymbol{\pi}^{sim}\mathbf{X}_t + \boldsymbol{\kappa}^{sim}\mathbf{M}_{i,t}^{sim} + \mu_{i,t}^{sim}$,

where i is for individual and t is for period, i.e., time. The core $\mathbf{X}_t$ in the simulations are the same as in the lab experiment, period by period, but there are no demographic controls, $\mathbf{D}$ data, included. Again, the θ_i and φ_i represent random person effects, although they are likely nil here, since the automaton decision behavior was not

programmed differently from agent to agent in the simulations. The error distributions

are $\varepsilon_{i,t} \sim N(0,\sigma^2)$ and $\mu_{i,t} \sim N(0, \sigma^2)$, since spherical errors should be supported in this case.

However, in running these regressions, I use the exact same estimation procedures as

with the lab data, which seek to adjust for heteroskedasticity and autocorrelation,

regardless, though no harm should be done in such adjustments.

4.3   Hypotheses Considered and Tested

In this section I present the hypotheses considered and tested for this laboratory

experiment; they are made relative to the empirical model described in Section 4.2. I first

present the hypotheses formally, and I then give an intuitive discussion of my predictions

and hypotheses.

4.3.1   Formal hypotheses tested. In this section, I present the hypotheses that I

test with the laboratory data. In the following section, I discuss intuitions about likely

relationships related to these hypotheses. In many cases, the hypothesis tests are carried

out by running restricted versions of the models, by directly comparing the estimated

coefficients across runs of the empirical model with different subsets of the sample data,

or by comparisons with results from benchmark simulations.

Below I describe the hypotheses tested for the <u>Level</u> models. Analogous tests are

also run for the <u>Rate</u> models, with the $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ vectors replaced by the $\boldsymbol{\pi}$, $\boldsymbol{\kappa}$ and $\boldsymbol{\lambda}$

vectors, respectively, though these rate hypothesis tests are not explicitly shown here.

(1L) Jointly, the coefficient on Loss Rate is not zero, and the coefficient on Loss Rate

squared is not zero.

$$H_0 : \alpha_1 = 0 \text{ and } \alpha_2 = 0 \qquad\qquad H_1 : \alpha_1 \neq 0 \text{ or } \alpha_2 \neq 0$$

This is a weak test for whether the linear term is positive and the quadratic term is negative, both of which are needed for the graph to first rise and then fall in the first quadrant. If the estimated $\hat{\alpha}_1 > 0$ and $\hat{\alpha}_2 < 0$, then the joint test for $\alpha_1 \neq 0$ and $\alpha_2 \neq 0$ could represent a lower bound on whether $\alpha_1 > 0$ and $\alpha_2 < 0$.

(2L) Jointly, the coefficient on Offer Rate is not zero, and the coefficient on Offer Rate squared is not zero.

$$H_0 : \alpha_3 = 0 \text{ and } \alpha_4 = 0 \qquad\qquad H_1 : \alpha_3 \neq 0 \text{ or } \alpha_4 \neq 0$$

This is a weak test for whether the linear term is positive and the quadratic term is negative, both of which are needed for the graph to first rise and then fall in the first quadrant. Again, if the estimated $\hat{\alpha}_3 > 0$ and $\hat{\alpha}_4 < 0$, then the joint test for $\alpha_3 \neq 0$ and $\alpha_4 \neq 0$ could represent a lower bound on whether $\alpha_3 > 0$ and $\alpha_4 < 0$.

(3L) The coefficient on Cost is negative.

$$H_0 : \alpha_5 = 0 \qquad\qquad H_1 : \alpha_5 \neq 0$$

This is a weak test of whether network investment is obeying an uncompensated law of demand, in which Cost is standing in for price. Fully-rational agents in the G&M model would have a strong negative response to rising cost.

(4L) Jointly, the estimated coefficients on all the Analysis Variables equal zero.

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_6 = \beta_7 = 0 \qquad H_1 : \beta_1 \neq 0 \text{ or } \beta_2 \neq 0 \ldots \text{ or } \beta_6 \neq 0 \text{ or } \beta_7 \neq 0$$

This is a test for whether the additional analysis variables jointly do not have any explanatory power for network investment.

(5L) Jointly, the estimated coefficients on all the Demographic Controls equal zero.

$$H_0 : \gamma_1 = \gamma_2 = \cdots = \gamma_{16} = \gamma_{17} = 0 \qquad H_1 : \gamma_1 \neq 0 \text{ or } \gamma_2 \neq 0 \cdots \gamma_{16} \neq 0 \text{ or } \gamma_{17} \neq 0$$

This is a test of whether the demographic control variables jointly do not have any explanatory power for network investment.

(6L) The individual coefficients on the core **X** data are equal between the model run with the lab data from information level 3, 'in3,' versus from information level 1, 'in1.'

$H_0:$ $(a)\,\delta^{in3}=\delta^{in1}$; $(b)\,\alpha_1^{in3}=\alpha_1^{in1}$; $(c)\,\alpha_2^{in3}=\alpha_2^{in1}$; $(d)\,\alpha_3^{in3}=\alpha_3^{in1}$; $(e)\,\alpha_4^{in3}=\alpha_4^{in1}$; $(f)\,\alpha_5^{in3}=\alpha_5^{in1}$

$H_1:$ $(a)\,\delta^{in3}\neq\delta^{in1}$; $(b)\,\alpha_1^{in3}\neq\alpha_1^{in1}$; $(c)\,\alpha_2^{in3}\neq\alpha_2^{in1}$; $(d)\,\alpha_3^{in3}\neq\alpha_3^{in1}$; $(e)\,\alpha_4^{in3}\neq\alpha_4^{in1}$; $(f)\,\alpha_5^{in3}\neq\alpha_5^{in1}$

And similarly between information levels 2 and 3, etc. This is a test for whether the information level matters for effects of individual covariates. I expect there could be correlations between the different information-level regressions run that may need to be accounted for, and so I run these comparisons at multiple levels of assumed correlation.

(7L) Jointly, the coefficients on the **X** data are equal between the model run with the lab data from information level 3, 'in3,' versus from information level 1, 'in1.'

$H_0:$ $\delta^{in3}=\delta^{in1}$ and $\alpha_1^{in3}=\alpha_1^{in1}$ and $\alpha_2^{in3}=\alpha_2^{in1}$ and $\alpha_3^{in3}=\alpha_3^{in1}$ and $\alpha_4^{in3}=\alpha_4^{in1}$ and $\alpha_5^{in3}=\alpha_5^{in1}$

$H_1:$ $\delta^{in3}\neq\delta^{in1}$ or $\alpha_1^{in3}\neq\alpha_1^{in1}$ and $\alpha_2^{in3}\neq\alpha_2^{in1}$ or $\alpha_3^{in3}\neq\alpha_3^{in1}$ or $\alpha_4^{in3}\neq\alpha_4^{in1}$ or $\alpha_5^{in3}\neq\alpha_5^{in1}$

And similarly between information levels 2 and 3, etc. This is a test for whether the information level matters overall. Again, there could be correlations between the different information-level regressions run that may need to be accounted for, and so I run these comparisons at multiple levels of assumed correlation.

(8L) The individual coefficients on the **X** data are equal between the empirical model run with the lab data and the same model run with the simulation data, 'sim.'

$H_0:$ $(a)\,\delta=\delta^{sim}$; $(b)\,\alpha_1=\alpha_1^{sim}$; $(c)\,\alpha_2=\alpha_2^{sim}$; $(d)\,\alpha_3=\alpha_3^{sim}$; $(e)\,\alpha_4=\alpha_4^{sim}$; $(f)\,\alpha_5=\alpha_5^{sim}$

$H_1:$ $(a)\,\delta\neq\delta^{sim}$; $(b)\,\alpha_1\neq\alpha_1^{sim}$; $(c)\,\alpha_2\neq\alpha_2^{sim}$; $(d)\,\alpha_3\neq\alpha_3^{sim}$; $(e)\,\alpha_4\neq\alpha_4^{sim}$; $(f)\,\alpha_5\neq\alpha_5^{sim}$

This is a test for whether the lab subjects behave like the programmed automatons with respect to individual covariates. Again, the different simulations run include optimal, random, MAB and pooled. Given the large number of t-tests at hand, there may be 'multiple comparisons' issues to consider. If so, then the actual significance level of the individual t tests may not equal the stated significance level, and, so the reported t-statistics should ideally be compared to higher cutoffs. I expect there are no correlations between the lab and simulation data to account for.

(9L) Jointly, the coefficients on the **X** data are equal between the empirical model run with the lab data and the same model run with the simulation data, 'sim.'

$$H_0 : \delta = \delta^{sim} \text{ and } \alpha_1 = \alpha_1^{sim} \text{ and } \alpha_2 = \alpha_2^{sim} \text{ and } \alpha_3 = \alpha_3^{sim} \text{ and } \alpha_4 = \alpha_4^{sim} \text{ and } \alpha_5 = \alpha_5^{sim}$$

$$H_1 : \delta \neq \delta^{sim} \text{ or } \alpha_1 \neq \alpha_1^{sim} \text{ or } \alpha_2 \neq \alpha_2^{sim} \text{ or } \alpha_3 \neq \alpha_3^{sim} \text{ or } \alpha_4 \neq \alpha_4^{sim} \text{ or } \alpha_5 \neq \alpha_5^{sim}$$

This is a test for whether the lab subjects behave like the programmed automatons with respect to all the variables, considered at once. As mentioned above for test **8L**, given the large number of t-tests at hand, there may be 'multiple comparisons' issues to consider. I expect there are no correlations between the lab and simulation data to account for.

4.3.2   Intuition of Hypotheses. I start by discussing likely relationships between the dependent variable and the core variables and the effect of information level. I then discuss hypotheses related to the additional analysis variables, and finally with regards to the demographic, income and prior-experience controls.

4.3.2.1   Regarding the base case model and information levels. If the lab subjects behave according to the G&M theory, then, qualitatively, I would expect that the

quadratic response of network investment to both job loss rate and job offer rate should

be supported, with a positive sign on the linear variable and a negative sign on the

squared variable; also, the estimated relationship with cost should be negative.

Additionally, the average level of lab network investment should be close to average

level of theoretical network investment across the various job-market conditions.

Given how G&M models the job loss rate in a similar way to the job offer rate,

and given how my laboratory materials discuss the job offer rate in a similar way to the

loss rates, I expect that the estimated coefficients on the job loss and job offer linear

terms will not be statistically different from one another, and likewise for the estimated

coefficients on the job loss squared and job offer squared terms.

Making use of my benchmark simulations, if the lab subjects behave according to

the G&M theory, then I expect that the extent of curvature in the quadratic relationship

between the laboratory network investment and both the job loss and job offer rate should

be nearly equal between the laboratory data and the optimal simulation data, and thus

should not be equal between the laboratory data and the random simulation data. The

effect of cost should likewise be the same in magnitude (i.e., economic significance) as

that from the optimal simulation and should differ from that in the random simulation.

Finally, since my MAB simulation combines a mix of optimal investment and random

investment, I expect that the curvature of the lab data will not be equal to that of the

MAB simulation data, but the differences will be smaller than for the random simulation.

Importantly, regarding information levels, if the lab subjects understand the game

and behave according to the G&M theory, then the information level should not matter.

However, if the more expansive information truly helps lab subjects understand the game better, then I predict that the additional information will raise the degree of curvature in the quadric relationship between job loss and job offer rates relative to network investment level and increase the subjects' cost sensitivity. However, I cannot predict whether the average level of network investment would rise or fall. On the one hand, the additional information may increase the lab subjects' confidence, allowing them to leave the status quo of zero investment. On the other hand, if the lab subjects are more discerning, they may be less inclined to overinvest.Regarding predictions in the rate models versus the level models, I expect to obtain qualitatively similar results, even though the coefficient estimates in the rate models will naturally be different than those for the level models.

    4.3.2.2   Regarding the additional analysis variables. I here discuss my predictions for each of the additional analysis variables sequentially. Starting with the "Period" variable, I expect that in later periods the subjects will tend to invest closer to the optimal levels and that a greater share of their responses will display inverse-U curvature. However, the direction of these changes is hard to predict. On the one hand, if lab subjects start out by investing what they eventually feel is too high, and then lower their investments later on, then I would expect the coefficient on the period variable to be negative. On the other hand, if lab subjects start out by investing too low and eventually grow more comfortable in exploring after initially getting their feet wet, then I would expect exactly the opposite.

    Regarding the variable for the amount of time allotted for subjects to respond, I

do not have a prediction a priori regarding how that might affect network investment. Regarding time spent before replying, I predict that those who spent shorter amounts of time deciding are more likely to invest zero or randomly on average.

Regarding the past average number of neighbors variable, it is worth noting that the subjects are provided data each period regarding the number of neighbors they had that period and in all prior periods, as well as the historical job loss and offer rates that prevailed in each of these prior periods. But, overall, the number of neighbors variable provided a noisy signal regarding the level of network investment from others in the groups that they have been in. To the extent that the subjects would want to conform or be doing their 'fair share' in terms of sending jobs on the network, I expect that the higher the historical (geometric weighted) average number of neighbors, the higher the future network investment, i.e., a positive coefficient estimate for this variable. However, to the extent that lab subjects think that bucking the trend might lead them to obtain higher gains, I would expect to see the opposite effect, i.e., a negative coefficient estimate for this variable.

Regarding the variable for history of getting jobs through the network, the more the network benefit a subject has experienced, assuming he/she notices this, the more he/she may be eager to invest in the network in the future, i.e., a positive coefficient estimate for this variable. For similar reasons, I expect a positive relationship with future network investment for the variable about past history of subject sharing jobs. Specifically, someone who has shared jobs has seen firsthand the way the network can help other lab subjects, and so may be more inclined to invest in the network again

him/herself.

Regarding the variable for historical experienced job loss rate, I believe this variable would matter, but I cannot predict a direction. On the one hand greater experienced job loss could make someone feel a greater need to insure against future bad states of the world. On the other hand, if someone had already invested a lot in prior periods and still experienced high unemployment rates, then he/she may give up on the job-contact market institution and invest less. So, conditional on investing greater than the group average in the past, I predict that higher job loss rates will lower future network investment. However, conditional on investing less than the group average in the past, I predict that higher job loss rates will raise future network investment.

4.3.3.3 Regarding the demographic control variables. A priori, I have no expectation regarding the included demographic and income variables on the level of network investment being higher or lower than that of the others. Although gender effects have been documented in a number of laboratory experiments, it is not clear in which direction a gender effect might work in the situation from this lab experiment. Regarding sociality, I weakly predict that those who have more friends in real life would choose slightly higher network investment on average, assuming they might have a small bias in seeking social connections, though, admittedly, the lab situation is very different from a typical social setting. Similarly, for those who have in the past found a job through a social contact, they might be inclined to invest a bit more during this lab experiment, having firsthand known the benefits of a job-contact network. Finally, I expect that students who indicated they have greater mathematical aptitude and/or

interest in mathematics on average will more often tend to exhibit the expected curvature in their choices of network investment against the job loss and offer rates.

4.4 Regression Results

In this section, I present and discuss the results from running the lab experiment data in the empirical model presented in Section 4.2. Although my discussion in this section is fairly casual, my formal statistical test results of the lab data are reported in the next section, Section 4.5.

In the regression output that follows, t-statistics are shown in a smaller font below the model coefficient estimates. To help assess the statistical significance of the coefficient estimates, in Table 7, below, I include an excerpt from a reference table for critical values of Student's t distribution, for $v = 120$ degrees of freedom, for two-tailed hypothesis tests, based on values from Box, Hunter and Hunter (2005). Given my sample size in all cases greatly exceeds 120, using this table is slightly conservative.

Table 7. Critical values of Student's t distribution with $v = 120$ degrees of freedom
For two-tailed tests; based on values from Box, Hunter and Hunter (2005), Table B1

Combined two-tail area probability	0.10	0.05	0.02	0.01
Critical values	1.658	1.980	2.358	2.617

Below, Table 8 and Table 9, together, depict the regression results for the Level models base case, regarding relationships between the network investment level and the core covariates, **X**, from G&M, the additional covariates, **M**, mentioned above, and the demographic control and prior experience variables, **D**, from the post-questionnaire.

Table 8. Regression results for the level models base case, by information level
t-statistics are shown below the coefficient estimates in a smaller font

(Level Models)
Regression Results for Base Case, for Human Subjects

	All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.		All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.
# of Observations	8,763	3,998	3,055	1,710		8,788	4,023	3,055	1,710
Root-Mean Square Error	2.385	2.496	1.921	2.413		2.695	2.740	2.149	2.884
R-Squared	0.2918	0.2845	0.2420	0.3678		0.1000	0.1419	0.0443	0.0840
Intercept	3.213	2.101	-7.066	8.405		2.341	2.215	0.084	2.295
	5.44	2.35	-6.42	5.72		11.15	7.05	0.67	5.01
Loss Rate	4.435	3.636	3.653	6.091		4.675	3.917	3.338	5.975
	14.42	7.14	9.42	8.08		13.47	7.04	7.72	6.71
Loss Rate ^ 2	-2.485	-0.733	-2.871	-3.791		-2.920	-1.147	-2.621	-3.908
	-8.43	-1.52	-7.67	-5.22		-8.79	-2.17	-6.28	-4.52
Offer Rate	3.343	2.769	3.060	2.651		2.921	4.004	2.447	0.900
	10.07	5.07	7.52	2.28		7.91	6.80	5.57	0.75
Offer Rate ^ 2	-4.127	-3.855	-3.282	-4.040		-4.072	-5.414	-2.769	-2.372
	-13.15	-7.40	-8.49	-3.71		-11.62	-9.74	-6.60	-2.09
Cost	-18.494	-18.827		-16.068		-20.584	-21.378		-19.790
	-5.09	-3.49		-3.01		-5.02	-3.62		-3.19
Period	-0.028	-0.035	-0.012	-0.082					
	-23.24	-10.24	-7.69	-3.78					
Time Limit (in seconds)	0.001	-0.017	0.004	-0.065					
	0.47	-4.20	0.64	-2.47					
Seconds Used / Session Avg	0.677	0.290	0.979	0.652					
	5.27	1.46	4.96	2.40					
Past Num Neighbors / Session Avg	1.721	1.375	1.666	3.285					
	28.49	18.34	10.32	19.59					
Past Lost Job Rate	-0.038	-0.030	0.266	-0.054					
	-1.03	-0.74	1.87	-0.36					
Past Got Job Through Network Rate	0.028	0.020	0.073	0.0000					
	2.25	1.07	2.89	0.00					
Past Shared Job Rate	0.060	0.091	-0.274	0.035					
	1.36	1.79	-1.89	0.22					

As shown in Table 8 and Table 9, there are roughly 8,700 observations included in the main regression, representing about 47 observations for each of about 180 lab subjects. In order to constrain the R-squared measure between 0 and 1 while using a GLS routine, I use a generalization of R-squared from Buse (1973) as a measure of goodness of fit. According to this alternative measure, the base model explains about 29 percent of the variation in the network investment.

Regarding the core covariates, **X**, the expected negative quadratic relationship

between job loss rate and network investment is observed, in that both the coefficients on the linear term and the quadratic term have the expected sign and are statistically significant. The same is true for the estimated relationship between job offer rate and network investment. Given the estimated concavity among the modeled covariates, the network investment is first increasing in both the job loss and offer rates, but then after an inflection point, network investment is decreasing in both the job loss and offer rates. There also appears to be an effect of information level. The negative curvature seems to become more pronounced the greater the amount of information the subjects were supplied. These statements are true regardless of whether one looks at the model with the additional covariates (on the left side of Table 8) or the restricted model with just the core covariates (on the right side of Table 8). Also, the coefficient estimate on the cost covariate is negative and statistically significant.

Regarding the additional analysis variables, **M**, from the results shown on the left side of Table 8, there appears to be a negative period effect, suggesting that, all else being equal, the lab subjects invest less as the experiment continues on. There does not appear to be an effect from the time limit allotted for subjects to respond. However, there may be a positive effect on time spent before deciding, in which those taking longer to respond typically ended up investing more on average. The variable for the 'average past number of neighbors relative to the session average' appears to have a positive effect, such that if subjects had a lot of neighbors in the past, they will likely invest more in the network in the current period, but, on the other hand this could likely just reflect autocorrelation in the lab subject choices, not an actual dependence relationship. Also,

173

there may be a positive effect from past job-contact networking success, as suggested by the positive estimated coefficient on the past-got-job-through-network rate. However, when evaluating these regression results, it is important to note that including these history-related variables is somewhat suspect because they may lead to violations in exogeneity between the errors and modeled covariates. Also, the estimated coefficients for these additional variables may occur simply due to patterns in the particular sequence of the job loss rate or offer rate across the periods. For instance, if there are more high-rate scenarios earlier or later, then that could cause some correlations that the additional modeled variables pick up, and these of course would not be causal relationships.

Table 9. Regression results for the level models base case continued, for the demographic control variables
t-statistics are shown below the coefficient estimates in a smaller font

	(Level Models) Regression Results for Base Case, for Human Subjects (. . . Continued)			
	All Infor Levels Combined	Medium Infor.		High Infor.
		Low Infor.		
Gender	0.306	0.313	0.419	0.433
	5.38	3.60	4.18	3.21
Age	0.019	0.065	0.101	-0.057
	1.63	3.82	4.36	-1.89
Race Black	0.318	0.181	1.262	0.132
	3.70	1.38	8.20	0.70
Race Asian	0.290	-0.067	0.689	0.968
	3.92	-0.52	6.30	4.87
Origin Hispanic	-0.043	0.052	0.793	0.025
	-0.39	0.30	3.69	0.11
Of Mixed Race	-0.576	-0.413	-0.143	0.037
	-3.69	-1.59	-0.71	0.08
Of Unknown Race	2.333	1.404	4.370	2.948
	9.06	3.53	12.28	4.03
Log Family Income Range	-0.066	0.200	0.696	-0.778
	-0.74	1.38	4.47	-3.92
Math Apt and Interest	-0.124	-0.154	-0.034	-0.097
	-3.07	-2.42	-0.50	-0.90
Sociality / Session Avg	0.138	0.069	0.122	0.036
	3.20	1.02	1.62	0.34
Num Friends / Session Avg	0.066	0.020	-0.021	0.095
	1.61	0.32	-0.27	1.03
Work Experience	-0.225	-0.184	-0.330	-0.077
	-5.56	-3.03	-3.85	-0.86
Ever Found Job Through Social Ties	-0.101	0.002	0.068	0.013
	-1.83	0.03	0.67	0.10
U.S. Citizenship	-0.243	-0.363	-0.021	0.431
	-2.94	-2.82	-0.14	2.06
Risk Loving	0.011	-0.019	0.137	0.151
	0.28	-0.33	1.91	1.46
Previous Lab Experience	-0.380	-0.352	-0.230	-0.185
	-10.65	-6.30	-3.64	-1.86
Clarity of the Instructions	-0.084	-0.142	0.640	-0.276
	-1.90	-2.14	6.84	-2.93

Above, Table 9, separately, shows the estimated coefficients on the demographic control and prior experience variable for the same models from the left-hand panel of Table 8. [The reason for the separate table is just that the combined table with all variables shown vertically would not fit on a single page.] There appears to be a statistically significant gender effect, with female on average choosing a higher level of

network investment, across each information level alone, as well as with all information levels combined. Finding a gender effect has been common among experimental studies, and it would be worthwhile to consider whether the gender effect from this lab experiment is in the expected direction or not given the structure of the game. Next, subjects that entered their race as "N/A" or left the question blank tend to invest higher amounts across all three information levels.   Interestingly, log family income is estimated to have a positive effect for subjects in the middle level of information, while log family income is estimated to have a negative effect for subjects in the highest level of information, but if the effect is so inconsistent it may just be statistical noise. Also, at the low information level, mathematical aptitude and interest is estimated to lower the network investment choices of lab subjects. In the all-information-levels model, there appears to be a positive effect of sociality, though this does not hold up across the separate information levels. Finally, having more work experience and/or prior lab experiment experience may lower the average level of network investment chosen.

As discussed in Section 3.6, in order to bridge the lab exercise to the underlying theory, it is helpful to have estimation results from an 'optimal' simulation, since these provide a ceiling for the size of coefficient estimates one could expect to see in the lab data if lab subjects were behaving according to the G&M theory. Results from a random simulation illustrate what a no-relationship model should look like, and if there were yet any significant effects in that case, this could serve as a red flag for variables that may appear to be significant in the lab data for the wrong reasons (e.g., just due to the specific ordering of job loss and offer rates scenarios). Finally, results from a multi-armed bandit

(MAB) simulation could provide a sense of what some form of boundedly rational agents might decide in the experiment, and, likewise, for the pooled data simulation.

Table 10. Regression results for the level models base case, relative to simulation benchmarks
t-statistics are shown below the coefficient estimates in a smaller font

	(Level Models) Regression Results for Base Case, for Human Subjects				(Level Models) Regression Results for Base Case, for Simulations			
	All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.	Optimal	Random	Multi-Armed Bandit	All Sim's Pooled
# of Observations	8,763	3,998	3,055	1,710	14,160	14,160	14,160	42,480
Root-Mean Square Error	2.385	2.496	1.921	2.413	0.694	2.915	2.490	2.841
R-Squared	0.2918	0.2845	0.2420	0.3678	0.6183	0.0005	0.1557	0.0427
Intercept	3.213	2.101	-7.066	8.405	0.631	5.119	1.685	2.478
	5.44	2.35	-6.42	5.72	17.75	34.28	13.22	29.50
Loss Rate	4.435	3.636	3.653	6.091	6.431	-0.272	3.438	3.199
	14.42	7.14	9.42	8.08	101.84	-1.02	15.17	21.43
Loss Rate ^ 2	-2.485	-0.733	-2.871	-3.791	-6.280	0.217	-2.471	-2.845
	-8.43	-1.52	-7.67	-5.22	-103.05	0.85	-11.30	-19.74
Offer Rate	3.343	2.769	3.060	2.651	4.856	-0.123	2.462	2.399
	10.07	5.07	7.52	2.28	80.25	-0.48	11.34	16.76
Offer Rate ^ 2	-4.127	-3.855	-3.282	-4.040	-4.938	0.150	-1.515	-2.101
	-13.15	-7.40	-8.49	-3.71	-86.96	0.63	-7.43	-15.65
Cost	-18.494	-18.827		-16.068	-36.848	-0.573	-14.176	-17.199
	-5.09	-3.49		-3.01	-41.94	-0.16	-4.50	-8.28
Period	-0.028	-0.035	-0.012	-0.082	0.001	-0.001	-0.016	-0.005
	-23.24	-10.24	-7.69	-3.78	2.47	-0.39	-11.85	-5.88
Time Limit (in seconds)	0.001	-0.017	0.004	-0.065				
	0.47	-4.20	0.64	-2.47				
Seconds Used / Session Avg	0.677	0.290	0.979	0.652				
	5.27	1.46	4.96	2.40				
Past Num Neighbors / Session Avg	1.721	1.375	1.666	3.285	0.000	0.348	1.927	1.277
	28.49	18.34	10.32	19.59	-0.02	2.11	42.33	30.75
Past Lost Job Rate	-0.038	-0.030	0.266	-0.054	-0.002	-0.013	0.050	0.004
	-1.03	-0.74	1.87	-0.36	-0.19	-0.31	1.40	0.17
Past Got Job Through Network Rate	0.028	0.020	0.073	0.000	-0.001	0.009	0.013	0.010
	2.25	1.07	2.89	0.00	-0.43	0.69	1.28	1.39
Past Shared Job Rate	0.060	0.091	-0.274	0.035	0.004	-0.012	0.087	0.001
	1.36	1.79	-1.89	0.22	0.32	-0.23	1.95	0.05

In this spirit, the right side of Table 10 presents regression results from the optimal, random and multi-armed bandit (MAB) simulations. For the optimal simulation, the estimated coefficient on the Loss Rate is positive, and the estimated coefficient on the Loss Rate squared is negative, and these two estimated coefficients are nearly equal in

absolute value. The same is true for the estimated coefficients on the Offer Rate and

Offer Rate squared variables. As expected, the sign on the Cost variable is negative. For

the random simulation, as expected, there are no statistically significant coefficient

estimates, except the Intercept is significant. And the results from the MAB simulation

and pooled data appear to be somewhere in between the optimal and random data results.

Comparing these simulation results with the lab results, included in the left side of

Table 10, it appears that the relationships amongst all five of the core covariates are

weaker in the lab data than in the optimal data. For instance, the coefficient on Loss

Squared in the lab results is just -2.485, whereas, in the optimal simulation, the

corresponding estimate is -6.280. [Formal statistical tests of these differences are

included in the next section, Section 4.5.] The relationships are much stronger in the lab

data relative to the non-existent relationships in the random simulation data, also as

expected. Finally, the coefficient estimates from the lab data bear some resemblance to

those from the MAB simulation and pooled data regressions, which represent something

between optimal and random responses.

As discussed in Section 4.2, I also run a Rate version of the models in which the

dependent variable, network investment, is defined as 1 if the network investment

exceeds two in value and 0 otherwise. Again, the main goal of these rate regressions is to

produce output that will be more comparable with G&M's empirical exercise.

Table 11. Regression results for the rate models base case, by information level
t-statistics are shown below the coefficient estimates in a smaller font

(Rate Models)
Regression Results for Base Case, for Human Subjects

	All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.		All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.
# of Observations	8,763	3,998	3,055	1,710		8,788	4,023	3,055	1,710
Root-Mean Square Error	0.274	0.256	0.225	0.342		0.309	0.281	0.251	0.409
R-Squared	0.4057	0.4309	0.3348	0.4013		0.1391	0.2150	0.0612	0.0917
Intercept	0.671	0.584	-1.030	1.530		0.489	0.615	0.012	0.418
	6.68	3.77	-5.37	6.26		13.68	11.35	0.56	5.49
Loss Rate	0.986	1.034	0.709	1.280		1.039	1.113	0.648	1.255
	18.83	11.76	10.49	10.20		17.59	11.59	8.60	8.47
Loss Rate ^ 2	-0.678	-0.601	-0.542	-0.953		-0.797	-0.940	-0.495	-0.983
	-13.53	-7.20	-8.31	-7.89		-14.10	-10.32	-6.80	-6.84
Offer Rate	0.703	0.741	0.602	0.691		0.615	1.072	0.481	0.234
	12.46	7.86	8.48	3.58		9.78	10.54	6.28	1.18
Offer Rate ^ 2	-0.838	-0.924	-0.662	-0.860		-0.827	-1.298	-0.558	-0.505
	-15.69	-10.27	-9.81	-4.74		-13.86	-13.54	-7.64	-2.67
Cost	-2.528	-2.641		-2.270		-2.813	-2.999		-2.796
	-4.09	-2.84		-2.56		-4.03	-2.94		-2.71
Period	-0.005	-0.005	-0.002	-0.009					
	-21.67	-9.19	-7.89	-2.40					
Time Limit (in seconds)	0.001	-0.002	0.0003	-0.004					
	1.63	-3.34	0.26	-0.92					
Seconds Used / Session Avg	0.118	0.095	0.125	0.121					
	5.40	2.79	3.64	2.67					
Past Num Neighbors / Session Avg	0.269	0.217	0.300	0.472					
	26.15	16.74	10.66	16.93					
Past Lost Job Rate	-0.012	-0.005	0.006	-0.061					
	-1.95	-0.74	0.23	-2.45					
Past Got Job Through Network Rate	0.004	0.004	0.011	0.002					
	1.98	1.15	2.49	0.37					
Past Shared Job Rate	0.019	0.025	-0.036	0.006					
	2.53	2.81	-1.45	0.24					

So, turning to the Rate model results, Table 11 is the analog to Table 8 from the Level model results. It provides results for the rate model base case and across information levels, both for the model including the additional covariates and for the restricted model with just the core covariates.

179

Table 12. Regression results for the rate models base case continued, for the demographic variables
t-statistics are shown below the coefficient estimates in a smaller font

	All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.
(Rate Models) Regression Results for Base Case, for Human Subjects (. . . Continued)				
Gender	0.037	0.051	0.039	0.044
	3.85	3.42	2.23	1.96
Age	-0.002	0.000	0.016	-0.014
	-1.22	-0.07	3.91	-2.74
Race Black	0.015	-0.037	0.185	0.033
	0.99	-1.65	6.89	1.07
Race Asian	-0.009	-0.085	0.060	0.124
	-0.71	-3.84	3.15	3.75
Origin Hispanic	-0.017	0.000	0.141	-0.002
	-0.91	0.00	3.77	-0.04
Of Mixed Race	-0.151	-0.168	-0.066	0.009
	-5.68	-3.74	-1.88	0.11
Of Unknown Race	0.280	0.139	0.598	0.330
	6.39	2.03	9.64	2.71
Log Family Income Range	-0.028	0.004	0.094	-0.171
	-1.82	0.14	3.46	-5.17
Math Apt and Interest	-0.028	-0.027	-0.013	-0.030
	-4.13	-2.45	-1.09	-1.70
Sociality / Session Avg	0.010	0.000	-0.008	0.015
	1.42	-0.03	-0.62	0.84
Num Friends / Session Avg	0.012	0.015	-0.023	0.006
	1.75	1.39	-1.73	0.42
Work Experience	-0.030	-0.014	-0.044	-0.028
	-4.42	-1.38	-2.92	-1.84
Ever Found Job Through Social Ties	-0.016	-0.007	0.014	0.026
	-1.74	-0.51	0.80	1.20
U.S. Citizenship	-0.065	-0.105	-0.006	0.017
	-4.63	-4.72	-0.23	0.49
Risk Loving	-0.005	-0.010	0.023	0.015
	-0.73	-0.96	1.82	0.86
Previous Lab Experience	-0.046	-0.036	-0.026	-0.036
	-7.51	-3.74	-2.40	-2.18
Clarity of the Instructions	0.000	-0.006	0.131	-0.043
	0.04	-0.57	8.06	-2.72

Similarly, Table 12 is the Rate model analog to Table 9 for the Level model. It is a continuation of Table 11, and it shows the estimated coefficients on the demographic, income and prior experience control variables. [The reason for the separate table is just that the combined table with all variables shown vertically would not fit on a single page.]

Table 13. Regression results for the rate models base case, relative to simulation benchmarks
t-statistics are shown below the coefficient estimates in a smaller font

	(Rates Models) Regression Results for Base Case, for Human Subjects				(Rates Models) Regression Results for Base Case, for Simulations			
	All Infor Levels Combined	Medium Infor.			Optimal	Multi-Armed Bandit		
		Low Infor.		High Infor.		Random		All Sim's Pooled
# of Observations	8,763	3,998	3,055	1,710	18,360	18,360	18,360	55,080
Root-Mean Square Error	0.274	0.256	0.225	0.342	0.291	0.432	0.457	0.419
R-Squared	0.4057	0.4309	0.3348	0.4013	0.6098	0.0007	0.1383	0.2989
Intercept	0.671	0.584	-1.030	1.530	-0.152	0.717	0.067	0.055
	6.68	3.77	-5.37	6.26	-12.49	28.28	3.28	5.44
Loss Rate	0.986	1.034	0.709	1.280	1.540	-0.024	1.161	0.847
	18.83	11.76	10.49	10.20	63.66	-0.66	30.53	42.11
Loss Rate ^ 2	-0.678	-0.601	-0.542	-0.953	-1.546	0.010	-1.031	-0.828
	-13.53	-7.20	-8.31	-7.89	-66.34	0.30	-28.13	-42.72
Offer Rate	0.703	0.741	0.602	0.691	0.867	-0.039	0.366	0.374
	12.46	7.86	8.48	3.58	34.87	-1.05	9.59	18.45
Offer Rate ^ 2	-0.838	-0.924	-0.662	-0.860	-0.869	0.056	-0.257	-0.320
	-15.69	-10.27	-9.81	-4.74	-36.68	1.61	-7.12	-16.63
Cost	-2.528	-2.641		-2.270	-4.818	0.461	-2.389	-3.353
	-4.09	-2.84		-2.56	-21.57	1.43	-6.92	-18.57
Period	-0.005	-0.005	-0.002	-0.009	0.021	0.000	0.006	0.004
	-21.67	-9.19	-7.89	-2.40	46.67	-0.38	11.43	15.70
Time Limit (in seconds)	0.001	-0.002	0.000	-0.004	0.002	0.000	-0.002	-0.001
	1.63	-3.34	0.26	-0.92	10.26	0.40	-9.90	-6.92
Seconds Used / Session Avg	0.118	0.095	0.125	0.121	-0.091	-0.030	-0.016	-0.171
	5.40	2.79	3.64	2.67	-4.59	-0.96	-0.50	-10.32
Past Num Neighbors / Session Avg	0.269	0.217	0.300	0.472	-0.017	0.122	0.560	0.227
	26.15	16.74	10.66	16.93	-0.31	1.63	6.25	5.08
Past Lost Job Rate	-0.012	-0.005	0.006	-0.061	0.105	-0.006	-0.022	-0.061
	-1.95	-0.74	0.23	-2.45	6.55	-0.25	-0.84	-4.56
Past Got Job Through Network Rate	0.004	0.004	0.011	0.002	-0.016	0.002	0.317	0.146
	1.98	1.15	2.49	0.37	-0.38	0.19	30.67	23.08
Past Shared Job Rate	0.019	0.025	-0.036	0.006	0.090	0.005	-0.254	-0.017
	2.53	2.81	-1.45	0.24	2.20	0.49	-21.62	-2.64

Likewise, Table 13 is the Rate model analog to Table 10 for the Level model, providing the results from running the simulation data (including for the optimal, random, MAB and pooled versions) with the dependent variable in the rate form.

In order to most easily study the Level model and Rate model results relative to one another, I include them side by side in Table 14.

Table 14. Regression results for the level and rate models base case, side by side
t-statistics are shown below the coefficient estimates in a smaller font

	(Level Models) Regression Results for Base Case, for Human Subjects				(Rates Models) Regression Results for Base Case, for Human Subjects			
	All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.	All Infor Levels Combined	Low Infor.	Medium Infor.	High Infor.
# of Observations	8,763	3,998	3,055	1,710	8,763	3,998	3,055	1,710
Root-Mean Square Error	2.385	2.496	1.921	2.413	0.274	0.256	0.225	0.342
R-Squared	0.2918	0.2845	0.2420	0.3678	0.4057	0.4309	0.3348	0.4013
Intercept	3.213	2.101	-7.066	8.405	0.671	0.584	-1.030	1.530
	5.44	2.35	-6.42	5.72	6.68	3.77	-5.37	6.26
Loss Rate	4.435	3.636	3.653	6.091	0.986	1.034	0.709	1.280
	14.42	7.14	9.42	8.08	18.83	11.76	10.49	10.20
Loss Rate ^ 2	-2.485	-0.733	-2.871	-3.791	-0.678	-0.601	-0.542	-0.953
	-8.43	-1.52	-7.67	-5.22	-13.53	-7.20	-8.31	-7.89
Offer Rate	3.343	2.769	3.060	2.651	0.703	0.741	0.602	0.691
	10.07	5.07	7.52	2.28	12.46	7.86	8.48	3.58
Offer Rate ^ 2	-4.127	-3.855	-3.282	-4.040	-0.838	-0.924	-0.662	-0.860
	-13.15	-7.40	-8.49	-3.71	-15.69	-10.27	-9.81	-4.74
Cost	-18.494	-18.827		-16.068	-2.528	-2.641		-2.270
	-5.09	-3.49		-3.01	-4.09	-2.84		-2.56
Period	-0.028	-0.035	-0.012	-0.082	-0.005	-0.005	-0.002	-0.009
	-23.24	-10.24	-7.69	-3.78	-21.67	-9.19	-7.89	-2.40
Time Limit (in seconds)	0.001	-0.017	0.004	-0.065	0.001	-0.002	0.000	-0.004
	0.47	-4.20	0.64	-2.47	1.63	-3.34	0.26	-0.92
Seconds Used / Session Avg	0.677	0.290	0.979	0.652	0.118	0.095	0.125	0.121
	5.27	1.46	4.96	2.40	5.40	2.79	3.64	2.67
Past Num Neighbors / Session .	1.721	1.375	1.666	3.285	0.269	0.217	0.300	0.472
	28.49	18.34	10.32	19.59	26.15	16.74	10.66	16.93
Past Lost Job Rate	-0.038	-0.030	0.266	-0.054	-0.012	-0.005	0.006	-0.061
	-1.03	-0.74	1.87	-0.36	-1.95	-0.74	0.23	-2.45
Past Got Job Through Network	0.028	0.020	0.073	0.000	0.004	0.004	0.011	0.002
	2.25	1.07	2.89	0.00	1.98	1.15	2.49	0.37
Past Shared Job Rate	0.060	0.091	-0.274	0.035	0.019	0.025	-0.036	0.006
	1.36	1.79	-1.89	0.22	2.53	2.81	-1.45	0.24

Overall, the results are qualitatively similar between the rate and level models, which perhaps is not that surprising given that the two models differ only in the data transformation of the dependent variable. Specifically, there is an estimated positive relationship on the Loss Rate variable and an estimated negative relationship on the Loss

Rate squared variable. Likewise, for the Offer Rate and Offer Rate squared variables. The estimated effects of Cost are negative in both models. Regarding the additional analysis variables, in most cases the same variables that have statistical significance in the level model also have statistical significance in the rate model. The same is true for the demographic control and prior experience variables. It is interesting to note that the R-squared measure of model fit is higher in the rate model transformation than in the level model transformation. Also, regarding the effect(s) of information level, the rate models appear to show moderate effects, in which additional information tends to raise the extent of curvature in the loss rate. However, the additional information does not seem to raise the extent of curvature of the offer rate in the rate form of the model.

  4.4.1 Network matching rate, etc., results. As discussed in Section 4.2.1.1, I also ran similar models for the laboratory 'network matching rate' and for the laboratory 'share of subjects receiving a job through the network,' with the corresponding binary responses as the dependent variable (as opposed to the network investment level or network investment rate). However, I do not view the results from these regressions as a useful test of the G&M theoretical predictions of agent behavior since an inverse-U shape is almost assured in these concepts regardless of the agents' network investment choices, as long as the network investment is not too close to zero. Although I do not here formally present the results from these models, I provide a brief summary, as follows.

  In my 'share of subjects receiving a job through the network' models, with the lab experiment data, I find strong positive estimated coefficients on the job loss and offer rate linear terms, and strong negative estimated coefficients on the job loss rate squared and

offer rate squared quadratic terms. This is true for each information level separately, as well as for all information levels combined. Interestingly, however, the curvature is the strongest in the Information Level 1 models, as compared to the Information Levels 2 and 3 models, and this is different from what was found in the models with network investment as dependent variable. Also, in the all-information-levels run, I continue to estimate a negative effect of cost, though it is only marginally significant in this setting.

But most striking are the findings from my *simulations* for the 'share of subjects receiving a job through the network' models. While I find the expected signs and magnitudes for the coefficients in the optimal simulation, I yet also find the same signs and nearly the same magnitudes for the coefficients in the random simulation, even despite the fact that network investment choice had been made entirely randomly in this scenario. This finding mildly supports the idea that concave curvature is nearly a given for the 'share of subjects receiving a job through the network' concept, regardless of the patterns in chosen network investment levels. These additional results help give some perspective to the results found in the basic models with network investment as the dependent variable. Next, I review the related formal hypothesis test results.

4.5 Hypothesis Test Results

In this section, I report the hypothesis test results, starting with Test 1L below.

• Test 1L: With an F-statistic of 330.60, I reject the null hypothesis that the coefficients on the Loss Rate and Loss Rate-squared covariates are zero.

• Test 2L: With an F-statistic of 124.90, I reject the null hypothesis that the coefficients on the Offer Rate and Offer Rate-squared covariates are zero.

• <u>Test 3L</u>: With a t-statistic of -5.09, I reject the null hypothesis that the coefficient on the Cost covariate is zero.

• <u>Test 4L</u>: With an F-statistic of 205.52, I reject the null hypotheses that the coefficients on all the additional analysis covariates, from **M**, are zero.

• <u>Test 5L</u>: With an F-statistic of 21.62, I reject the null hypothesis that the coefficients on all the demographic control and prior experience covariates, from **D**, are zero.

• Test results from <u>Test 6L</u> and <u>Test 8L</u> are presented in the text and tables below.

The following tables contain grids of t-statistics for individual tests of the difference between the coefficients when the models are run using lab data collected under different information levels and between the coefficients when the models are run with human subjects versus with automatons (in simulations). The tests are run at three levels of assumed correlation, r=0.0, r=0.5 and r=1.0. Given the collection of so many individual statistical tests, 'multiple comparisons' issues may arise, which could imply that the probability that I find statistically significant differences is greater than the stated significance levels of the individual tests. However, no related adjustments are made here. As a result, the findings could be somewhat discounted accordingly.

The tests were executed by subtracting one model's coefficient estimates from the other model's coefficient estimates and dividing this difference by the 'standard error of the difference.' As usual, the standard error of the difference is computed as the square root of the sum of the squares of the reported standard errors of the two coefficient estimates minus two times the assumed correlation coefficient times the product of the reported standard errors.

Table 15. Statistical test results across information levels, part 1

Infor. Level 1 vs. All Infor. Levels			
t-statistics from the standard error of a difference computation			
by correl. coefficient (r) assumption			
	r=0.0	r=0.5	r=1.0
Intercept	-1.04	-1.41	-3.64
Loss Rate	-1.34	-1.80	-3.96
Loss Rate ^{2}	3.09	4.15	9.28
Offer Rate	-0.90	-1.21	-2.69
Offer Rate ^{2}	0.45	0.60	1.32
Cost	-0.05	-0.07	-0.19

Infor. Level 2 vs. Infor. Level 1			
t-statistics from the standard error of a difference computation			
by correl. coefficient (r) assumption			
	r=0.0	r=0.5	r=1.0
Intercept	-6.46	-9.05	-45.00
Loss Rate	0.03	0.04	0.13
Loss Rate ^{2}	-3.50	-4.87	-19.53
Offer Rate	0.43	0.59	2.10
Offer Rate ^{2}	0.88	1.22	4.26

The left-hand panel shows Information Level 1 results relative to All Information Level results.
The right-hand panel shows Information Level 2 results relative to Information Level 1 results.

The left-hand panel of Table 15 shows t-statistics from the individual comparisons of coefficient estimates in the Information Level 1 setting relative to those in the combined, all-information setting; these coefficient estimates are taken from Table 8, left-hand panel. Under a correlation of 0.0, only the Loss Rate-squared variable has a statistically significant difference relative to the negative coefficient estimate, and the direction of the difference is positive. So, the curvature of the network investment against the job loss rate appears to be less pronounced in the Information Level 1 setting; this matches what is shown in Figure 16, from Section 4.1.1. At a correlation of 0.5, the Loss Rate-squared variable again has a statistically significant difference, but it is lower in the Information Level 1 setting. At a correlation of 1.0, three other variables have a statistically significant difference.

The right-hand panel of Table 15 analyzes the differences between the Information Levels 2 and 1 settings. Even at correlation 0.0, there are the following statistically significant differences: negative difference in the Intercept and negative

186

difference in Loss Rate-squared. So, in the Information Level 2 setting, the Intercept is smaller (enough that the Intercept is negative even), and the coefficient estimate on Loss Rate-squared is larger in absolute value, indicating greater curvature in the job loss rate in the Information Level 2 setting. This greater curvature can be seen in Figure 17, from Section 4.1.1, which plots results from Information Level 2. At correlation 0.5, these same differences just have larger t-statistics. At correlation 1.0, the coefficient on Offer Rate-squared also has a statistically significant positive difference; thus, the coefficient estimate on the Offer Rate squared is smaller in absolute value under the Information Level 2 setting.

Table 16. Statistical test results across information levels, part 2

Infor. Level 3 vs. Infor. Level 2				Infor. Level 3 vs. Infor. Level 1		
by correl. coefficient (r) assumption				*by correl. coefficient (r) assumption*		
t-statistics from the standard error of a difference computation				t-statistics from the standard error of a difference computation		
	r=0.0	r=0.5	r=1.0		r=0.0	r=0.5	r=1.0
Intercept	8.43	11.69	41.92	Intercept	3.66	4.92	11.00
Loss Rate	2.88	3.73	6.65	Loss Rate	2.70	3.68	10.02
Loss Rate ^{2}	-1.13	-1.46	-2.61	Loss Rate ^{2}	-3.50	-4.77	-12.58
Offer Rate	-0.33	-0.40	-0.54	Offer Rate	-0.09	-0.12	-0.19
Offer Rate ^{2}	-0.66	-0.79	-1.08	Offer Rate ^{2}	-0.15	-0.20	-0.33
				Cost	0.36	0.51	56.89

The left-hand panel shows Information Level 3 results relative to Information Level 2 results.
The right-hand panel shows Information Level 3 results relative to Information Level 1 results.

Regarding Table 16, the left-hand panel compares the results under Information Levels 2 and 3, and it shows that Intercept is higher and the coefficient on Loss Rate is higher in the Information Level 3 setting, relative to the Information Level 2 setting, at both correlation 0.0 and 0.5. And the right-hand panel of Table 16 compares the estimation results from Information Levels 1 and 3. It shows that the Intercept is larger, the coefficient on the Loss Rate is large, and the coefficient on the Loss Rate squared is

larger in absolute value (i.e., more negative), indicating greater in the job loss rate in the

Information Level 3 setting; these are true regardless of the assumed level of correlation

between the Information Levels 1 and 3 lab-collected data. The greater curvature can be

seen in Figure 18, from Section 4.1.1, which plots results from Information Level 3.

Table 17. Statistical test results of simulations relative to lab data

	Simulations vs. Lab Data, All Infor. Levels			
t-statistics from the standard error of a difference computation				
	Optimal	Random	MAB	Pooled
Intercept	-4.37	3.13	-2.53	-1.23
Loss Rate	6.35	-11.59	-2.61	-3.61
Loss Rate ^{2}	-12.61	6.92	0.04	-1.10
Offer Rate	4.48	-8.29	-2.22	-2.61
Offer Rate ^{2}	-2.54	10.85	6.98	5.93
Cost	-4.91	3.46	0.90	0.31

Comparison of simulation data (optimal, random, MAB, pooled) relative to lab data

Table 17 presents results from comparison of the simulation data regression

coefficient estimates relative to those of lab experiment data; these coefficient estimates

are taken from Table 10, right-hand panel. Specifically, for the optimal simulation, the t-

statistics indicate stark, statistically significant differences for each variable. Although

the signs of the estimated coefficients agree between the optimal simulation and the lab

data for all five of the core covariates, the absolute value for each variable is much large

for the optimal simulation; the Intercept is smaller for the optimal simulation than for the

lab data. Regarding the random simulation, there are statistically significant differences

as well; as discussed earlier, the estimated coefficients for the random simulation or all

near zero, so these statistically significant differences are not surprising given the non-

zero values of the coefficient estimates in the lab data, as well as the large sample size in

the random simulation. Regarding the multi-armed bandit (MAB) simulation, the

Intercept is smaller, the coefficient on the Loss Rate is smaller, the coefficient on the

Offer Rate is smaller, the coefficient on the Offer Rate squared is smaller in absolute

value, and the difference in the coefficient on Cost is not statistically different. So,

overall, the core **X** relationships are weaker in the MAB simulation than in the lab data.

Finally, the pooled data (i.e., from all simulations) also has mostly weaker relationships

than does the lab data, except that the coefficient on the Loss Rate squared variable is

larger in absolute value.

Taking these statistical results together, regarding information level, it appears

that the extent of Information provided to lab subjects has a positive effect on the extent

of curvature in the Loss Rate variable, and so the lab subjects in the Information Level 3

treatment qualitatively match the G&M predictions more frequently than in the

Information Level 1 treatment. However, this is not the case for the Offer Rate variable,

which has a weaker relationship under Information Level 3 than under Information Level

1. Regarding the simulations, it appears that the lab data do not have nearly as strong

curvature in Job Loss Rate or Job Offer Rate as do the optimal simulation data.

Likewise, the lab data show a weaker effect on the Cost of network investment. On the

other hand, the lab data also have statistically significant differences relative to the

random simulation behavior, as expected. The differences from comparing the lab data

model coefficients and the MAB simulation and pooled data model coefficients are

somewhat between the differences found for the optimal simulations and the differences

found for the random simulations. Some of the relationships with network investment are

weaker in the MAB and pooled data than in the lab data, but the differences are much less stark than in the comparisons with the optimal and/or random simulation data.

Having gone through these hypothesis test results for the Level models in detail, I do not explicitly go through the analogous test results for the Rate models here. However, the results of these Rate model hypothesis tests come out very similar overall.

4.6   Some Interpretations

Based on the results from my empirical model, the concavity I observed in the average network investment in my laboratory data relative to both the job loss and offer rates is less than that predicted in the G&M theory, but the resulting estimated polynomials peak at nearly the same job loss and offer rates as do the theoretical prediction-based polynomials. So, while I find the right direction of curvature in the lab experiment data, it is more mild than predicted in the theory.

In the early periods of the lab sessions, a large share of subjects, roughly 55 percent, tends to exhibit an upward-sloping strategy in their network investment choice versus the job loss rate, and a small share, roughly 9 percent, of subjects tends to invest in all zeros. As the experiment proceeds, the upward-sloping strategy appears to fall out of favor, down to roughly 15 percent share, while the all-zero strategy becomes more prevalent, up to a roughly 55 percent share. Regarding the share of subjects choosing an inverse-U strategy versus the job loss rate, this falls from about 45 percent to about 30 percent over the course of the experiment. Against the job offer rate, the trends in the network investment across periods are similar except that the shares choosing an upward-

sloping strategy start from a lower level, about 20 percent, and ultimately falling to about 5 percent.

Lab subjects tend to spend less time deciding about their investment choices as the lab experiment progresses across rounds. Also, those investing with an all-zero strategy tend to reply more quickly than those investing with either inverse-U or upward-sloping strategies.

Looking at the individual data, although a large share of lab subjects exhibit the expected curvature, their trend behavior is somewhat covered up by the choices of the lab subjects that exhibit upward-sloping investments. Since these upward-sloping-trend lab subjects invest large amounts at the high job loss rates, those amounts greatly raise the average network investment above the theoretical prediction of near zero. So, the trends in the median lab participant's choices appear to be more in line with the G&M theory than the trends in the mean lab choices.

Especially during the early periods of the lab sessions, many lab subjects overinvest in the network relative to the G&M theory, and, thus, the total costs of these investments are not covered by the network benefits they receive, on average. However, the average amount of overinvestment falls incrementally during the experiment, ending up fairly close to the theoretical prediction levels by the final periods. Still, these closing average amounts are based on a combination of lab subjects choosing all zeros (i.e., too low) and lab subjects choosing inverse-U strategies at too-high levels of network investment. It is not the case that most lab subjects ultimately select the G&M optimal levels of network investment, even in these closing lab periods.

The initial high levels of overinvestment could occur for many reasons; for example, by investing a lot, one could have peace of mind that he/she has done his/her best to reduce the chance of a loss, even at the significant expense to average income. The reasons why more lab subjects begin to choose all zeros in the later rounds are likely also myriad; for example, they may feel there is not a large traceable benefit from the network when sifting through their historical data across the periods.

5   Discussion

In this section, I take stock of the lab findings presented and consider what may be worthwhile to study next in order to further advance knowledge in this area.

5.1   Summary

In this chapter I have discussed a theoretical paper regarding job-contact formation and usage, articulated laboratory procedures in order to implement a test of this theory under controlled conditions. The predictions of Gaelotti and Merlino (2014) [G&M] are that the rate of finding jobs through social ties will bear an inverse-U relationship over the course of good to bad economic conditions, and that people will or should consider investing most in their personal job-contact networks when the job loss and /or job offer rates are at middle values, likely corresponding to when the economy is in the midst of a growth phase. It is only in these middle ranges where there is a large enough chance that a person will lose his/her job to make him/her wish to insure against this loss, yet not so large that everyone is keeping any jobs they find for themselves. G&M's empirical exercise using data from the U.K. Labor Force Survey supported the

predictions regarding curvature in the network matching rate and in the extent of network investments. The goal of this work has been to document findings from an experimental job-contact network and to see whether the G&M predictions hold up in this context, as well as to add to the overall body of empirical findings related to endogenous network formation and use.

Overall, my laboratory results are consistent with those predicted in the G&M model to some degree. Specifically, from fitting my empirical model with the laboratory experiment data, I find some amount of negative concavity of network investment choices against both the job loss rate and job offer rate, though the extent of concavity is much less than that predicted in the G&M model, and the average amount invested is somewhat more than that predicted in the G&M model. Also, I find a negative effect of cost on network investment choice. Providing additional information to the lab subjects tends to increase the concavity of the network investment curve to some degree and also tends to reduce the average amount invested, though still leaving the lab results materially different from the G&M predictions. The simulation benchmarks I ran were very helpful for tracing out what the G&M theoretical results would look like from within my particular laboratory framework.

In the my initial descriptive analyses of the laboratory data, I noticed that the choice of network investment appears to be weakly concave as the job loss rate increases from low to high. Upon introducing an additional information sheet that states the benefits of the network at different job market conditions, the curvature of subjects' average network investment increases and is thus more closely aligned with the

theoretical prediction. Upon introducing yet a more visual and intuitive information delivery, the curvature of subjects' average network investment is yet more pronounced.

Looking across periods, while a large share of lab subjects started with an upward-sloping strategy against the job loss rate, by the end of the experiment, only a small share of lab subjects invested with an upward-sloping strategy against the job loss rate. In contrast, while a small share of subjects started with an all-zero strategy against the job loss rate, by the end of the experiment a large share of subjects chose all zeros. Regarding the inverse-U shape, the share of subjects investing with that pattern declined from about 45 percent to 30 percent during the course of the experiment. The patterns against the job offer rate were similar, except that the share of upward-sloping investment did not start out as high.

Finally, it is worth noting that some lab subjects choose to make large network investments at the high loss rate (or low offer rate), thus exhibiting an upward-sloping trend in their network investment against job loss rate. These particular lab subjects greatly raise the average investment across all lab subjects in the high loss rate case, pressuring the average curvature in network investment to fall farther short of the theoretical amount of curvature, even while many lab subjects do exhibit some degree of curvature in their network investment choices. Also, partly as a result, the median network investment patterns tend to match the G&M predictions better than do the mean network investment patterns, since the averages tend to be skewed upwards by some high network investment choices at the high job loss rate, mostly by those subjects exhibiting the upward-sloping trend in their data, as mentioned above.

5.2   Commentary on G&M Model

I here provide some broader comments on the G&M model and my lab test results. First, the reason I tested for lab subject response over a wide range of job loss and job offer rates in this experiment, namely from 0 percent to 100 percent, was due to the theoretical optima in network investment from the G&M model, which is at around 40 percent job offer rate and 50 percent job offer rate. However, these kinds of job offer or loss rates would be fairly extreme to witness in reality. Even during the Great Recession, reported layoffs peaked at about 1.9 percent in a given month (January 2009), and at 20.7 percent a year (over October 2008 through September 2009), which is much less than 50 percent or 90 percent. [31] Also, it seems unlikely that anything like 50 percent or 90 percent of the working-age population would ever be receiving job offers or tips at a given time. If the economy only varies within a small range of job loss or offer rates, like say 5 percent to 15 percent, then the scope of possible gains from job-contact networking in the G&M model would likely be fairly small. So, there could be a question about the relevance of the G&M framework to the much smaller range of job loss and job offer rates that is more typically observed in actual economies. [However, to make sure that I am understanding everything in the G&M work correctly, it may be best for me to also act the G&M authors to confirm my interpretation(s) of their model.]

Although G&M's companion empirical exercise had found curvature in the authors' proxy variables of network investment against their proxy variable for job loss

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[31] I computed the 1.9 percent and 20.7 percent figures as the estimated 2.573 million nonfarm employees laid off from work in January 2009 divided by the January 2009 nonfarm payroll employment of 134.053 million, and as the total of 27.498 million people being laid off between October 2008 and September 2009 divided by the average employment of 132.701 million between October 2009 and September 2009. These figures are based on publicly available data from the Bureau of Labor Statistics.

rate, the curvature was quite extreme. For instance, the quadradic function fit using their data is only positive over the range of roughly 0 percent to 15 percent. It is interesting that, under G&M's empirical exercise, even small changes in job loss rate were met with material changes in the choices of job-contact networking. However, it is hard to reconcile this sharper curvature in G&M's empirical exercise with the somewhat more diffuse curvature in the G&M base case scenario. So, even if people really do exhibit an inverse-U pattern in their social network investment as the local job conditions improve or erode, the G&M theoretical predictions, which peak at near 50 percent job loss rate, may not be able to rationalize the G&M's empirical data, which may peak around 6 or 7 percent. With this difference in mind, perhaps there is another important mechanism(s) at work even beyond what is presented in the G&M model instead.

In that direction, perhaps the G&M curvature is relatively diffuse because in G&M, the role of the job-contact network, by the authors' definitions, is only to allow job seekers to find out about the *existence* of job offers. For instance, the G&M model does not account for using job-contact networks to handle asymmetric information or to find matches with high productivity matches that may be very enduring. If the real-world job-contact networks studied in G&M's empirical exercise have these additional roles and/or yet other roles beyond just informing about the existence of job offers, then these additional roles could help to explain the large observed gap in the concavity between the G&M model predictions and the G&M empirical exercise results.

In order to set up the G&M framework in the laboratory, I studied G&M's setup in great detail, and I ran simulations of the model with thousands of iterations. I saw the

impact of changing different assumptions, such as change in group size, change in costs.

I found that there exist only modest benefits from the network, namely, a roughly 7.5

percent rise in expected earnings at most, and a large amount of that could easily be

absorbed by any costs from network investment. While technically an optimum exists for

any given job-market conditions, the benefits from obtaining that optimum appear to be

fairly small. Given the personal monetary costs from social networking and the mental

costs from trying to understand the forces that G&M see at work, the benefits from

networking in this framework may not be large enough to motivate much change in

individual behavior. Small amount(s) of potential gain from the network still are enough

to motivate the fully rational imagined agents, but they may not be enough to motivate

lab subjects think very seriously about the right level of network investment.

The network formation process used by G&M, borrowed from Cabrales, et al.

(2011), determines bilateral link probabilities as the product of two individuals'

investments divided by the sum of all persons' investments. This is a convenient

approach, however, there are many times in which the computed probability will exceed

one, as in the example provided earlier in Chapter 2. Moreover, the link probabilities

depend critically on the scale of choices allowed. For example, one might not expect that

allowing a range of 1 and 10 as opposed to a range of 0.1 to 1 would matter at all.

However, the link probabilities end up being a factor of 10 higher in the case of choices

from 1 to 10 as compared to 0.1 to1.0. As a simple way to keep the link probabilities

constant for a given share distribution of network investment, one could simply multiply

link probability formula by a constant; that way, one could target link probabilities in any desirable range.

Finally, it is worth noting that, even among many of the laboratory subjects that appeared to understand the logic of the lab setup based on their choice behavior, the strategies they described in their post-experiment questionnaires often seemed different from the logic presented in G&M, so it is possible that the G&M theory is somewhat descriptive of actual choice behavior, but for reasons other than the authors ascribe.

5.3 Extensions Addressed in Chapter 3

Chapter 3 of this dissertation discusses three extensions or augmentations to the basic G&M framework in order to assess the robustness of the results and to study any possibly confounding factors. I review the essence of each extension separately below.

G&M provide an elegant job-contact model that implements endogenous network formation in a tractable way. However, the potential welfare gains from investing some positive amount in the network versus not investing at all are fairly small in this environment, possibly peaking at around 7.5 percent of expected wages (for the case of near 50 percent job loss and offer rates), and dropping below 1 percent for many other cases.[32] Moreover, factoring in the costs of network investment, even those modest peak benefits are easily eroded for even low cost assumptions. Simply put, a very large percentage of subjects' potential earnings may already be available without the job-contact network. If the rewards from optimal play are not salient, then it would be hard

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[32] These figures are computed from my simulations of the G&M framework under various job loss rates, job offer rates and network investment choice levels.

to interpret the lab results, and it could be impossible to test the theory at hand. Partly to address this observation, in Chapter 3, I explore the effects of substantially raising the reward from finding a job via the job-contact network (versus from the formal job market) relative to the standard case in which there is only one common wage.

The social aspect of the network investment decisions makes the G&M setup fairly complex. The expected number of links a subject may have depends not just on his/her own investment choice, but also on the investment level(s) of his peers. One's investments may only pay off if at least some other subjects likewise invest in the network. In order to optimize in this setting, subjects may be looking for investment choices that might be seen as focal points among the other lab subjects. There may also be concerns about interpersonal comparisons regarding gains or losses. In order to tune out many of the social aspects at hand (such as guessing about peers' motivations and choices), and to minimize feelings about the distribution of earnings, in Chapter 3 I explore a setting in which human subjects plays only against pre-programmed 'optimizing' agents instead of against other humans.

Finally, in the G&M model, the job loss and offer rates are assumed to be the same across agents; even under comparative statics, the rates vary for all agents in exactly the same way. However, in reality, there tends to be variation across individuals in the likelihood that they will lose jobs and/or receive job offers. Also, people may not actually be aware of each others' job prospects or even their own. In order to gauge the effects of having variable job prospects spread amongst a group, in Chapter 3 I implement a lab scenario in which job loss and job offer rates vary amongst the lab

subjects, and I do so in two cases: one in which the lab subjects know the rates they individually face and another in which they do not know the rates they individually face. This heterogeneous rates scenario can also help to gauge the extent to which lab subjects understand and appreciate the implications of their own job loss and offer rates relative to those faced by others in the economy.

CHAPTER THREE: EXTENSIONS OF JOB-CONTACT NETWORKS IN THE LABORATORY

This chapter builds on the laboratory test of endogenous job-contact models discussed in the last chapter, in which I had found a mix of agreement and disagreement with the theoretical predictions. In order to rule out some alternative explanations of laboratory-observed phenomena and to assess the overall robustness of the benchmark results, in this chapter I present results from augmentations of the benchmark job-contact networks setup in the laboratory, which step beyond the formal theory. In particular, three variations are considered: (1) Higher payoffs for jobs found via network matching than for jobs found through other sources; (2) Human players grouped with computer players that follow predetermined strategies (i.e., instead of with other people); (3) Heterogeneous job loss and offer rates among players. The chapter closes with a discussion motivating further model development and/or experimentation related to job-contact networks in the future. If results from such settings bear very different results from those in the basic G&M setting, then this could motivate related refinements to the underlying theory.

1   Introduction

In this chapter I present and test a few different augmentations to the base case scenario of the Galeotti and Merlino (2014) framework in order to rule out some possible

alternative explanations and to further substantiate the base case results. I hereafter refer

to the Galeotti and Merlino (2014) work and authors as *G&M*. Regarding the base case

G&M model to which these extensions refer, please see Chapter 2, which covers the

model in detail and discusses related literature, background materials, illustrations and

empirical results. This chapter builds upon these earlier ideas and findings.

In particular, first, I explore the effect(s) of offering a higher wage for jobs found

through the network as opposed to the formal job market. In this case, it was explained

to lab subjects that if one received a job from through one of his/her connected neighbors,

then their wage for that period would be $5 instead of just $1; and in some of the later

periods this network-based wage was raised again up to $25. The goal of this treatment

was to more strongly incentivize investment in the job-contact network in response to the

prevailing job market conditions. Under the base case G&M scenario, the incentive(s)

for playing optimally are fairly modest, since the optimization has a fairly flat maximum;

my simulations had shown a roughly 7.5 percent maximum expected benefit from the

network before even subtracting the investment costs. In contrast, under these higher-

wage-through-the-network scenarios, the level and curvature in the reward function are

greatly amplified by payment of the higher network-based wage. The impact of the job

market conditions and high network-based wage was made clear in the Information Level

3 handout (see Chapter 2, Section 3.4) provided to lab subjects in this treatment.

Second, I explore the effect(s) of having the lab subjects play versus pre-

programmed computer players instead of against other human subjects. The lab

instructions inform the lab subjects that these computer players or automatons all play the

202

same pre-programmed strategy for the highest long-term personal winnings on average, and that the strategy varies according to each period's job market conditions. The goal of this treatment was, first, to eliminate the chance that social concerns amongst the players were affecting subjects' game decisions. Thus, for instance, lab subjects would not feel any need to send and/or infer signals among their peer players. The second goal was to make it easier for the lab subjects to infer the strategies of the other players, and thus respond accordingly. For instance, in this setting, the other players' strategies were fixed over time, for any given job market conditions, and so they were not the possibly moving target that they are in the situation of other live human players that are also learning and likely strategizing differently across the periods.

And, third, I explore the effect(s) of having heterogeneous job loss and offer rates across the population of lab subjects at a given time. The lab instructions inform the subjects that they would, individually, face a random job loss and/or job offer rate, and that the other lab subjects likewise would face their own random job loss and/or offer rate, but that this same particular rate or rates would persist for the next several periods. The random rates were implemented under a systematic pattern described in Section 2.3: To clarify, in the *known* rate scenarios, the lab subjects would see the particular job loss and/or offer rate that applied to them on their screen before deciding on their level of network investment, while in the *unknown* rate scenarios, they did not. The goal of this treatment was to see if lab subject behavior would change if, as in the 'real world,' individuals faced job loss and offer rates idiosyncratic to them instead of just the same for everyone. This arrangement could also help to estimate what share of lab subjects

thought only about the rate(s) that applied to themselves versus those that also considered the rate(s) that applied to those in the broader economy.

Taken together, these three augmentations to the basic G&M framework facilitate a greater understanding of the phenomena that take place upon implementing a job-contact network in the laboratory.

2   Details and Predictions

In this section I review the details regarding each of the three extensions tested. Regarding the base case G&M model to which these extensions refer, again, please see Chapter 2, which covers the model and related information in detail.

2.1   High Network-Based Wage

In this first laboratory extension, as mentioned, I substantially raise the reward from finding a job from the job-contact network, and I then see if there is a difference in lab subject behavior in response. A key motivation for this extension is the observation that, in the later periods of the lab sessions, a large share of lab subjects were investing with an all-zero strategy, and they were doing so with a short response time; these trends were documented in Chapter 2, Section 4.1.3. These all-zero responses could occur for several possible reasons. One possibility is that the lab subjects found the empirical return on the network to be too low to justify investing or too low to be worth doing the mental computations to invest optimally. Another possibility is that the lab subjects were not very engaged or bored in the experiment at that point. Related to these ideas, in my simulations of the G&M framework, I had found a fairly small benefit of the network, a

peak gain of roughly 7.5 percent in expected wages, relative to simply staying out of the job-contact network, even prior to factoring in the network investment costs, and often the gain in expected wages was even less than 1.0 percent.

The higher network-based wage in this treatment both raises the overall expected value as well as the differences in expected value between the low, middle and high rate scenarios. If raising the stakes of optimal play as such decreases the share of all-zero investment choices, then this might suggest that network returns in the base case of the G&M model are relatively low; it could also be an opportunity to observe inverse-U curvature chosen by a larger share of lab subjects.

This extension is also motivated by empirical studies that show that in some cases people who find jobs through social contacts receive higher wages, such as Brown, Setren and Topa (2016), as well as by theoretical models that incorporate higher wages from the informal job market, such as Mortenson and Vishwanath (1994). [See Chapter 1, Section 1.5 for additional detail.] If higher network-based wages are a realistic aspect of some jobs, then it is compelling to check whether incorporating a high referral-based wage into the laboratory setting would make a difference relative to the base case.

Regarding lab materials provided to the subjects for this treatment, they were almost exactly the same as in the base case from Chapter 2, Section 3. Specifically, all lab subjects started with the basic lab instructions, for which a snippet was shown in Figure 12 from Chapter 2, Section 3.4. The full instructions are included for viewing in the Appendix. In particular, *sub-sections 10* and *11* of the Appendix contain text specific to the high network-based wage scenario.

As in the informational-level 3 version of the base case from Chapter 2, at the beginning of Period 4, the subjects were shown the information level 3 handout from Figure 14, depicting the laboratory conditions and key related variables under scenarios of lower (10 percent), medium (50 percent) and high (90 percent) job loss rate, while holding the job offer rate constant at the medium (50 percent) level. Also, each period, the Figure 15 image appeared on their screen briefly, highlighting the current job market conditions and benefits.

Starting in Period 13, a high network-based wage of $5 was introduced, and it continues until Period 18. Then, during Periods 19 to 36, a very high network-based wage of $25 was implemented. Finally, during the closing Periods 37 to 47, the prior high network-based wage of $5 was re-introduced. Both the Information Level 3 handout and screen images were updated in order to depict the likely average effects of the network in the higher network-based wage setting, for subjects who are connected to at least one other subject via the job-contact network.
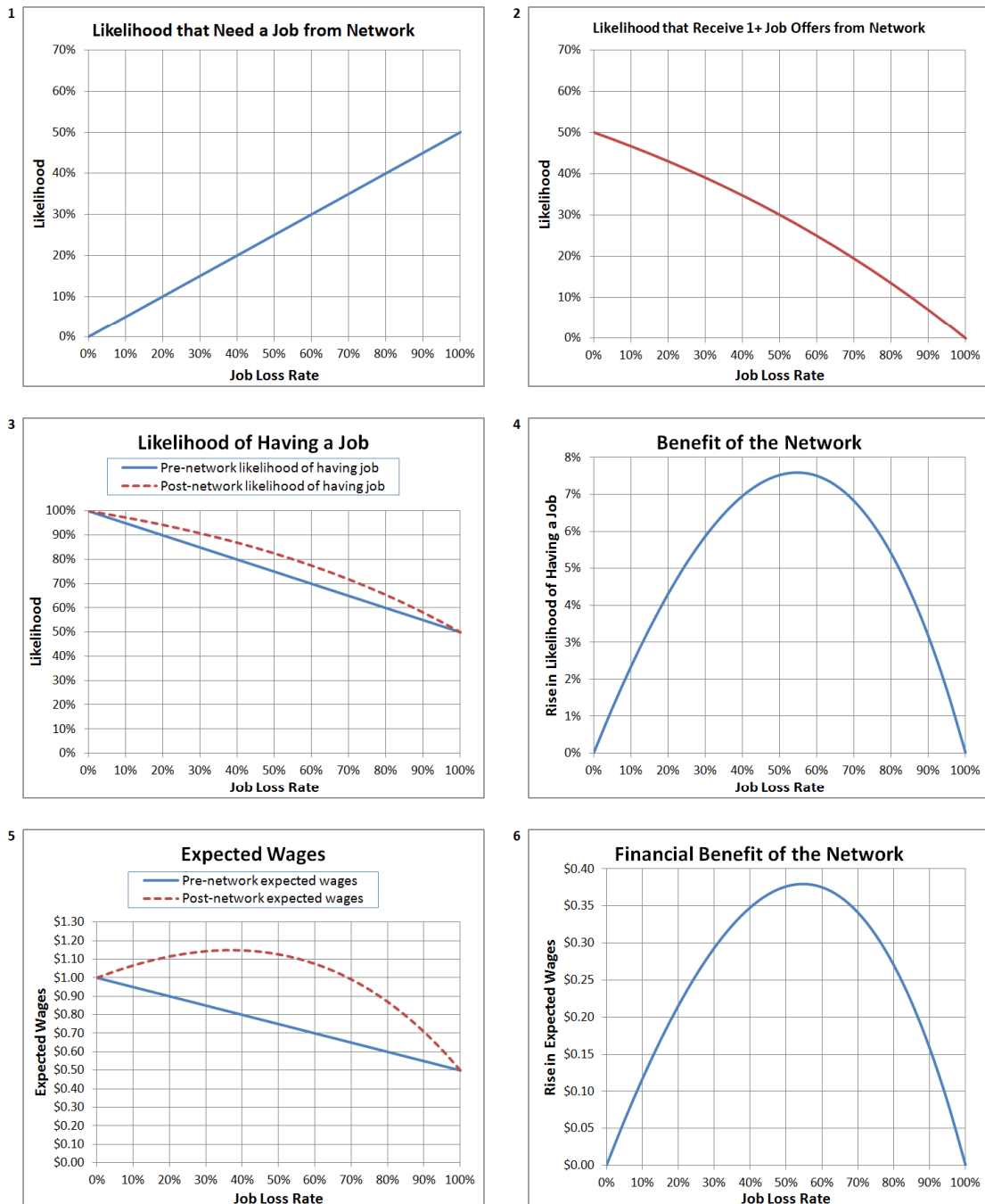
Figure 34. Information level 3 handout, for network-based wage of $5, graphical information
For job offer rate of 0.5 or 50 percent

207
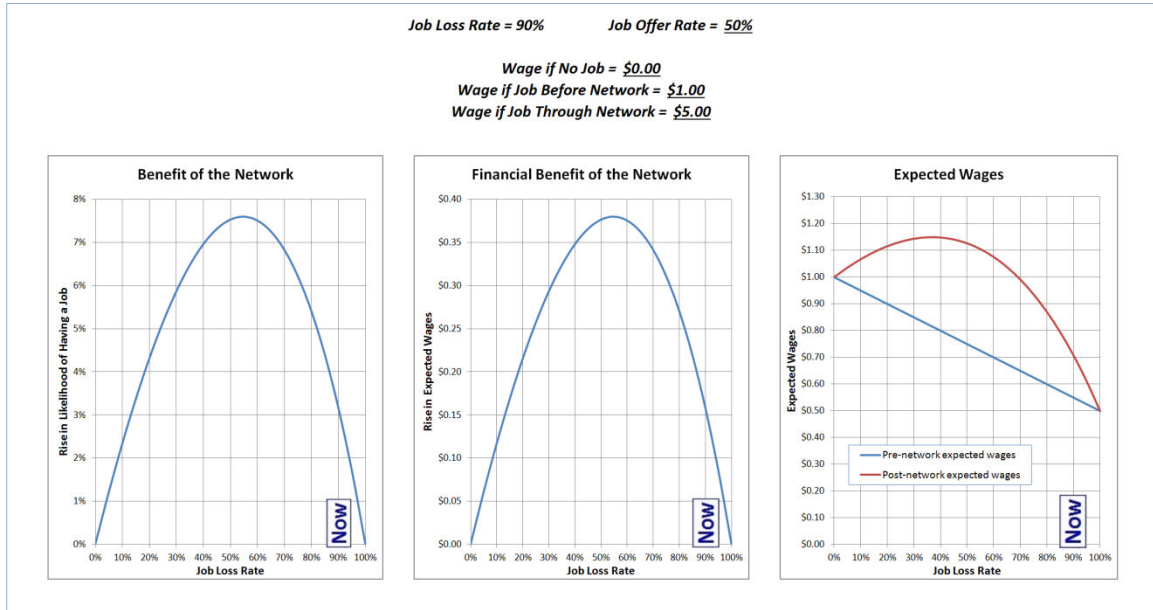
Figure 35. Screen display for network wage of $5, for job loss rate of 90%
This is what subjects would see before each period under information level 3. The "Now" icon shows the current job-market conditions that apply, which, in this example is for a job loss rate of 90%, while the job offer rate is 50%.

For the case of $5 network-based wage, Figure 34 shows the paper handout provided, and Figure 35 shows the corresponding screen image that appeared briefly at the start of each period to highlight the current job market conditions and benefits. In particular, Panel 5 of Figure 34 and the right-most panel of Figure 35 show the large impact on expected wages from the job-contact network, for those subjects which are connected to at least one other lab subject.

208
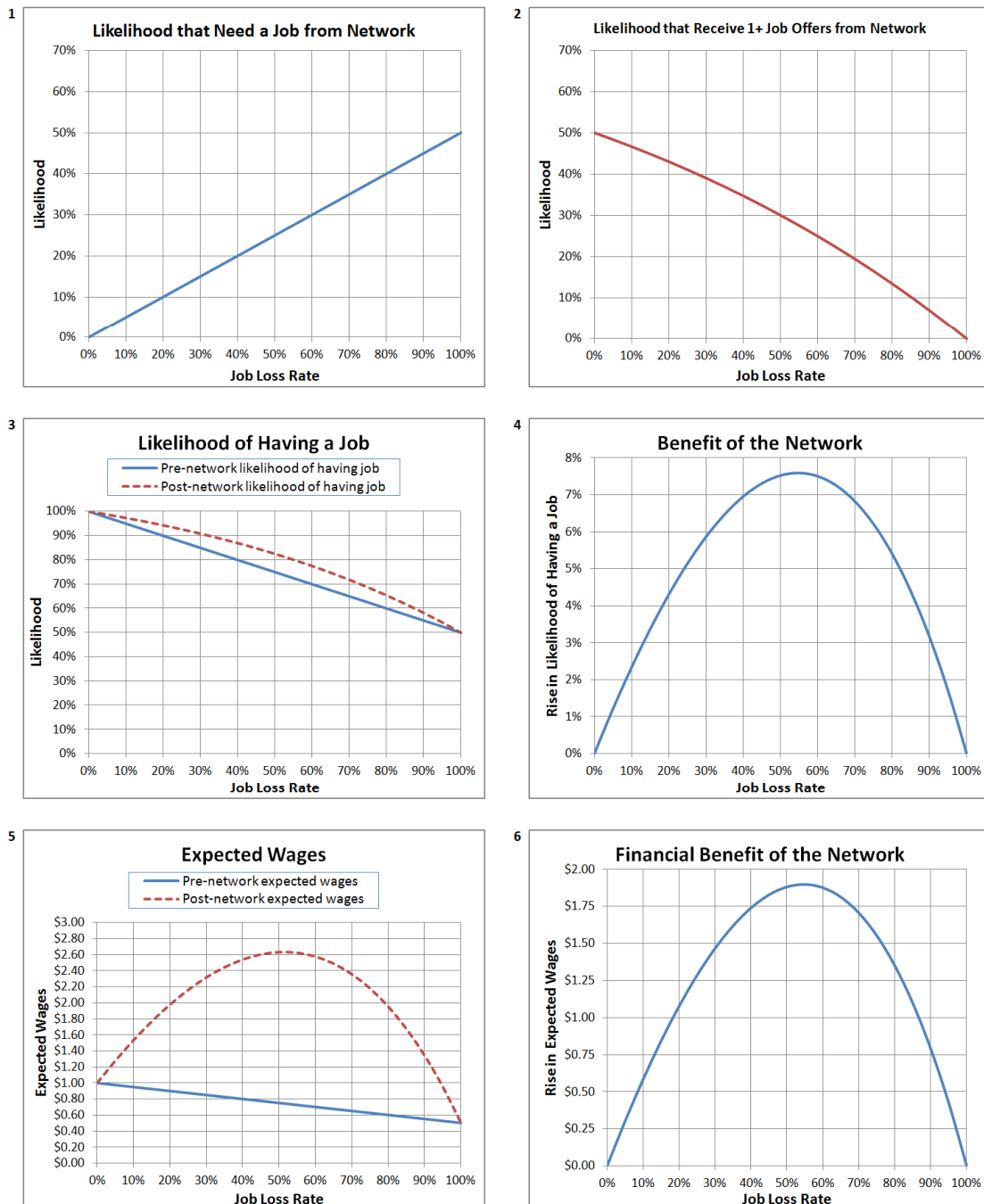
Figure 36. Information level 3 handout, for network-based wage of $25, graphical information
For job offer rate of 0.5 or 50 percent
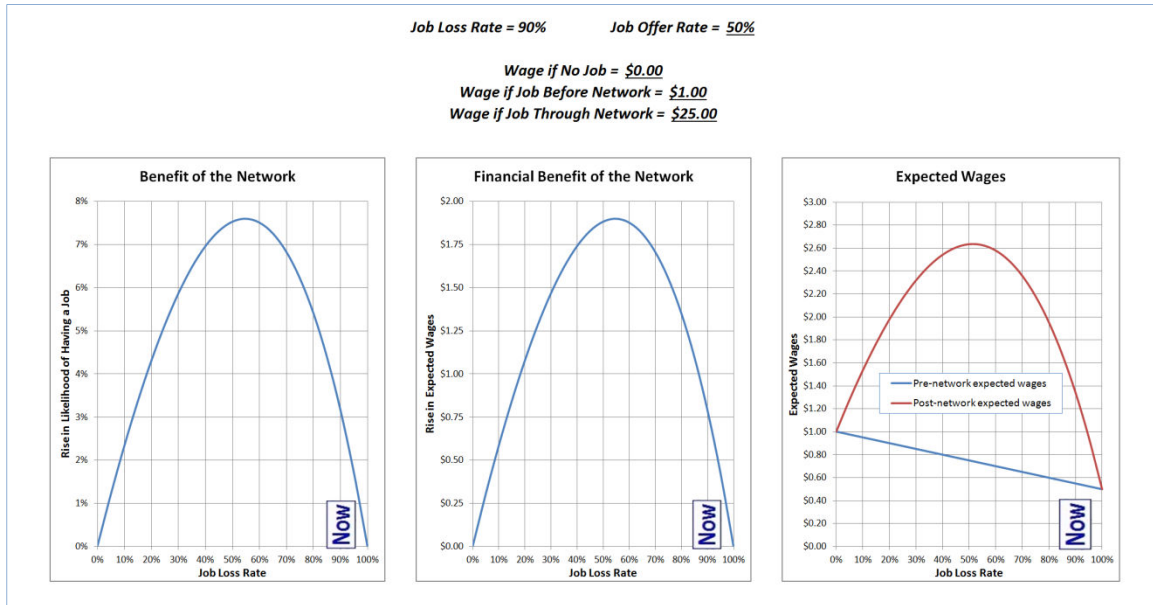
Figure 37. Screen display for network wage of $25, for job loss rate of 90%
This is what subjects would see before each period under information level 3. The "Now" icon shows the current job-market conditions that apply, which, in this example is for a job loss rate of 90%, while the job offer rate is 50%.

For the case of $25 network-based wage, Figure 36 shows the paper handout provided, and Figure 37 shows the corresponding screen image that appeared briefly at the start of each period to highlight the current job market conditions and benefits. In particular, Panel 5 of Figure 36 and the right-most panel of Figure 37 show the extremely large impact on expected wages from the job-contact network, for those subjects which are connected to at least one other lab subject.

Overall, the financial incentive was greatly amplified in these higher network-wage settings of $5 and $25 relative to the base case in which the network-based wage was simply equal to the formal job market wage of $1. Moreover, the incentives for investment in the middle cases (of 50 percent rate) grow by even more than the incentives grow for the low cases (of 10 percent rate) and for the high cases (of 90 percent rate). In

theory this might lead to not only higher levels of network investment overall, but also to more curvature against the job loss and offer rates. Although the $25 seems like a large payout for just one period of play, it is worth pointing out that this large payout only would happen in small number of cases, and so its costs to the experimenter were still manageable.

2.2 Playing Versus Computer Players

In the second laboratory extension, as mentioned, I study the effects of having the human subjects play only against four pre-programmed 'optimizing' agents, rather than against other live human subjects. The motivation for this setting is to remove some of the complexity packed into the G&M framework. Consider that in G&M the expected number of links a subject may have depends not just on his/her own investment choice, but also on the investment level(s) of his peers. One's investment level may only pay off if at least some other subjects likewise invest in the network. For instance, subjects may be looking for focal points among the investment choices. This level of complexity may make it difficult for lab subjects to focus on other key aspects of the situation. Without having to consider interpersonal strategy, lab subjects may be freer to focus on the greater repercussions that result from the rises and falls in the job loss and offer rates.

Another key advantage of countering human players with computer-programmed agents is that the strategies of the computer players, while varying according to the current job market conditions, would not otherwise vary over time. This could make them easier for the lab subjects to infer than in the case of human competitors. Also, lab subjects would be less likely to spend energy thinking about possible social repercussions

211

from their choices and wondering if there is any subtle signaling in the choices of their peers. Moreover, lab subjects may be less inclined to spend energy guessing about the motivations behind peers' choices and making interpersonal comparisons regarding gains or losses. A subject could pick his/her strategy without using 'intentionality detection' or 'mindreading' approaches (McCabe, Smith, LePore, 2000) on other humans. However, on the other hand, he/she may still try to put him/herself in the shoes of the computer players he/she is playing against, as an analog. But, overall, it should be easier, in this context, for the lab subjects to focus on the main impacts of the varying job loss and offer rates and to decide accordingly.

The computer agents are the same automaton agents described in Chapter 2, Section 3.6's optimal simulation, except in this case one of the players is a human player, instead of all five players being computer players. Again, I programmed the computer players to always select the G&M theoretically predicted response, according to the prevailing job market conditions. So, the computer players would respond exactly as perfectly 'rational' actors would. Since only integers are allowed for entry in the lab setting, when the optimal choice under G&M is not an integer, as described in Chapter 2, Section 3.6, I add and subtract a uniform random number between 0 and 1 and then round the result. This way, the integer that is closer to the optimal value is chosen with a bit higher frequency, in proportion to its distance from the optimal value.

Hypothetical Example of Lab Subjects and Computer Players					
Subject #	Group #	Computer Player #'s			
1	N/A	16	17	18	19
2	N/A	20	21	22	23
3	N/A	24	25	26	27
4	N/A	28	29	30	31
5	N/A	32	33	34	35
6	N/A	36	37	38	39
7	N/A	40	41	42	43
8	N/A	44	45	46	47
9	N/A	48	49	50	51
10	N/A	52	53	54	55
11	N/A	56	57	58	59
12	N/A	60	61	62	63
13	N/A	64	65	66	67
14	N/A	68	69	70	71
15	N/A	72	73	74	75

Figure 38. Hypothetical example of lab subjects and computer players
Depicts 15 lab subjects with 60 computer players, for 75 players total

Figure 38 provides a hypothetical example of lab subjects and computer players, depicting 15 lab subjects with 60 computer players, for 75 players total. So each lab subject is grouped with four computer players. Again, all computer players are identical, and are programmed to play the same way, according to G&M's theoretical prediction. Each computer player receives random job losses and job offers, just like the live lab subjects do. The random draws come from a common distribution each period, though the draws themselves are not literally identical across the computer players.

The only information that the lab subjects receive regarding the computer players' choices each period comes in the data shown on subjects' results and history screens at the end of each period. These include the following variables: the number of neighbors that subjects had each period; the number of jobs they received through the job-contact network; and the number of redundant job offers that they shared to others on the job-contact network. With only these limited pieces of information, the lab subjects would only be able to infer the computer players' strategies fairly indirectly.

213

In the data analyses that follow later on, I only report the human lab subject

responses and outcomes, and so I exclude the computer player responses and outcomes

from the various tables and figures shown. So, for example, regarding Figure 38, I would

only report the results from the 15 lab subjects, not from the full 75 game players.

2.3 Heterogeneous Rates Simultaneously

In the third laboratory extension, I explore the impact of varying the job loss and

offer rates across lab subjects within each period, while holding the *average* job loss and

offer rates constant across periods. This setting is motivated partly by the fact that

employment success can vary substantially across different types of people,[33] and this

diversity could make a material difference to the G&M equilibrium outcomes. This

heterogeneous rate scenario is in contrast to the base case G&M model in which the rates

change for all agents simultaneously (representing different phases of the economic

cycle), and the rates are identical across agents.

The unknown rates case is considered (in addition to the known rates case) in

order to mimic the situation in which one's employability is only revealed over time and

experience, for example through months of searching for work. It also mimics the

situation in which industry or technology changes occur faster than people can update

their self-assessment of their employment opportunities. Both the unknown and known

rates cases also capture the reality that the job prospects faced by other individuals are

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[33] Some evidence of cross-sectional variation in employment success is provided by unemployment rate data by age, sex and race/Hispanic origin, such as those shown in BLS (2017f).

typically hard to know, and, so, the individual may respond only to the average job prospects across people in the broader lab session or economy.

Subject #	Group #	Heterogen. Job *Loss* Rates		Heterogen. Job *Offer* Rates		Het. Loss *and* Offer Rates	
		Loss Rate	Offer Rate	Loss Rate	Offer Rate	Loss Rate	Offer Rate
1	2	90%	50%	50%	10%	50%	90%
2	4	10%	50%	50%	50%	90%	10%
3	1	50%	50%	50%	90%	10%	50%
4	3	10%	50%	50%	10%	10%	10%
5	4	10%	50%	50%	90%	50%	50%
6	2	90%	50%	50%	10%	90%	90%
7	1	10%	50%	50%	50%	90%	90%
8	3	50%	50%	50%	10%	10%	10%
9	2	50%	50%	50%	90%	50%	50%
10	4	90%	50%	50%	50%	90%	90%
11	3	10%	50%	50%	90%	10%	50%
12	1	90%	50%	50%	50%	10%	90%
13	4	50%	50%	50%	90%	90%	10%
14	1	90%	50%	50%	10%	90%	10%
15	3	10%	50%	50%	10%	50%	90%
16	2	50%	50%	50%	90%	10%	50%
17	4	50%	50%	50%	50%	50%	10%
18	3	90%	50%	50%	90%	90%	90%
19	1	10%	50%	50%	50%	10%	10%
20	2	90%	50%	50%	10%	50%	50%
Session Average		50%	50%	50%	50%	50%	50%

Hypothetical Example of Random Heterogeneous Job Loss and Offer Rates

Figure 39. Hypothetical example of random heterogeneous job loss and offer rates
Depicts 20 subjects total, spread among 4 groups of 5 subjects each, with session average rates of 50 percent.

Figure 39 illustrates a hypothetical example of heterogeneous job loss and offer rates for a given period. In this example, there would be 20 subjects total, spread among 4 groups of 5 subjects each. Note the job loss and offer rates would still average to 50 percent even when these rates are heterogeneous across subjects. The left-hand third of the figure depicts a situation of heterogeneous job *loss* rates while the job offer rate is held fixed at 50%. The middle third of the figure depicts a situation of heterogeneous job *offer* rates while the job loss rate is held fixed at 50%. The right-hand third of the figure

depicts a situation of heterogeneous job loss rates *and* heterogeneous job offer rates at the same time.

I implemented heterogeneous rates that vary randomly across lab subjects through a sequence of periods of known and unknown job loss and offer rates. In particular, I pursued six distinct variations across periods:

(1) Random job <u>loss</u> rates, *known* to the subjects, while holding the job offer rate constant at 0.5. [Repeated for 3 periods.]

(2) Random job <u>loss</u> rates, *unknown* to the subjects, while holding the job offer rate constant at 0.5. [Repeated for 10 periods.]

(3) Random job <u>offe</u>r rates, *known* to the subjects, while holding the job loss rate constant at 0.5. [Repeated for 3 periods.]

(4) Random job <u>offe</u>r rates, *unknown* to the subjects, while holding the job loss rate constant at 0.5. [Repeated for 10 periods.]

(5) Random job <u>loss</u> *and* <u>offer</u> rates, *known* to the subjects, while holding the job offer rate constant at 0.5. [Repeated for 3 periods.]

(6) Random job <u>loss</u> *and* <u>offer</u> rates, *unknown* to the subjects, while holding the job offer rate constant at 0.5. [Repeated for 10 periods.]

To be clear, the difference between the known and unknown rate scenarios was that, in the known rate scenarios, the lab subjects would see on their screen the particular job loss and/or offer rate that applied to them before deciding on their levels of network investment, while in the unknown rate scenarios, the lab subjects would not see on their screen the particular job loss and/or offer rate that applied to them.

Regarding the 'random' rates that applied for each lab subject, these rates would randomly be taken from one of three possible values: 10 percent, 50 percent and 90

percent. There was an equal chance of a subject having any of these three rates, and so, the lab session *average* was held fixed at 50 percent across the periods. [34]

Also, regarding the period repetitions, I reused the same random rate draws across the repetitions. For instance, if Subject #6 faced a randomly drawn job loss rate of 10 percent and a job offer rate of 50 percent for the first trial of ten repetitions, then these are the same rates that he/she would face each time. However, the results of those rates would not be held fixed across periods, so Subject #6 might be unemployed in the first repetition, then employed in the second repetition, then unemployed in the third and fourth repetitions, and so forth.

In the case of unknown rates, at first, the lab subjects would have no way to know what rates they face, and so I capture their choices in response to somewhat unknown job market conditions. In studying the resulting lab data, I can then try to infer what underlying strategies are at work. However, the lab subjects can eventually come to guess the rates that apply to them by noticing the empirical distribution of job losses and offers they receive. I repeat the same job conditions ten times in a row for the unknown rates situations in order to give the lab subjects a reasonable chance to divine what job market conditions they face. If/when the lab subjects come to realize the job loss and offer rates they face, they can then optimize relative to those rates. In contrast, for the

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[34] Another interesting possibility is a hybrid situation among heterogeneous rates and time-varying session average rates. More specifically, there could heterogeneous job and offer rates in the cross-section, but also a tilt in the distribution of rates, so that the average across the agents or lab subjects would not always be 50 percent for a given period. For instance, the average job loss rate could be varied to as low as, say, 35 percent (i.e., the economic bad times) and to as high as, say, 65 percent (i.e., the economic good times), while the individual rates are always either 10 percent, 50 percent or 90 percent, just in different proportions. This approach would enable economic down and up phases at the same time as rates were yet heterogeneous across subjects.

known job loss and offer rates, I repeat the same job conditions only three times in a row, since the lab subjects would not need several periods to pass before they knew what rates they faced; they would know all alone.

The goal of these heterogeneous rate scenarios is, first, to see if lab subject behavior is different in a setting possibly more familiar to them, namely, in which the employment prospects (including job loss and offer rate) vary across individuals, and some people may be persistently unemployed. A second goal is to gauge the extent to which lab subjects understand and appreciate the implications of good and bad economic times on the benefits from the job-contact network relative to just the job opportunities that they alone face. Specifically, the low and high rates faced by individuals would no longer imply anything about the overall economic conditions for any period, because regardless of the rates the face individually, the mean job loss and offer rates across all other lab subjects would be the same, namely 50 percent.

Regarding this second goal, note the G&M base case assumes that all agents face the same job loss and offer rates simultaneously. And so in this base case there is a one-for-one correspondence between low or high individual job loss and offer rates and the overall good or bad economic conditions faced by all others in the lab, which could correspond to economic downturns and economic booms. In contrast, in this extension to G&M, by varying the rates across lab subjects *within* each period but not on average across periods, I effectively wash out the trend in the economic cycle; the average job loss and offer rates across lab subjects would be constant at 50 percent each period. As such, this scenario could allow me to study whether the lab subjects factor in not only

their own job prospects but also the average or preponderance of rates that take place in the broader lab session or economy. Only conditions for the former (i.e., the rates that apply to the individual) should affect the likelihood that individual lab subjects would need the network in the first place, while only conditions for the latter (i.e., for the overall lab group) should affect the likelihood that individual lab subjects would receive a forwarded job offer through the job-contact network.

3 Empirical Results

In this section, I review the laboratory findings from implementing the three extensions discussed.

3.1 Trends by Period

I start with a summary of the lab data across periods. The trends studied include the level of network investment, the slope of the choices across job loss rates, and the time spent in responding per period. I use multi-period averages in order to reduce some of the apparent random noise in the period by period raw data. Only data from the high network-based wage scenario are presented in this subsection.

Figure 40 shows the network investment average and median choices from the high network-based wage treatment of the laboratory experiment. As was seen in the base case from Chapter 2, the mean and median series tend to trend together, though the gap between them widens a bit in the later periods. In this treatment, near the start of the experiment, subjects invest in roughly 3.5 units of network investment, then around 4 units during the middle rounds, and then with roughly 3 units in the closing rounds; so,

overall, the network investment amount stays fairly constant throughout the experiment. In contrast, in the base case setting from Chapter 2, the level of network investment (as well as the spread relative to the theoretical predictions) fell substantially between the earlier and later periods of the experiment, from roughly 3.5 units down to roughly 1 unit, on average. It is possible that this difference is attributable to the high network-based wage, which is introduced in Period 13.
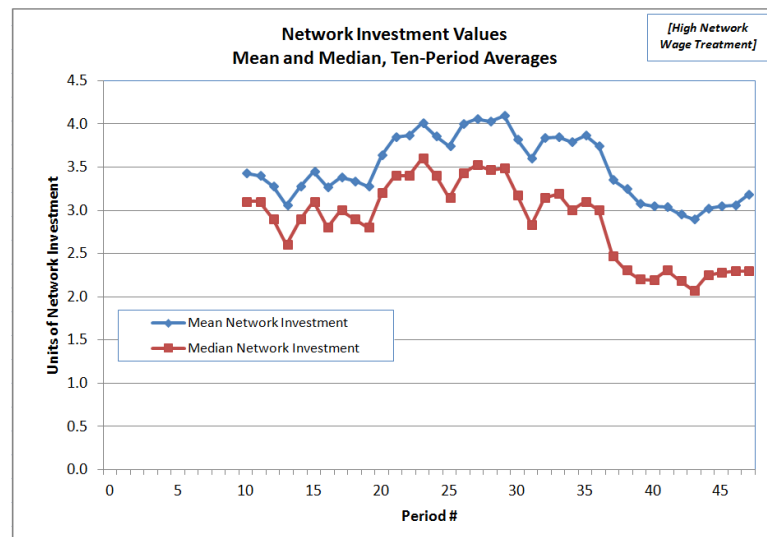
Figure 40. Spread between network investment lab average and theory, under high network wage treatment

Whereas in Chapter 2 I plotted the spread between the lab network investment and the theoretical predictions, here I simply plot the level of network investment because the theoretical predictions have not been formally created for the scenario of high network wage, and that would represent a major change relative to the core theory. So, the 'offroading' of this lab extension could provide some insight into this new situation and perhaps ultimately motivate further development of the corresponding theory.

Using the trend categorizations discussed in Chapter 2, Section 3.5, Figure 41 shows the results from grouping the lab subjects' data into trios of job loss rates across a fixed job offer rates; the 'trios' concept was described in reference to Table 2 of Chapter 2, Section 3.1. These results are from the high network-based wage treatment. Near the start of the experiment, more than 60 percent of subjects choose an upward-sloping strategy across the three sequential job loss rates, and this later declines down to around 35 or 40 percent. Regarding the inverse-U trios, they start at around 45 percent and rise up to about 60 percent. Finally, less than 10 percent of lab subjects play all zeros in any of the periods. Speaking casually, these results appear very different than in the base case from Chapter 2. There, the share of subjects choosing zero grew very high by the end of the experiment; the share of subjects choosing the inverse-U approach declined rather than rose between the start and end of the experiment; and the share choosing the upward-sloping approach had declined even below 10 percent. As mentioned at the end of Chapter 2, Section 3.5, the sum of the shares across types of trend will not always equal 100 percent due to some value combinations that could be classified among more than one type of trend.
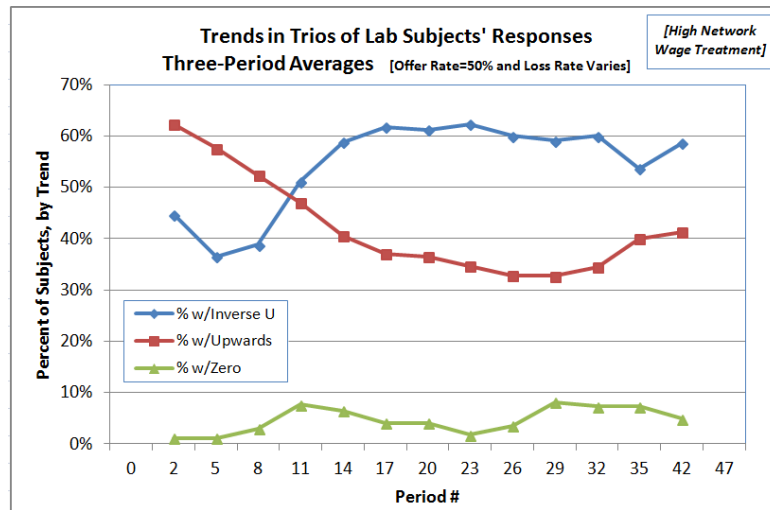
Figure 41. Percent of subjects with trends in their loss-rate trios, under high network wage treatment

Figure 42 shows the average response time of the lab subjects, by period, in the high network-based wage treatment. In the early periods, the average time spent is about seconds, and this incrementally falls to an average time spent of about 3.5 seconds by the end of the experiment. This is relative to the 30 second time allotment, and so on average subjects leave a large amount of time on the table, when they otherwise could have still been making computations. Thus, the time allotment does not appear to be literally binding. But the amount of time spent is systematically about 2 seconds lower amongst subjects who simply choose zero for all three periods in a given trio, relative to the amount of time spent by subjects whose responses trace out either an inverse-U or upward-sloping trend. This suggests that the zero strategy is easier to quickly compute, or that these lab subjects intentionally pay less attention to the period-specific details. The decline in response time occurs about equally regardless of the trend in lab subject data, and so the 2-second spread between those playing zero and those not playing zero

remains fairly constant across the periods. These findings are fairly close in line with those in the base case from Chapter 2.
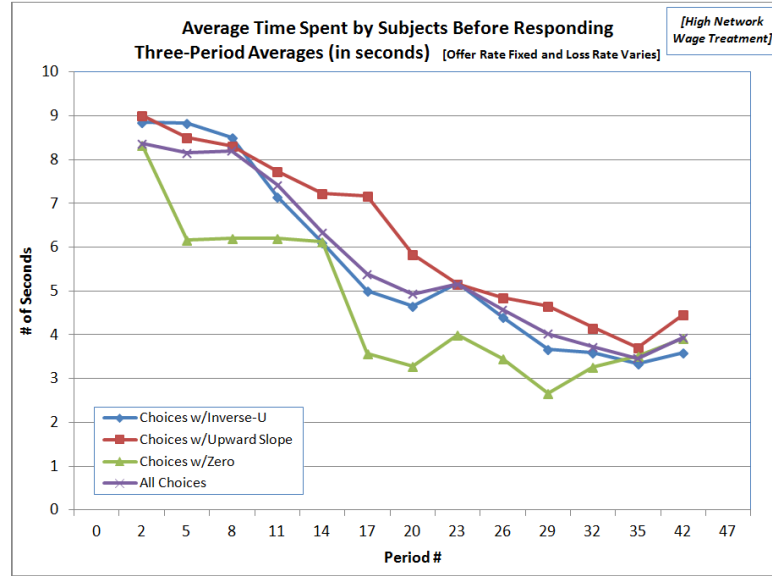
Figure 42. Avg. time spent by subjects according to loss-rate trio trends, under high network wage treatment

3.2   Empirical Model

For each extension (e.g., high network wage, computer players, heterogeneous known or unknown rates), I use the same empirical model discussed in Chapter 2's Section 4.2.1, with some additional superscripting of the variables to label the particular extension at hand. Likewise, the same variables are used as described in Chapter 2's Section 4.2.2, with the exception of one new variable, that is included in some versions of the high network-based wage model, discussed below.

3.2.1   High Network-Based Wage. I use the following models for the high network-based wage scenario.

Level model:

$$Y_{i,t}^{hnw} = \delta^{hnw} + \theta_i^{hnw} + \boldsymbol{\alpha}^{hnw}\mathbf{X}_t + \boldsymbol{\beta}^{hnw}\mathbf{M}_{i,t}^{hnw} + \boldsymbol{\gamma}^{hnw}\mathbf{D}_i + \varepsilon_{i,t}^{hnw}$$

223

Rate model:

$$Z_{i,t}^{hnw} = \Pr(Y_{i,t}^{hnw,*} > 2 \mid \mathbf{X}, \mathbf{M}^{hnw}, \mathbf{D}) = \rho^{hnw} + \varphi_i^{hnw} + \boldsymbol{\pi}^{hnw}\mathbf{X}_t + \boldsymbol{\kappa}^{hnw}\mathbf{M}_{i,t}^{hnw} + \boldsymbol{\lambda}^{hnw}\mathbf{D}_i + \mu_{i,t}^{hnw}$$

in which the 'hnw' refers to 'high network wage,' the i is for individual and t is for

period, i.e., time.

Importantly, I run two versions of these models, one in which the $\mathbf{X}_t$ contains the

network wage as an additional covariate and one in which the $\mathbf{X}_t$ does not contain the

network wage as a covariate. The results from running both versions of the model are

shown in the regression results tables, and included in the hypothesis testing. Below is

more information about the network-based wage covariate:

Additional Covariate:

Additional Core Job-Market Factor ($\mathbf{X}$):
- Network-Based Wage (X_6): This variable connotes the wage paid to any lab
  subjects that obtain a job through the job-contact network in the current period.
  In the base case, the network-based wage is simply \$1, i.e., identical to the basic
  wage from the formal job market. But in other treatments it is \$5 or \$25.

The θ_i and φ_i in the model represent random person (subject) effects, and, as will

be discussed in Section 3.2.4, I estimate them using the Fuller and Battese (1974)

method. Since the error terms, $\varepsilon_{i,t}$ and $\mu_{i,t}$ may involve heteroskedasticity and

autocorrelation in this setting, I use the Newey-West (1994) estimator to estimate the

covariance structure, as discussed in Section 3.2.4. I then use the estimated variance-

covariance matrix to run a feasible generalized least squares estimation routine. These

steps lead to heteroskedasticity- and autocorrelation-consistent standard errors in the

model runs.

3.2.2 Computer Players. I use the following models for the computer players

scenario.

Level model:

$$Y_{i,t}^{cp} = \delta^{cp} + \theta_i^{cp} + \boldsymbol{\alpha}^{cp}\mathbf{X}_t + \boldsymbol{\beta}^{cp}\mathbf{M}_{i,t}^{cp} + \boldsymbol{\gamma}^{cp}\mathbf{D}_i + \varepsilon_{i,t}^{cp}$$

Rate model:

$$Z_{i,t}^{cp} = \Pr(Y_{i,t}^{cp} > 2 \mid \mathbf{X}, \mathbf{M}^{cp}, \mathbf{D}) = \rho^{cp} + \varphi_i^{cp} + \boldsymbol{\pi}^{cp}\mathbf{X}_t + \boldsymbol{\kappa}^{cp}\mathbf{M}_{i,t}^{cp} + \boldsymbol{\lambda}^{cp}\mathbf{D}_i + \mu_{i,t}^{cp}$$

in which the 'cp' refers to 'computer players,' the i is for individual and t is for period,

i.e., time. The other information given in Section 3.2.4 applies, regarding the estimation

of random subject effects using the Fuller and Battese (1974) method and the use of

Newey-West (1994) heteroskedasticity- and autocorrelation-consistent standard errors in

the model runs.

3.2.3 Heterogeneous Job Loss and Offer Rates. I use the following models for

the heterogeneous job loss and offer rates scenario.

Level models:

Heterogen. known rates:

$$Y_{i,t}^{hk} = \delta^{hk} + \theta_i^{hk} + \boldsymbol{\alpha}^{hk}\mathbf{X}_t + \boldsymbol{\beta}^{hk}\mathbf{M}_{i,t}^{hk} + \boldsymbol{\gamma}^{hk}\mathbf{D}_i + \varepsilon_{i,t}^{hk}$$

Heterogen. unknown rates:

$$Y_{i,t}^{hu} = \delta^{hu} + \theta_i^{hu} + \boldsymbol{\alpha}^{hu}\mathbf{X}_t + \boldsymbol{\beta}^{hu}\mathbf{M}_{i,t}^{hu} + \boldsymbol{\gamma}^{hu}\mathbf{D}_i + \varepsilon_{i,t}^{hu}$$

Rate models:

Heterogen. known rates:

$$Z_{i,t}^{hk} = \Pr(Y_{i,t}^{hk} > 2 \mid \mathbf{X}, \mathbf{M}^{hk}, \mathbf{D}) = \rho^{hk} + \varphi_i^{hk} + \boldsymbol{\pi}^{hk}\mathbf{X}_t + \boldsymbol{\kappa}^{hk}\mathbf{M}_{i,t}^{hk} + \boldsymbol{\lambda}^{hk}\mathbf{D}_i + \mu_{i,t}^{hk}$$

Heterogen. unknown rates:

$$Z_{i,t}^{hu} = \Pr(Y_{i,t}^{hu} > 2 \mid \mathbf{X}, \mathbf{M}^{hu}, \mathbf{D}) = \rho^{hu} + \varphi_i^{hu} + \boldsymbol{\pi}^{hu}\mathbf{X}_t + \boldsymbol{\kappa}^{hu}\mathbf{M}_{i,t}^{hu} + \boldsymbol{\lambda}^{hu}\mathbf{D}_i + \mu_{i,t}^{hu}$$

in which the 'hk' refers to 'heterogeneous known,' the 'hu' refers to 'heterogeneous unknown,' the i is for individual and t is for period, i.e., time. The other information given in Section 3.2.4 applies, regarding the estimation of random subject effects using the Fuller and Battese (1974) method and the use of Newey-West (1994) heteroskedasticity- and autocorrelation-consistent standard errors in the model runs.

3.2.4   Model Estimation. As with the base case model from Chapter 2, in fitting the models, I run a one-way random effects method from Fuller and Battese (1974) to estimate the covariance matrix and then use this to run an iterated feasible generalized least squares (GLS) routine. Using Hausman (1978)'s m-statistic, I, again, do not reject the null hypothesis that there does not exist a correlation between the person effects and the covariates. Given person effects can also be reasonably treated using fixed effects, I separately also ran the estimation using fixed effects, and the results were very much the same as with random effects.

I, again, address the serial dependence in the subject choice data by using the Newey-West (1994) form of heteroskedasticity- and autocorrelation-consistent (HAC) standard errors based on a multivariate kernel density estimation. This is in contrast to creating a dynamic model with some form(s) of lagged dependent variable on the right-hand side of the equation. So, using HAC standard errors, I avoid having to possibly violate the assumption of independence in the would-be lagged random intercepts.

Regarding multicollinearity amongst the regressors, again, the variance inflation factors do not indicate high collinearity except for between the linear and quadratic terms

of the job loss rate and the job offer rate. However, given the computation of these squared terms as **X** data times itself, this finding is not surprising. It may raise the standard errors of the coefficients on these variables and make them overly sensitive to even small changes in the model specification.

In order to constrain the R-squared measure between 0 and 1 while using a GLS routine, I, again, use a generalization of R-squared from Buse (1973) as a measure of goodness of fit.

For the high network wage model, in one version of the regression runs, I also include a wage dummy variable which may absorb some of the potentially higher network investment, as mentioned in Section 3.2.1.

3.3   Hypotheses Considered and Tested

In this section I discuss the hypotheses related to each of the three G&M model augmentations that I test in the lab. The main strategy is to compare the coefficient estimates from the extension model results with those from the 'comparable base case' model results. The 'comparable base case' data are subsets of the overall base case data used in the analyses from Chapter 2 that are most relevant to the extension being run. Note that simulations are not used in testing these extension results because the theory has not been derived. However, the results of the laboratory experiment could yield some insights regarding stylized facts that future authors may be able to take into consideration upon deriving related theory.

3.3.1   Formal Hypotheses Tested.   The formal hypotheses tested for these three treatments are made relative to the empirical models explicitly described in Section 3.2,

which are, with small modifications, identical to those from Chapter 2's Section 4.2 regarding the base case scenario. The hypothesis tests run here are also very similar to those run in Chapter 2, Section 4.3.1, for the base case scenario. Again, the hypothesis tests are carried out by running constrained versions of the models or by directly comparing the estimated coefficients across runs of the empirical model with different subsets of the sample data.

Below I describe the hypotheses tested for the <u>Level</u> models. Analogous tests are also run for the <u>Rate</u> models, with the **α**, **β**, and **γ** vectors replaced by the **π**, **κ** and **λ** vectors, respectively, though these rate hypothesis tests are not explicitly shown here.

(1L) Jointly, the coefficient on Loss Rate is not zero, and the coefficient on Loss Rate squared is not zero.

$$H_0 : \alpha_1 = 0 \text{ and } \alpha_2 = 0 \qquad\qquad H_1 : \alpha_1 \neq 0 \text{ or } \alpha_2 \neq 0$$

This is a weak test for whether the linear term is positive and the quadratic term is negative, both of which are needed for the graph to first rise and then fall in the first quadrant. If the estimated $\hat{\alpha}_1 > 0$ and $\hat{\alpha}_2 < 0$, then the joint test for $\alpha_1 \neq 0$ and $\alpha_2 \neq 0$ could represent a lower bound on whether $\alpha_1 > 0$ and $\alpha_2 < 0$.

(2L) Jointly, the coefficient on Offer Rate is not zero, and the coefficient on Offer Rate squared is not zero.

$$H_0 : \alpha_3 = 0 \text{ and } \alpha_4 = 0 \qquad\qquad H_1 : \alpha_3 \neq 0 \text{ or } \alpha_4 \neq 0$$

This is a weak test for whether the linear term is positive and the quadratic term is negative, both of which are needed for the graph to first rise and then fall in the first quadrant.

(3L) The coefficient on Cost is negative:

$$H_0 : \alpha_5 = 0 \qquad\qquad H_1 : \alpha_5 \neq 0$$

This is a weak test of whether network investment is obeying an uncompensated law of demand, in which Cost is representing price. Fully-rational agents in the G&M model would have a strong negative response to rising cost.

(4L) Tests for whether the individual coefficients are equal between the model run with the lab data from the high network-based wage, 'hnw,' scenario versus from the comparable base case, 'cbc.'

$$H_0 : \quad (a)\, \delta^{hnw} = \delta^{cbc}; \ (b)\, \alpha 1^{hnw} = \alpha_1^{cbc}; \ (c)\, \alpha_2^{hnw} = \alpha_2^{cbc}; \ (d)\, \alpha_3^{hnw} = \alpha_3^{cbc}; \ (e)\, \alpha_4^{hnw} = \alpha_4^{cbc}; \ (f)\, \alpha_5^{hnw} = \alpha_5^{cbc}$$

$$H_1 : \quad (a)\, \delta^{hnw} \neq \delta^{cbc}; \ (b)\, \alpha_1^{hnw} \neq \alpha_1^{cbc}; \ (c)\, \alpha_2^{hnw} \neq \alpha_2^{cbc}; \ (d)\, \alpha_3^{hnw} \neq \alpha_3^{cbc}; \ (e)\, \alpha_4^{hnw} \neq \alpha_4^{cbc}; \ (f)\, \alpha_5^{hnw} \neq \alpha_5^{cbc}$$

(5L) Tests for whether the individual coefficients are equal between the model run with the lab data run from the computer player, 'cp,' scenario versus from the comparable base case, 'cbc.'

$$H_1 : \quad (a)\, \delta^{cp} \neq \delta^{cbc}; \ (b)\, \alpha_1^{cp} \neq \alpha_1^{cbc}; \ (c)\, \alpha_2^{cp} \neq \alpha_2^{cbc}; \ (d)\, \alpha_3^{cp} \neq \alpha_3^{cbc}; \ (e)\, \alpha_4^{cp} \neq \alpha_4^{cbc}; \ (f)\, \alpha_5^{cp} \neq \alpha_5^{cbc}$$

$$H_1 : \quad (a)\, \delta^{cp} \neq \delta^{cbc}; \ (b)\, \alpha_1^{cp} \neq \alpha_1^{cbc}; \ (c)\, \alpha_2^{cp} \neq \alpha_2^{cbc}; \ (d)\, \alpha_3^{cp} \neq \alpha_3^{cbc}; \ (e)\, \alpha_4^{cp} \neq \alpha_4^{cbc}; \ (f)\, \alpha_5^{cp} \neq \alpha_5^{cbc}$$

(6L) Tests for whether the individual coefficients are equal between the model run with the lab data from the heterogeneous known rates, 'hk,' scenario versus from the comparable base case, 'cbc.'

$$H_1 : \quad (a)\, \delta^{hk} \neq \delta^{cbc}; \ (b)\, \alpha_1^{hk} \neq \alpha_1^{cbc}; \ (c)\, \alpha_2^{hk} \neq \alpha_2^{cbc}; \ (d)\, \alpha_3^{hk} \neq \alpha_3^{cbc}; \ (e)\, \alpha_4^{hk} \neq \alpha_4^{cbc}; \ (f)\, \alpha_5^{hk} \neq \alpha_5^{cbc}$$

$$H_1 : \quad (a)\, \delta^{hk} \neq \delta^{cbc}; \ (b)\, \alpha_1^{hk} \neq \alpha_1^{cbc}; \ (c)\, \alpha_2^{hk} \neq \alpha_2^{cbc}; \ (d)\, \alpha_3^{hk} \neq \alpha_3^{cbc}; \ (e)\, \alpha_4^{hk} \neq \alpha_4^{cbc}; \ (f)\, \alpha_5^{hk} \neq \alpha_5^{cbc}$$

(7L) Tests for whether the individual coefficients are equal between the model run with the lab data from the heterogeneous unknown rates, 'hu,' scenario versus from the

comparable base case, 'cbc.'

$$H_1: \quad (a)\, \delta^{hu} \neq \delta^{cbc}; \; (b)\, \alpha_1^{hu} \neq \alpha_1^{cbc}; \; (c)\, \alpha_2^{hu} \neq \alpha_2^{cbc}; \; (d)\, \alpha_3^{hu} \neq \alpha_3^{cbc}; \; (e)\, \alpha_4^{hu} \neq \alpha_4^{cbc}; \; (f)\, \alpha_5^{hu} \neq \alpha_5^{cbc}$$

$$H_1: \quad (a)\, \delta^{hu} \neq \delta^{cbc}; \; (b)\, \alpha_1^{hu} \neq \alpha_1^{cbc}; \; (c)\, \alpha_2^{hu} \neq \alpha_2^{cbc}; \; (d)\, \alpha_3^{hu} \neq \alpha_3^{cbc}; \; (e)\, \alpha_4^{hu} \neq \alpha_4^{cbc}; \; (f)\, \alpha_5^{hu} \neq \alpha_5^{cbc}$$

Regarding tests 4L, 5L, 6L and 7L, I expect there could be correlations between the different information-level regressions run that may need to be accounted for. Also, given the multiple t-tests at hand, there may be multiple comparisons issues. Specifically, the actual significance level may not equal the stated significance level.

3.3.2 *Intuitions Regarding Hypotheses.* In this subsection, I describe rationales for the hypotheses tested as well as some expectations about the likely findings.

3.3.2.1 *High Network Wage.* In the first extension, as discussed, the lab subjects receive a higher wage if they find a job through the network (i.e., informal labor market) than if they have a job from the initial job losses and offers that transpired (i.e., formal job market). Although G&M's model is not solved for the case in which the network wage differs from the basic wage, I conjecture that there will be more curvature in the network investment against the job loss and offer rates, as well as higher levels of network investment overall. I believe this to be the case because of the much higher return on the network in this setting, and because of the magnified differences in network benefit across scenarios in this setting. I discuss the details behind these predictions in greater detail in Section 3.3.2.1.1. So, when fitting my empirical models, I would expect to see regression coefficients on the linear job loss term and the quadratic job loss terms that are larger in absolute value than they are in the base case, and I would expect the Intercept to be larger as well. Also, regarding the cost covariate, I have no specific

230

prediction regarding the likely effect of this higher network-based wage.

In addition to the basic high network-based wage model, I run another version of this which includes the level of the network wage (with values of either $1, $5 or $25) as an additional covariate. In this version of the model, qualitatively, I would expect this new network wage covariate to have a positive sign. But, as a result, this additional covariate would likely absorb some of the explanatory power of the other explanatory variables, lowering their economic and statistical significance slightly.

3.3.2.1.1 Details behind conjectures about high network-wage scenario. In this subsection, I go over the details of my logic for predictions regarding the case of high network-based wage. In order to gauge the incentive to invest in the high network-wage setting, it is helpful to approximate the new 'benefit of the network,' by scaling up old 'benefit of the network,' computed in the way discussed at the end of Chapter 2, Section 3.4, by the higher network-based wage being paid. [35] For example if the new network wage were $5, compared to the basic network wage of $1, and if the computed benefit of the network, hypothetically, is 0.06 for a given set of job-market conditions, then the rise in expected wage from the network would be approximately $5 times 0.06, or $0.30, in this case. Therefore, the optimal network investment in this case should be $0.30 higher than under the case of plain $1.00 wage, or $1.30 in total.

Similarly, to predict whether the extent of *curvature* in the network investment choices will show a rise and fall as the job loss rate rises, it is helpful to consider the

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[35] Although the higher network-based wage would likely lead to more network and investment and thus more network connectivity, some of the benefit of the connectivity is likely crowded out by the negative externality from having more links on the network, in which additional links of a neighbor reduce the chance of that neighbor forwarding one a job offer due to the rivalry of the job information in the job-contact model. So the net effect of the higher network-based wage is uncertain and possibly near zero.

shape of G&M's implied optimal network investment curve, presented in the left-hand panel of Figure 5 in Chapter 2, Section 2.4. As discussed at the end of Chapter 2, Sections 2.6 and 3.4, the 'benefit from the network' curve should be one for one with this optimal network investment curve. As an approximation, one could consider that a higher network-based wage, relative to the basic, non-network wage, might simply scale that shape of optimal investment (from Figure 5) upwards by however many multiples of the basic wage. In that case, the rise in absolute expected benefit of the network would be largest when the job loss rate is roughly 50 percent, and the rise in absolute expected benefit from the network would necessarily be smaller when the job loss rate is 10 percent or 90 percent.

[However, one reason why these statements are just approximations is that there also are feedback effects that one cannot easily account for, aside from actually solving the augmented model. Specifically, when all agents know that the other agents face these higher investment incentives, the exact choices of those other agents' behavior could have second-, third-, etc. round effects on the optimal level of network investment by any individual agent.]

Thus, when the network-based wage rises relative to the non-network wage, not only does the expected network benefit rise, but the increase is largest toward the middle of the job loss rates distribution. Although this rationale is based on an approximation, if reasonable, it predicts that a higher network wage would raise the incentives for a fully rational actor (playing against other fully rational actors) to increase his/her network investment in general, but especially for job loss rates in the middle range. Thus, not

only would the rational actor choose to invest more overall, but he/she would also exhibit stronger inverse-U curvature than in the base case in which the network wage and the non-network wage are equal.

3.3.2.2 Computer Players. In the second extension, as discussed, the lab subjects play against four computerized players instead of with other human subjects. The subjects are told that the computer is programmed to play the game optimally, seeking only to maximize their expected earnings from the game. The G&M model is not solved for this case of mixed types of players. Despite considering several possibilities, I have no particular conjecture regarding the effect of including these computer players with human subjects on the level or curvature of the network investment choices relative to the job loss and job offer rates, and nor with regards to the effect of cost. I discuss some of the possibilities I considered in Section 3.3.2.2.1.

It is worth noting that, even if the human subjects wanted to follow and mimic the strategies of the computer-programmed optimal players, it would not be easy to do so, since each period there is not very much information is available about the investments of other players. For instance, the average network investment levels from other players is not reported. Specifically, what *is* reported includes: the subjects' number of neighbors, an indicator on whether he/she received a job through the network, an indicator on whether he/she shared a job to others on the network, and the history of these variables across all prior periods. These variables alone would be difficult to use in order to reverse engineer the computer players' game strategies, especially, given the variation in job offer and loss rates (i.e., a moving target.).

3.3.2.2.1   Some possibilities related to the computer players scenario. In this subsection I go over some thoughts related to the computer players scenario, and I conclude that there is no clear prediction to be made regarding the effects.

First, a corollary assumption in this situation is that the computer players are unaware of the existence of the one human actor, and so they continue to just optimize assuming that all other players are rational value-maximizing agents just like themselves. Otherwise, factoring in the unknown responses of human subjects, the computer players' strategies would then not be optimal. So, the ignorance of the computer players about the human subjects' participation is critical. Overall, this laboratory experiment/extension provides information about what people would do if they were the one inhabitant of an economy with fully rational actors that are unaware of the existence of the one human actor.

Although the G&M model is not designed for this situation of rational agents mixed with human subjects having unknown preferences and computation abilities, it is possible to make some conjectures. It is possible that the essence of the human-subject behavior is already adequately modeled via the rational-actor computer players. Perhaps people, by and large, behave 'rationally,' and they may believe that the strategies used by their fellow human subjects are mostly optimal or rational as well. In that case, it should not matter if computer players take the place of human players, and the G&M predictions might still apply. If human subjects' choices of network investment were already rational in the base case against other 'rational' subjects, then they should still be rational in this case against human players.

On the other hand, if the laboratory subjects do not tend to behave akin to how rational actors behave, as has been shown in many prior laboratory experiments (see Duffy (2015), for some examples), then it is harder to pin down theoretical predictions for this mixed case. Or even if the lab subjects knew how the rational actors make their choices, despite these human vs. rational actor trend differences, it is still hard to guess what will transpire. If people do not believe that their peer human subjects are choosing optimally, then the direction of the effect on network investment could be either higher or lower. In the simplest of terms, if the human subjects think that the rational actors tend to invest 'too little' in the network on average, or 'too much' on the network, as discussed in Chapter 2, Section 1.4, then 'best response' to such an assumption is not easy to work out, and it likely varies with the job market conditions (i.e., with the job loss and offer rates) as well. There is no clear prediction regarding the direction or effect on the level or curvature of the network investment choices relative to the job loss and job offer rates, and nor with regards to the effect of cost.

3.3.2.3 Heterogeneous Rates Simultaneously. In the third extension, as discussed, the job loss and job offer rates, i.e., the formal job market prospects, are *heterogeneous* across agents, at any given time, instead of being homogeneous as in the base case. Only the average of the job loss and offer rates is known to the agents, namely 50 percent, but not the instantiations (i.e., draws) of these rates that apply independently to each subject. As discussed, the motivation for the case of heterogeneous job loss and offer rates is to better match some real-world phenomena, for example, in which some people are better positioned to find employment through the formal job market than are

235

others, or in which the job prospects for certain classes of workers may rise or fall relative to those of others (for example, as different sectors of the economy relatively expand and/or as technology differentially impacts job functions). Moreover, there are different settings in which information about the heterogeneous job prospects of oneself or of others may be known or unknown to the agents.

Although the G&M model is not solved for this situation, the predictions likely hinge on what the agent and the others know about the job loss and offer rates they and others face. [The fact that these are one-shot games, as opposed to dynamic games is also likely important.] The heterogeneous rate(s) that an individual faces probably informs him/her about the likelihood that he/she will need the network at all. The average rate that the other people in the lab sessions face probably informs the individual about the likelihood that he/she would receive a redundant job offer forwarded to him/her over the job-contact network from these other people.

In the case of heterogeneous self-*known* rates, the individuals would know the specific job loss and offer rates that they face, but they would not know those faced by others. In these scenarios, I conjecture that there would be a flatter network investment profile against the job loss rate because others' investment choices are the same on average regardless of the individual's rates. However, it would not be completely flat because there are some individual effects from the lower or higher rates. More specifically, I would expect that both the quadratic and linear terms in the fitted regression models would be reduced, corresponding to a more muted relation between network investment and the job loss and offer rates. I go into some details behind these

236

predictions in Section 3.3.2.3.1 below. Regarding the job offer rate, the logic is very similar, though somewhat reversed. So, overall, I also expect to see a flatter network investment profile against the job offer rate in the case of heterogeneous job offer rates. And in the case of heterogeneous loss rates and heterogeneous offer rates at the same time, I expect to see flatter network profiles in network investment against both the job loss rate and job offer rate simultaneously.

In the case of heterogeneous self-*unknown* rates, while the individual would still know the average rate that prevails amongst the other lab subjects, he/she would now not know the rate(s) that apply to him/herself. I would expect that the individuals would simply invest based on the average rates that would prevail both for him/herself and for others, however, noting that even when rates average to 50 percent, this average is composed of about one third of individual rates at 10 percent and about one third of individual rates at 90 percent. Since the optimal network investment in such cases is lower than at the 50 percent level, I would expect the average network investment to be substantially lower here than in the case of 50 percent rates.

It is possible that through repetition of a given scenario (i.e., in which the rates were held constant across periods), an individual may be able to learn the likely rate(s) that applies to him/her by studying the empirical distribution of job loss and offers that have transpired across the periods. This is partly why the lab design has ten sequential repetitions of the exact same job market conditions per lab subject for the cases of heterogeneous job loss and offer reates. To the extent that the individual develops confidence in his/her assessment of the likely job loss and/or offer rates he/she faces, I

would expect his/her network investment choices to start to conform to those from the case of self-*known* heterogeneous rates discussed further above.

To actually solve this case analytically is challenging because one must take into account not just partial equililbrium first-round responses, as I have somewhat done above, but also, the feedback that those decisions have on the productivity of the job-contact network, and then that change in productivity's effect on agents' inclination to invest, and so forth, recursively, until new general equilibrium might be reached. Superficially, it is easy to run simulations in which the loss and offer rates faced by individuals vary from agent to agent. This itself could lead to slightly different network topology and network matching rates. However, to be more realistic, the simulation would need to take into account the changed incentives at hand, which, as discussed above, would lead to different network investment choices, and then have further effects. In order to obtain accurate simulation results, it would be helpful to have the closed-form solution or optimizing equation at hand, which might be challenging to produce.

3.3.2.3.1 Details behind conjectures about heterogeneous job loss rates. In this subsection I run through some additional details behind the logic of my conjectures related to the network investment choices heterogeneous job loss rates.

Specifically, when an individual faces a <u>*low*</u> <u>job loss rate</u>, normally (i.e., in the homogenous rates case) low investment is predicted because he/she and his peers are unlikely to lose their jobs. However, in this heterogeneous rates case, the average job loss rate of the others is still the same (at 50 percent) even when it is low for any individual, and so the economy-wide average chance of losing a job is higher than the

238

low rate this individual faces. These other people could, thus, on average, choose a moderate amount of network investment. Relative to the homogeneous rates case, this would raise the chance of the individual receiving a job offer forwarded to him/her from others over the job-contact network. Thus, I predict the network investment for low individual job loss rate would not be as low as in the G&M base case.

And when an individual faces a *high* job loss rate, normally (i.e., in the homogenous rates case) low investment is predicted because he/she and his peers do not expect there to be many jobs floating around the job-contact network. However, in this heterogeneous rates case, the average job loss rate of the others is still the same (at 50 percent) even when it is high for any individual, and so the economy-wide average chance of losing a job is lower than the high rate this individual faces. These other people could, thus, on average, choose a moderate amount of network investment. Relative to the homogeneous rates case, this would raise the chance of the individual receiving a job offer forwarded to him/her over the job-contact network. Thus, I predict the network investment for high individual job loss rate will not be as low as in the G&M base case.

Finally, when an individual faces a *middle* job loss rate, normally (i.e., in the homogenous rates case) high investment is predicted because he/she expects there would be both a moderate chance that he/she would lose his job and a moderate chance that of some redundant job offers being shared with him/her by others on the job-contact network. However in this heterogeneous rates case, although the average job loss rate of the others is still the same (at 50 percent), within that average, many people are facing 10

percent job loss rates and 90 percent job loss rates, both of which are scenarios that would incentivize lower network investment relative to the levels normally predicted at 50 percent rates. Since the network benefits to the individual are likely to be less then in the homogeneous rates case, I predict that the individual would invest less in the job-contact network for middle individual job loss rate than in the G&M base case.

3.4 Regression Results

In this section I review the results from estimating the regressions. Although my discussion is fairly casual in this section, the formal hypothesis test results between the treatments and comparable base cases are reported in the next section, Section 3.5.

In the regression output that follows, t-statistics are shown in a smaller font below the coefficient estimates. To help assess the statistical significance of the coefficient estimates, I include the below re-printed Table 7 from Chapter 2, which references critical values of Student's t distribution, for $v = 120$ degrees of freedom, for two-tailed hypothesis tests, based on values from Box, Hunter and Hunter (2005). Given my sample size in all cases greatly exceeds 120, using this table is slightly conservative.

Table 7 (re-printed from Chapter 2). Critical values of Student's t distribution with v = 120 degrees of freedom
For two-tailed tests; based on values from Box, Hunter and Hunter (2005), Table B1

Combined two-tail area probability	0.10	0.05	0.02	0.01
Critical values	1.658	1.980	2.358	2.617

Regression results, for the <u>level</u> models, from all three extensions relative to their comparable base cases, are shown in Table 18.

Table 18. Regression results for level models extensions
t-statistics are shown below the coefficient estimates in a smaller font

				(Level Models)				
			Regression Results for Extensions, for Human Subjects					
	Normal Wages			Normal Play		Homogen.	Unknown Heterogen.	
		High Network Wage		Against Computers		Known Heterogen.		
# of Observations	4,255	2,615	2,615	8,700	1,700	10,400	645	1,775
Root-Mean Square Error	2.122	2.575	2.575	2.498	2.389	2.519	1.895	1.724
R-Squared	0.3122	0.3052	0.3052	0.2380	0.3221	0.2297	0.5715	0.5114
Intercept	0.234	1.511	3.181	1.242	-0.811	1.055	9.232	7.976
	0.28	1.04	2.23	1.99	-0.43	1.84	4.52	8.54
Loss Rate	4.530	8.307	8.333	5.439	6.742	5.715	2.994	0.804
	12.14	12.82	12.79	16.80	9.53	19.15	2.60	1.26
Loss Rate ^ 2	-3.293	-6.631	-6.598	-3.619	-3.809	-3.695	-0.499	0.335
	-9.14	-10.57	-10.46	-11.74	-5.55	-12.96	-0.46	0.55
Offer Rate	3.262	1.308	-2.375	0.556	0.295	0.539	-0.034	-1.768
	8.23	1.27	-2.99	1.82	0.29	1.86	-0.03	-2.57
Offer Rate ^ 2	-3.675	-0.858	2.912	-1.858	-2.156	-1.904	-1.863	1.642
	-9.78	-0.85	3.86	-6.26	-2.22	-6.75	-1.65	2.45
Cost		-21.966	-20.895					
		-7.01	-6.64					
Network Wage		0.039						
		5.57						
Period	-0.017	-0.024	-0.036	-0.023	-0.018	-0.024	-0.002	-0.005
	-11.98	-4.06	-6.39	-18.65	-1.76	-19.53	-0.47	-0.93
Time Limit (in seconds)	-0.008	-0.029	-0.032	0.000	0.033	0.001	-0.018	-0.071
	-1.48	-2.29	-2.50	-0.09	1.17	0.20	-0.80	-4.59
Seconds Used / Session Avg	0.806	-0.025	-0.020	0.712	1.871	1.068	0.528	0.257
	4.78	-0.09	-0.08	5.23	8.44	9.09	1.55	1.25
Past Num Neighbors / Session Avg	2.552	4.131	4.130	1.607	0.541	1.371	3.190	2.429
	21.96	23.11	22.97	24.18	4.63	23.84	14.41	25.74
Past Lost Job Rate	0.162	-0.024	-0.020	-0.034	-0.086	-0.094	-0.600	0.496
	1.34	-0.13	-0.11	-0.80	-0.98	-2.44	-2.67	3.57
Past Got Job Through Network Rate	0.037	0.011	0.011	0.043	-0.062	0.019	0.173	0.070
	2.07	0.24	0.24	3.06	-1.82	1.45	2.66	2.16
Past Shared Job Rate	-0.173	-0.253	-0.250	0.044	-0.100	-0.011	0.464	-0.047
	-1.40	-1.48	-1.45	0.86	-0.98	-0.23	2.05	-0.34

Regarding the *high network-based wage* scenario, the coefficients on Loss Rate

and Loss Rate squared both appear to be larger in absolute value than under the

comparable base case scenario, and the Intercept appears to be larger too. This would

indicate that the lab subjects are choosing higher levels of network investment as well as exhibiting additional inverse-U curvature against the job loss rate. The Network Wage variable has a positive and statistically significant coefficient estimate of 0.039, indicating that, on average, a $1 increase in the network wage leads to a 0.039 rise in the quantity of network investment. As mentioned in Section 3.2.1, the Network Wage is the amount paid to subjects when they find a job through the network, and it corresponds to $1 in the base case (i.e., in which the network-based wage and basic wage are the same), $5 in Periods 13-18 and Periods 37-47 of the high-network wage treatment, and $25 in Periods 19-36 of the high-network wage treatment. Back to the regression results, however, the coefficients on both Offer Rate and Offer Rate squared appear smaller in absolute value relative to the comparable base case, indicating less curvature against the job offer rate, and their difference from zero is no longer statistically significant. Moreover, in the version of the model lacking the Network Wage covariate, the coefficients on both Offer Rate and Offer Rate squared both change signs. Formal test results between the treatment and the comparable base cases are in Section 3.5.

Regarding the *computer players* scenario, the coefficient on Loss Rate appears larger in value than under the comparable base case scenario, and the coefficient on Loss Rate squared appears about the same. The coefficient on the Offer Rate appears smaller in value, and its difference from zero is not statistically significant; however, the coefficient on the Offer Rate squared appears larger in value, and its difference from zero is statistically significant. Also, the positive and statistically significant coefficient on the Seconds Used (relative to the session average) variable appears to be larger in value than

under the comparable base case, indicating that, in this treatment, there is a larger rise in network investment from lab subjects taking longer to reply than in the base case.

Regarding the *heterogeneous known rates* scenario, both the coefficients on Loss Rate and Loss Rate squared appear smaller in absolute value than under the comparable base case scenario, indicating less curvature in network investment against the job loss rate. Similarly, both the coefficients on Offer Rate and Offer Rate squared appear smaller in absolute value than under the comparable base case scenario, indicating less curvature in network investment against the job offer rate. Also, the Intercept appears much larger in value than under the base case. It is worth noting this treatment has the smallest sample size of 645 observed choices, and so it might be worthwhile to collect a bit more lab data in this setting to confirm the findings here.

Finally, regarding the *heterogeneous unknown rates* scenario, the coefficient on Loss Rate appears smaller in value, and the coefficient on Loss Rate squared flips sign and is no longer statistically significant, relative to under the comparable base case scenario. Moreover, the coefficients on the Offer Rate and Offer Rate squared both flip sign and are statistically significant in this unexpected direction. Also, the Intercept, again, appears much larger in value than under the base case.

Regression results from the <u>rate</u> models, from all three extensions relative to their comparable base cases, are shown in Table 19.

Table 19. Regression results for rate models extensions
t-statistics are shown below the coefficient estimates in a smaller font

	Normal Wages			Normal Play		Homogen.	Unknown Heterogen.	
(Rate Models) Regression Results for Extensions, for Human Subjects								
		High Network Wage		Against Computers		Known Heterogen.		
# of Observations	4,255	2,615	2,615	8,700	1,700	10,400	645	1,775
Root-Mean Square Error	0.284	0.260	0.255	0.217	0.303	0.212	0.517	0.462
R-Squared	0.3551	0.4310	0.4324	0.4246	0.4165	0.4286	0.3445	0.3452
Intercept	0.131	0.382	0.596	0.367	-0.228	0.282	0.635	0.952
	0.93	1.57	2.50	3.46	-0.70	2.89	1.71	5.09
Loss Rate	0.862	1.543	1.546	1.100	1.585	1.184	0.681	0.489
	13.80	14.23	14.21	19.98	12.86	23.32	3.26	3.81
Loss Rate ^ 2	-0.651	-1.282	-1.278	-0.809	-1.148	-0.867	-0.322	-0.228
	-10.81	-12.21	-12.13	-15.44	-9.59	-17.87	-1.64	-1.85
Offer Rate	0.633	0.470	-0.003	0.248	0.203	0.239	-0.013	-0.328
	9.54	2.73	-0.02	4.79	1.14	4.83	-0.06	-2.38
Offer Rate ^ 2	-0.711	-0.425	0.060	-0.465	-0.510	-0.467	-0.334	0.276
	-11.32	-2.51	0.47	-9.22	-3.02	-9.72	-1.62	2.06
Cost		-3.019	-2.881					
		-5.75	-5.48					
Network Wage		0.005						
		4.28						
Period	-0.003	-0.003	-0.004	-0.004	-0.003	-0.004	-0.002	-0.004
	-11.20	-2.59	-4.36	-17.58	-1.96	-17.99	-2.48	-3.52
Time Limit (in seconds)	-0.001	0.008	0.007	0.000	0.002	0.001	-0.008	-0.005
	-1.01	3.65	3.48	0.82	0.38	1.12	-2.04	-1.75
Seconds Used / Session Avg	0.113	0.109	0.110	0.114	0.328	0.180	-0.004	-0.002
	4.01	2.47	2.47	4.93	8.49	9.02	-0.06	-0.04
Past Num Neighbors / Session Avg	0.401	0.584	0.584	0.248	0.075	0.212	0.521	0.437
	20.64	19.52	19.45	21.93	3.70	21.63	12.94	23.12
Past Lost Job Rate	-0.021	0.010	0.011	-0.016	0.001	-0.020	-0.010	0.076
	-1.03	0.34	0.35	-2.20	0.07	-3.00	-0.25	2.73
Past Got Job Through Network Rate	0.005	-0.002	-0.002	0.006	-0.010	0.004	0.033	0.023
	1.74	-0.31	-0.30	2.62	-1.64	1.63	2.80	3.54
Past Shared Job Rate	-0.027	-0.032	-0.032	0.016	-0.010	0.007	0.132	-0.005
	-1.30	-1.13	-1.11	1.86	-0.54	0.92	3.21	-0.19

The results from these <u>rate</u> models are qualitatively very similar to those from under the level models. In particular, in the *high network-based wage* case, the curvature in the share of 'network investment exceeding two' variable against job loss rate appears to be stronger in the high network-based wage case than in the comparable base case,

however, the curvature against the job offer rate appears to be weaker. Moreover, if the Network Wage variable is not included, then the coefficient estimates on Offer Rate and Offer Rates flip sign. Regarding the *computer players* case, the curvature in the share of 'network investment exceeding two' against the job loss rate appears to increase, while the curvature against the job offer rate appears to be little changed. Regarding the *heterogeneous known rates* case, the curvature in the share of 'network investment exceeding two' variable against both the job loss rate and job offer rate appears to decrease. Regarding the *heterogeneous unknown rates* case, the curvature in the share of 'network investment exceeding two' variable against the job loss rate appears to decrease, and the coefficients on the Offer Rate and Offer Rate squared flip sign and are significant in this unexpected direction.

Taking an overall initial impression of the regression results from these three augmentations to the base case, it appears that under the *high network wage* scenario, the effect and curvature of the job loss rate are stronger, though the effect and curvature of the job offer rate are somewhat reduced, relative to the comparable base cases. Under the *computer players* scenario, the results are fairly comparable with those from the comparable base case. Under the *heterogeneous known rates* scenario, the effects of Job Loss and Offer Rate appear to decay somewhat relative to the comparable base case. Finally, under the *heterogeneous unknown rates* scenario, the effects of Job Loss and Offer Rate decay yet further, and even flip sign relative to expectation. These extension results help give some perspective to the results found in the base case models from Chapter 2. Next, I review the related formal hypothesis test results.

3.5 Hypotheses Test Results

In this section I review the results from the formal hypothesis testing of the three laboratory extensions relative to their comparable base cases.

- Test 1L: For the *high network-based wage* scenario, in the equation that includes the Network Wage variable, with an F-statistic of 113.27, I reject the null hypothesis that the coefficients on Loss Rate and Loss Rate-squared are zero; with a t-value of -7.01, I reject the null hypothesis that the coefficient on Cost is zero. In the equation that excludes the Network Wage variable, with an F-statistic of 110.99, I reject the null hypothesis that the coefficients on Loss Rate and Loss Rate-squared are zero; with a t-value of -6.64, I reject the null hypothesis that the coefficient on Cost is zero.

  For the *computer players* scenario, with an F-statistic of 157.05, I reject the null hypothesis that the coefficients on Loss Rate and Loss Rate-squared are zero. For the *heterogeneous known rates* scenario, with an F-statistic of 35.61, I reject the null hypothesis that the coefficients on Loss Rate and Loss Rate-squared are zero. For the *heterogeneous unknown rates* scenario, with an F-statistic of 22.83, I reject the null hypothesis that the coefficients on Loss Rate and Loss Rate-squared are zero.

- Test 2L: For the *high network wage* scenario, in the equation including the Network Wage variable, with an F-statistic of 9.54, I reject the null hypothesis that the coefficients on Offer Rate and Offer Rate-squared are zero. However, in the equation that excludes the Network Wage variable, with an F-statistic of 2.00, I fail to reject the null hypothesis that the coefficients on Offer Rate and Offer Rate-squared are zero.

  For the *computer players* scenario, with an F-statistic of 53.53, I reject the null

hypothesis that the coefficients on Offer Rate and Offer Rate-squared are zero. For the *heterogeneous known rates* scenario, with an F-statistic of 13.81, I reject the null hypothesis that the coefficients on Offer Rate and Offer Rate-squared are zero. For the *heterogeneous unknown rates* scenario, with an F-statistic of 3.32, I reject the null hypothesis, at the 5 percent significance level, that the coefficients on Offer Rate and Offer Rate-squared are zero.

• <u>Test 3L</u>: For the *high network wage* scenario, in the model including the Network Wage variable, with a t-value of -7.01, I reject the null hypothesis that the beta on Cost is zero. In the model that excludes the Network Wage variable, with a t-value of -6.64, I reject the null hypothesis that the beta on Cost is zero.

• Test results from <u>Test 4L</u>, <u>Test 5L</u>, <u>Test 6L</u> and <u>Test 7L</u> are presented in the below text and tables.

The following tables contain grids of t-statistics for individual tests of the difference between the coefficients from running the extensions models and from running the comparable base case models (i.e., with the most relevant subsets of the data analyzed in Chapter 2). The tests are run at three levels of assumed correlation, r=0.0, r=0.5 and r=1.0. Given the collection of so many individual statistical tests, 'multiple comparisons' issues may arise, which could imply that the probability that I find statistically significant differences is greater than the stated significance levels of the individual tests. However, no related adjustments are made here. As a result, the findings could be somewhat discounted accordingly.

The tests were executed by subtracting one model's coefficient estimates from the

other model's coefficient estimates and dividing this difference by the 'standard error of the difference.' As usual, the standard error of the difference is computed as the square root of the sum of the squares of the reported standard errors of the two coefficient estimates minus two times the assumed correlation coefficient times the product of the reported standard errors.

Table 20. Statistical test results of high network wage treatment relative to comparable base case

Higher Network Wage vs. Comparable Base Case			
by correl. coefficient (r) assumption			
t-statistics from the standard error of a difference computation			
	r=0.0	r=0.5	r=1.0
Intercept	0.76	1.01	2.08
Loss Rate	5.05	6.71	13.75
Loss Rate ^{2}	-4.62	-6.12	-12.50
Offer Rate	-1.77	-2.17	-3.09
Offer Rate ^{2}	2.61	3.19	4.44

Comparison of data from the higher network wage treatment relative to a comparable base case

Regarding the *high network-based wage* scenario, even with the assumption of zero correlation, the individual t-statistics reported in Table 20 suggest there are statistically significant differences in all of the coefficients, though the effect on Offer Rate may be only marginally so. These t-statistics suggest that the coefficients on Loss Rate and Loss Rate squared are larger in absolute value in the high network-based wage scenario than under the comparable base case. However, the opposite takes place for the Offer Rate. Note these results were created with the version of the high network-based wage model containing Network Wage as one of the covariates. So, under the high network wage scenario, the level effect and curvature of the Loss Rate are found to be stronger, but the level effect and curvature of the Offer rate are found to be weaker.

I conjecture that one possible reason for the diminished effects on the offer rates at the same that there were increased effects on the loss rates loss rates could be related to the explicit sequencing of the different job loss rate scenarios versus the mere implicit sequencing of the different job offer rate scenarios. Related to this, the impact of the different levels of job loss rate were shown right next to each other in the information-level-3 handout materials, whereas, the impact of the different levels of job offer rate could only really be seen in detail by comparing across separate pieces of paper. Perhaps this issue could be studied through additional data collection in a setting that switched the explicit versus implicit roles of the trios of job loss and offer rates.

Table 21. Statistical test results of computer treatment relative to comparable base case

Computer Treatment vs. Comparable Base Case			
t-statistics from the standard error of a difference computation			
	by correl. coefficient (r) assumption		
	r=0.0	r=0.5	r=1.0
Intercept	-1.03	-1.23	-1.63
Loss Rate	1.67	2.12	3.40
Loss Rate ^{2}	-0.25	-0.32	-0.50
Offer Rate	-0.24	-0.29	-0.36
Offer Rate ^{2}	-0.29	-0.35	-0.44

Comparison of data from the computer treatment relative to a comparable base case

Regarding the *computer players* scenario, even with an assumption of one-hundred percent correlation, the individual t-statistics reported in Table 21 suggest there are not statistically significant differences in the coefficients relative to the comparable base case scenario, except for the coefficient on the Loss Rate, which might be a bit stronger in the computer players scenario than under the comparable base case scenario. However, with an assumption of zero correlation, the difference in Loss Rate also may

not be statistically significant. Overall, the results are found not to be very different from the comparable base case scenario.

Table 22. Statistical test results of heterogen. rates treatment relative to comparable base case

Heterogeneous Known Rates vs. Comparable Base Case				Heterogeneous Unknown Rates vs. Comparable Base Case		
by correl. coefficient (r) assumption				by correl. coefficient (r) assumption		
t-statistics from the standard error of a difference computation				t-statistics from the standard error of a difference computation		
	r=0.0	r=0.5	r=1.0		r=0.0	r=0.5	r=1.0
Intercept	3.86	4.48	5.57	Intercept	6.32	8.49	19.22
Loss Rate	-2.29	-2.63	-3.20	Loss Rate	-6.95	-8.85	-14.35
Loss Rate ^{2}	2.86	3.30	4.03	Loss Rate ^{2}	5.95	7.57	12.23
Offer Rate	-0.50	-0.57	-0.69	Offer Rate	-3.09	-3.86	-5.81
Offer Rate ^{2}	0.03	0.04	0.05	Offer Rate ^{2}	4.87	6.08	9.13

The left-hand panel shows Heterogeneous Known Rates relative to comparable base case results.
The right-hand panel shows Heterogeneous Unknown Rates relative to comparable base case results.

Table 23. Statistical test results of heterogen. unknown rates relative to heterogen. known rates

Heterogen. Unknown Rates vs. Heterogen. Known Rates		
by correl. coefficient (r) assumption		
t-statistics from the standard error of a difference computation		
	r=0.0	r=0.5	r=1.0
Intercept	-0.56	-0.71	-1.13
Loss Rate	-1.66	-2.20	-4.30
Loss Rate ^{2}	0.67	0.89	1.80
Offer Rate	-1.32	-1.78	-4.02
Offer Rate ^{2}	2.66	3.56	7.60

Heterogeneous Unknown Rates treatment relative to Heterogeneous Known Rates treatment.

Regarding the *heterogeneous rates* scenarios, taken together, the individual t-statistics reported in Table 22 (both left-hand and right-hand panels) and Table 23 suggest that the heterogeneous rates tend to diminish the relationships of Loss Rate, Loss Rate squared, Offer Rate and Offer Rate squared with the models' dependent variable, network investment. This is especially true for the heterogeneous *unknown* rates case, but it is fairly evident even from the heterogeneous *known* rates case as well. [However, as mentioned earlier, it might be helpful to have additional sample collected for the heterogeneous known rates scenario, in order to be more certain of the effects at hand.]

Comparing the known and unknown rates cases directly to one another shows the benefit of having self-rate information. When lab subjects are told the specific job loss and/or offer rates that they face, they are more likely to invest closer to the G&M optimal levels than when they are not told the specific rates that they face. Still, overall, in the heterogeneous rates scenarios, the core variables are found to have weaker relationships with network investment than in the comparable base case scenario.

The <u>Rate</u> version of these hypothesis tests also come out with very similar results overall to those presented for the Level hypothesis tests above, but they are not explicitly included or reviewed here.

3.6   Some Interpretations

In this section I discuss the results presented in Sections 3.4 and 3.5 relative to those presented earlier in Chapter 2 for the G&M base case. To give perspective, it is worth recalling the conclusions from the base case analyses in Chapter 2. In particular, I had found some amount of qualitative agreement between the lab subject behavior and the G&M theory, however, quantitatively, the lab subjects invested more than in the theory, but with far less curvature than in the theory. Also, it appeared that providing additional information could stimulate optimal investment choices to some degree. A main goal for running the three extensions analyzed in this Chapter was to observe whether the gap between theory and the lab results from Chapter 2 could be reduced and/or better understood.

Regarding the *high network-based wage* scenario, the lab data show larger linear level and quadratic effects of the job loss rate on the chosen levels of network investment,

as expected, relative to the comparable base case. Perhaps the additional wage premium from network jobs (i.e., informal job market) keeps lab subjects from just resorting to the all-zeros strategy. Moreover, the lab subjects have stronger estimated curvature in their network investment against the job loss rate than in the comparable base case. However, despite these statistically significant differences, upon studying the shapes of the resulting polynomials, it is clear that the differences between the high network-based wage case and the comparable base case are not that economically meaningful. Even with high network-based wage, the curvature is still a good deal removed from the base case G&M theoretical predictions. Moreover, in this high network-based wage setting, the theoretical predictions, though not analytically worked out, likely would entail yet much sharper curvature than in the base case theoretical predictions. So, in the end, even with the sweetener of much higher network wages on the table, the lab results are still very different from what would be theoretically predicted under G&M. While I continue to find solid qualitative agreement with the G&M predictions, I still do not find quantitative agreement with the G&M predictions.

Regarding the *computer players* scenario, the results overall suggest there is not a major difference from arranging the lab subjects to create job-contact networks with pre-programmed automatons. The only statistically significant coefficient difference, depending on the degree of correlation assumed, is on the Loss Rate variable, and in that case the Loss Rate appears to have a stronger linear effect with the computer players scenario. So, perhaps the human-ness of the other players in the base case lab scenarios is not actually that large of a distraction for the lab subjects, and so it would be hard to

pin the lack of agreement between the base case lab results and the optimal simulation results on the fact that the lab subjects face other live human subjects instead of pre-programmed computer players.

Regarding the *heterogeneous rates* scenarios, as anticipated, they tend to weaken the G&M relationships, relative to the comparable base case scenarios. This is especially true for the *unknown* rates scenario, in which subjects may have great difficulty knowing the current job conditions they individually face, even after several periods of repetition with the same job market conditions. However, it is also the case for the *known* rates scenario in which the lab subjects do know their current specific job conditions. [Note that in both the unknown and known cases, the lab subjects are told what the *average* of the rates across all subjects in the lab is, namely, 50 percent.] Also, there appears to be a benefit from having self-rate information, since lab subjects are more likely to invest closer to the G&M optimal levels when they are told the specific job loss and/or offer rates that they face, than when they are not told the specific rates that they face. Still, overall, it appears that when lab subjects are unsure of their own job prospects or when they are unsure what conditions prevail for their peers in the experiment, they are less likely to invest according to the predictions of the G&M's model.

Taken together, these extensions of the base case have been valuable in informing me about the upside limits to curvature (from the high network-based wage scenario), the apparent (lack of) impact of playing against human versus computer competitors (from the computer players scenario), the importance of knowledge about the job-market conditions that other face for making strategic decisions (from the heterogeneous known

rates case), and the importance of knowledge about ones' own job prospects for making strategic decisions (from the heterogeneous unknown rates case). The base case lab results are generally confirmed, and it does not appear that some small augmentations to the lab environment are bound to change them very much. Also, the G&M model predictions are somewhat qualitatively supported in the lab experiment data in that there is some amount of curvature in network investment against both the job loss and offer rates. However, the support is only moderate given how different the estimated coefficient parameters are relative to those in the benchmark optimal simulation.

Finally, while this study of lab augmentations looked at a small number of variations, there could yet be many other aspects of the base case lab environment that are acting to restrain otherwise optimal network choices by lab subjects. It would be worthwhile to continue to consider any other such factors and, if they seem to be important, to pursue tests of the impact of these factors as well.

4   Conclusion

In this section I bring together the overall findings from the three laboratory extensions run, and I consider some ideas relevant for future related work.

4.1   In Summary

I here review the main findings from each extension sequentially. In the first extension, *high network-based wage*, I studied a situation in which jobs found on the informal job market paid a higher wage than those found on the formal job market. In this setting, I found that the estimated coefficients on the job loss rate linear and quadratic

terms, in absolute value, were larger than in the comparable base case, as expected. The lab subjects seemed motivated to invest more in the network overall, but especially in the middle range of the job loss rates. However, I also found that the estimated coefficients on the job offer rate linear and quadratic terms, in absolute value, were smaller than in the comparable base case. As mentioned in Section 3.5, I conjecture this could be due to the sequencing of periods (explicit for loss rates, but implicit for the offer rates), and, if so, then additional lab data collection could help resolve this question.

On the one hand, it is encouraging that the effects of the job loss rates on network investment choice grew larger under the much stronger incentives that were implemented via the high network-based wage. On the other hand, these results, while technically different, are still practically in the same ballpark as the base case results. Thus, even the larger observed effects with the high informal market wages still fall far short of the curvature found predicted in the G&M model, based on the empirical results from simulation data with rational optimizing agents.

Other observations from the high network-based wage setting include that, notably, once the higher wage from the informal job market is introduced, there is a rise in the share of lab subjects choosing an inverse-U strategy; also, the share of lab subjects choosing all zeros does note rise steadily across the periods, but, rather, stays fairly low throughout the experiment. These two observations are different from what is seen in the comparable base case in which, across the periods, the share choosing inverse-U strategy continued to fall somewhat and the share choosing all zeros rose fairly steadily. However, similar to what was seen in the comparable base case, as the periods go by, the

255

lab subjects, on average, tend to invest somewhat less overall, and the share of lab subjects choosing an upward-sloping strategy falls. Also, the amount of time spent by the lab subjects on each decision, again, falls during the course of the experiment, and those playing the all-zero strategy, again, tend to spend the least amount of time per decision.

In the second extension, I studied a situation in which laboratory subjects played against pre-programmed *computer subjects* instead of human subjects. There the laboratory results were fairly closely aligned with the base case laboratory results studied in Chapter 2. Similar trends as in the base case prevailed regarding lab subject choices across periods with respect to the level of network investment chosen, the shares of inverse-U, upward-sloping and all-zero behavior, and the amount of time spent per decision. On the one hand, it is encouraging to find similar lab results from using computer competitors against the lab subjects because it may suggest that the basic lab setup is not overly complex or overly influenced by interpersonal or social considerations, i.e., that the basic setup could be good enough. On the other hand, due to this treatment not exhibiting a big impact from the use of computer competitors, this treatment was possibly less revealing because large differences in the computer player setting may have suggested ways to improve the basic lab design and simplify things in order to allow optimal play to emerge among the lab subjects at a higher rate.

Finally, in the third extension, I studied a *heterogeneous rates* case, in which a mix of low, medium and high job loss rates and/or job offer rates existed across the lab subjects simultaneously, and in some settings the lab subjects knew their own job prospects (*known* case), while in other settings they did not (*unknown* case). Overall,

these lab results seem to be 'flatter' relative to the comparable base case, with less curvature in network investment against the job loss rate and job offer rate concepts, as expected. On the one hand, it is encouraging to see that lab subjects appear to be less capable at optimizing when they have less information about the conditions that they or their peers face at a given time; this suggests that the information provided in the base case settings is making a difference for the lab subjects' network investment choices. On the other hand, while implementing heterogeneous rates arguably brought the lab experiment a small step closer to reality (in which job prospects typically vary among people, and people may not always know the extent even of their own job prospects), the lab results moved farther away from the G&M predictions, not closer to them.

Taken together, these three extensions help to rule out some possible alternative explanations of the laboratory results that I obtained in the base case results reported in Chapter 2, and they help to give some perspective. Overall, the base case findings are confirmed, the *qualitative agreement* between my lab results and the G&M predictions are supported, and the *quantitative disagreement* between my lab results and the G&M predictions are likewise supported. Of course, these particular extensions tested had been chosen from among many other possibilities, and some ideas for additional follow-up studies are discussed in Section 4.2 below.

4.2 Looking Ahead

Beyond the three augmentations I explored in this chapter, there are likely many additional alterations of this laboratory experiment that are worth trying in order to more fully assess the impact of varying job market conditions on chosen social network

investment and the network matching rate. A first suggested variation responds to the observation that lab subjects are not nearly as sensitive to job market conditions as predicted in the theory. That is, the gap between their chosen investment levels at the middle job loss (or offer) rates and their chosen investment levels at the more extreme job loss or offer rates is not as large as expected. One reason for this, as discussed in Chapter 2, Section 5.2 (third paragraph), could be that the gains available from G&M's job-contact network appear to be fairly modest overall, and as a result, the lab subjects could be somewhat indifferent across the various job market conditions.

If the gains from G&M's job-contact network are indeed modest, this could have to do with the one-shot nature of the game. Despite any differences at the end of a period, at the start of the next period all subjects begin again at the same starting line together. It is hard to provide a lot of reward for having a job from just one period of the G&M framework. However, if the game continued across periods, then there could be persistence in job status across periods of play, and this could allow accumulation of much larger monetary differences for those who have a job versus those who do not; thus, the stakes would be higher. Moreover, since most jobs are long-term arrangements, allowing jobs to persist across periods in the experiment may seem more familiar as a job setting to the lab subjects, perhaps helping them to comprehend and accept the job-contact network setting and to also make the laboratory experiment more interesting for them. For example, a related job-contact network model described in Schmutte (2016b)

is dynamic, and, analytically, the benefits from the referral network appear to be larger in that setting.[36]

Implementing laboratory job-contact networks that are allowed to endure and evolve over time would also allow opportunities for quid pro quo, i.e., for trading job offers among preferred partners, though this would be at odds with the generic nature of the job-contact network in this setup. And the range of possibilities would be yet greater if subjects could not only create links, but maybe also sever links strategically. On the other hand, some of these aspects of realism may be better suited for a field study, in which there was ample time for relationships to form and operate more naturally. If, during the course of a short two-hour lab study, subjects were concerned about the specific individuals with which to connect and trade, this could be a distraction from the main aspect(s) of the G&M game regarding the productivity of the network in the face of varying job-market conditions.

On a related note, since most employment relationships take shape and last over long periods of time, it might be interesting to conduct job-contact analyses in dynamic settings over weeks or months, say, over the Internet. On the other hand, one should also be mindful that such experiments would be much less controlled, may have many confounding motivations behind the subject choice behavior, and could ultimately cost the experimenter(s) a lot of funds.

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[36] Of note, as mentioned in Chapter 2 at the end of Section 2.5, G&M also present a form of dynamic model, though the network investment choice is made only once (at time zero), ahead of the experience of the job market conditions. It could be worth studying whether the network benefit is larger in that setting.

There are many other possibilities that could add realism and/or fun to the experiment. For example, one could implement any of the following: individual-specific networking instead of generic networking, in which people choose the particular people to connect with; real-effort link costs, in which creating connections took some amount of time and energy, beyond just a monetary costs; variable tie strength based on the amounts invested; directed links instead of undirected links, so that the job offer information could only go in the direction of the person who invested; different default choice settings, for instance, settings in which the default is to invest some amount unless the subject proactively changes that. Some of these ideas might be meaningful augmentations to the base case G&M model. However, it is not clear how any of them would really solve what appear to be the two main limitations of this current experiment, namely, the minor nature of rewards available through G&M's job-contact network and the degree of subject comprehension about the way jobs are shared when the job loss rate rises or the job offer rate falls.

Although this is a 'labor' kind of laboratory experiment, there is not much that is specifically labor-related about it. For instance, the jobs shared could instead just be construed generically as, say, desired information or puzzle pieces, that help one get along in life. In Cabrales, et al. (2011), it is the lure of special parenting knowledge that leads parents to socially network amongst other parents. It would be worth seeing whether changing the frame of this experiment might make any difference in the subject responses. A related possibility would be to stay in a labor context, but to put the lab subjects in the employer's shoes, and the job contact network would instead provide the

hiring manager with job candidates that he/she would otherwise not meet. In this arrangement, employee departures and hires from the informal market would be the analogs to job losses and being hired. These types of changes to the frame of the experiment are logically superficial and should not change the overall patterns of choice in the game. However, as has been shown often, for example in Thaler (2008), framing problems can have a large effect on peoples' ultimate choices.

As another idea, given that the simple epsilon-greedy exploitation-exploration simulation I ran, discussed in Chapter 2, Section 3.6, was able to replicate some features of the empirical distribution of network investment, it might, similarly, be useful to offer subjects a menu of strategies across trios to select from, such as to invest in U-shaped, inverse-U, downward-sloping, upward sloping, flat, random, etc., patterns, rather than leaving the lab subjects to, themselves, have to trace out such strategies sequentially across periods as the job offer and loss rates fluctuate. These kinds of strategy menus might help the lab subjects to more quickly learn about the laboratory environment, and they might aid the lab subjects in seeing the bigger picture of things across periods, as opposed to just the details of individual periods in isolation. On the other hand, they might somewhat coax lab subjects into picking choices that they would not have picked themselves and/or do not really understand, and it would constrain the options available to the subjects, thus possibly preventing some patterns of behavior, and related network structures, from emerging.

A simple modification to the basic lab design would provide a lot more empirical feedback for lab subjects without taking a lot more time. Specifically, after asking lab

subjects to select their network investment choice for given job loss and offer rates, one

could then run several (say, around ten) repetitions of the job-contact network using their

chosen network investment amount and the prevailing job market conditions. The results

from these repetitions could then be provided in summary form. Next, the lab subjects

could select again, under the same or different job market conditions, and receive results

from another sequence of many repetitions. This situation might provide greatly

expanded learning opportunities. Perhaps in this situation, lab subjects would be more

likely to understand the tradeoffs at hand and respond according to the G&M theory.

This setup may also be somewhat in line with the dynamic form of G&M's model that

the authors present in their Section 3.3, in which the agents pick their network investment

levels only once (at time zero), and then bear the consequences of that choice in the job-

sharing that takes place over time. Moreover, this could be another way to greatly raise

the stakes of marginal investment decisions, as the investment costs would be charged

multiple times, and the benefits could be accumulated over the multiple trials.

Although I clustered the lab subject data based on simple observed patterns in the

data set, there more systematic and tested ways to cluster data. For instance, Rong and

Houser (2015b) provide a helpful approach to data clustering, which they illustrate with

an example to separate out the lab-subject data in ways to distinguish types of game

players from within given lab experiments. The authors point out how it is desirable to

cluster the data in such a way that the within-group variation is relatively low, while the

cross-group variation is relatively high. So, it might prove helpful to revisit my data

clustering with a more sophisticated approach in this or a similar direction.

Finally, it could be helpful to explore what, if anything, about the G&M framework is especially difficult for lab subjects to understand and react to, and to compare this setup to other situations that are associated with people making surprising choices. After all, although a large share of subjects in this lab experiment exhibit the expected inverse-U shape in their investing, a large share does not. Moreover, it seems important for the experimenter to provide extensive instructions and intuitions about the environment in order for lab subjects to understand the main tradeoffs at hand. For the lab subjects that choose an upward-sloping trend in their network investment against the job loss rate, it might be helpful to learn what is behind such choices. Although the laboratory instructions do not mention the word "insurance" at all, many subjects may immediately arrive at the idea of insurance, which is something people tend to invest more in when the risks are higher, like when the job loss rate is higher (or the job offer rate is lower). However, in the G&M setting, in reality, the network, or 'insurance' product will tend to fail people exactly when they need it most. That is, when the job loss rate is high (or job loss rate is low), everyone is looking for a job simultaneously. In that case, although people would want to build connections to share jobs, the network structure created ultimately is like a tree that may have lots of branches, but which bears little or no fruit. This non-monotonic aspect of the model is not very intuitive.[37]

In order to better understand this phenomenon of overinvestment when the job loss rate is high (i.e., the job market is weak), it may be worthwhile to look at any other

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[37] It may be hard for people to see that, even if they are connected to others, their opportunities to benefit from those contacts is highly correlated with those contacts' job prospects as well, and so they might not benefit much from the job-contact network when times are bad for the group in general, even though that might have been their specific aim when they chose a high level of network investment in the case of a high job loss rate (or low offer rate).

financial instruments or entities that may have a negative return in the event that many

people rush to obtain access at the same time, for example, with bank deposits during a

bank run. It might also be helpful to bring the rich literature on heuristics, bounded

rationality and behavioral decision-making to bear on this situation. For instance, Thaler

(2015) presents many documented anomalies or surprises in human behavior relative to

rational choice theory over the past few decades. Moreover, Dohmen (2014) provides

analysis of the impact of behavioral economics specifically on *labor economics* in recent

decades. Overall, it could be helpful to see how the lab data from this experiment might

fit in with behavioral findings about other seemingly-perplexing choices that many

people systematically make, especially in situations related to labor and insurance.

4.3   Bounded Rationality, Theory and Experiment

In order to advance job-contact network research, it could be worthwhile to seek

further closing known gap(s) between related theory and experiment. One way to do so

could be via designing and implementing better lab experiments that perhaps better

isolate and measure the key factors and choices at work in the underlying theory.

Another way to do so could be to pursue refined economic theory. One aspect of such

theory could be the assumptions made about the population of agents in the economy. In

this direction, I note that the human-subject behavior I observed from the laboratory

implementation of the G&M framework conforms neither to the perfectly rational case,

nor to the 'zero intelligence' case.[38] These 'in-between' kind of lab results, which

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[38] Specifically, in my hypothesis tests of the lab data relative to the simulations from Chapter 2, which are
mostly confirmed in Chapter 3, I found statistically significant differences between the model coefficients
for the lab data under the G&M base case scenario and those under the optimal and random simulations.

simultaneously are non-rational and non-random, could correspond to some form of boundedly rational behavior taking place among the lab subjects, in the sense of Simon (1957).[39]

With these ideas of 'in-between' behavior in mind, it may be worthwhile to revisit the G&M framework with some form of boundedly rational agents instead of with the assumed perfectly rational agents.[40] Or if more complex objective functions could make the model intractable to solve, simulations might offer another way to approximate predictions in such cases. Perhaps with some form of boundedly rational agents, the corresponding theoretical predictions in a G&M kind of framework could work out to be closer to the results I observed in the lab compared (i.e., with modest curvature) than to the results predicted in the theory with fully rational agents (i.e., with sharper curvature). For example, Houser and Rong (2012wp) take a step in this direction in their approximation of the likely impact of agents having risk-averse preferences in lieu of risk-neutral preferences, in the basic G&M model, as shown in Figure 4 of Chapter 2, Section 2.3. On the other hand, it is possible that the essential results of the G&M framework are already borne out with the simple agents that G&M assume, and that making the agents more complex would not materially help. So, I make this suggestion only with caution.

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[39] For instance, many factors, such as humans' known computation limits and memory constraints, their complex objectives over monetary and non-monetary rewards, the array of monetary and non-monetary costs they face, etc., may combine to make humans appear to be very irrational in their behavior relative to what is predicted by agents acting strictly as homo economicus.

[40] A wide range of decision-making frameworks can fall under the category of bounded rationality. For just one example, perhaps some lab subjects make decisions in line with case-based decision theory, in which, rather than just looking ahead and analyzing abstractly, one looks back to past analogous cases and remembers how they turned out (Gilboa and Schmeidler, 1995; 2001).

Even if job markets are very competitive overall, there are likely areas in which improvements could be made in the process of job-worker matching. Given the large amount of job turnover that takes place, as suggested in Chapter 1, Figure 1, and given the high stakes of effective placement of employees, it is instructive to further study and document best practices regarding hiring through social ties among myriad approaches. In particular, thoroughly tested and significant findings, if properly broadcast, could be used as guiding principles by individuals and within private-sector initiatives and/or public policies in order to ultimately improve some outcomes. In my laboratory study of job-contact networks under controlled conditions, the published theory was somewhat predictive of the lab subjects' responses, but not fully. Although it may be possible for ordinary people to exploit a relationship between job market conditions and network productivity, it would be critical to first have additional supporting data and analysis, in order to better understand and predict all important effects, intended and/or unintended. Hopefully, my lab study can help to encourage the creation of other studies in this regard, that together could provide a clearer picture of the key issues and available benefits, and ultimately allow for some reliable guidance or best practices for job-contact networking.

Channeling Vernon Smith's and F.A. Hayek's notions about two orders of rationality in economics (Smith, 2008), one understands that much observed human individual behavior is based on instincts that have proven survival value and thus is likely ecologically rational in some context; at the same time, constructivist rational theory brings structure and predictability to analysis that helps one understand human behavior more deeply. When a preponderance of empirical results does not conform with a

266

particular theory, constructivist rational or not, one might then seek to better understand, apply or refine this theory in support of the new data, and ultimately build a revised constructivist rational theory. Since economics lab experiments can help to confirm and/or provide new stylized facts about human behavior, upon careful questioning and repetition, such lab experiments can aid researchers in recognizing when different or richer theory is needed. In this mindset, my laboratory data set regarding the G&M model is one contribution, among many other empirical studies, that test some predictions of economics of networks theory. Hopefully my work, in its own small way, facilitates continued fruitful discussion between theorists and empiricists about key phenomena, ultimately allowing the best next step(s) to be taken in this area of research.

5   Closing Note

In summary, this dissertation adds to the endogenous network formation literature in economics, regarding how people strategically create links and use them with regards to finding employment. It provides insights about how people may or should optimize their job search, trading off between time and energy spent on traditional market searching versus on social networking, under varying job-market conditions. This entails studying how people form job-contact networks, optimize their network structure, and share information among their connections, and highlighting what may be best practices. Specifically, Chapter 1 reviewed related networking and job-market literature and data; Chapter 2 presented results from a laboratory test of job-contact networks; and Chapter 3 built on these the base case Chapter 2 results with additional laboratory extensions and ideas for related research. These job-search questions are important because small and

inexpensive changes in behavior for some individuals and some firms could greatly increase the chances of finding or filling a job at all and of achieving a good worker-job match that endures.

This dissertation also touches upon how people optimize over job qualities (e.g., pay/status level, match quality, working conditions) and over networking (e.g., to pursue strong vs. weak ties, socialize with this or that crowd, to socialize in person or electronically), but these topics are of secondary importance in this work. Overall, given how routine are the occurrences of switching jobs, looking for work, and hiring among the population, any insights gained regarding how to better search for work could offer material 'welfare' gains.

APPENDIX

In this appendix, I present the full instructions utilized during my laboratory experiment related to the results presented in this dissertation. The section headings, table numbers and figure numbers in these laboratory instructions do not match the rest of this document because they are left as they were in the actual laboratory materials distributed to lab subjects that were participating in the experiment.

In these instructions, I used the term 'round' to refer to one run of the job-contact network game, in contrast to the term 'period,' which I used throughout the dissertation text, but I mean the terms synonymously.

"Laboratory Instructions"

1. Welcome

Thank you for coming! You've earned $5 for showing up on time, and the instructions explain how you can make decisions and earn more money. You will have **15 minutes** to silently read and review these instructions and to make any notes. The rest of the experiment to follow depends very much on your understanding of these instructions. There should be no talking or cell phone use at any time during this experiment. If you have a question, please raise your hand, and the experimenter will assist you quietly.

2. Summary

This experiment is an employment game in which you will earn a "wage" each time you "have a job," and you will earn "no wage" each time you "do not have a job." During each Round you will be anonymously and randomly re-grouped with 4 other people (for a total of 5 people per Group) from this room. At any given time, these are the only other people you will interact with.

In each Round, you will be asked to make decisions about the how much you would like to spend (invest) in costly social "networking." Overall, the more you and others (in your Group of 5 people) invest in social networking, the more neighbors (i.e., links) you'll likely have on average, but at a cost. If it turns out that you do not have a job, these links could be helpful to you if a linked neighbor has an extra job to share with you through the network. If you invest at level 0.0, then you'll definitely have 0 neighbors, but you'll pay just 0.0 network investment cost. These ideas will be made clearer in the instructions and examples to follow.

Beyond the $5 show-up fee, for completing the experiment, you will earn an additional $5. Additionally, you will earn money based on your performance in six randomly chosen Rounds out of all the Rounds you complete today. So the results from each Round can potentially have a large impact on your take-home earnings. On average, participants will receive about $20 total (including the show-up fee and completion fee) for participating in this experiment today, though individual results will typically vary greatly between $10 and $20, with a small, outside chance of earning up to $40 or even up to $60.

2. Experiment Layout

This employment experiment consists of many *Rounds*, with each Round lasting 30-60 seconds. Each Round is independent of all other Rounds. All "jobs" in this experiment

are identical, and the "wage" rate is set the same for all people. Likewise, unless noted differently, the job offer rates and job loss rates faced by all people will be the same for any given Round.

Each of the Rounds in the experiment proceeds in the same basic way, though with varying details. In each Round, everyone starts with a job. Next everyone in your Group makes a choice about level of social network Investment between 0 and 10 (maximum possible choice). The cost for each unit of investment will be shown for each Round. If, for example the cost were $0.02, then purchasing 2 units of network investment would cost $0.04 (= 2 X $0.02). **The more you and the others in your Group Invest, on average the more neighbors (i.e., links) you'll have within your Group.** If you Invest 0.0, then you'll definitely have 0 neighbors, but you'll pay no Investment cost.

Then random job losses and job offers occur for all people in your Group. Then any redundant job offers are shared randomly amongst any linked neighbors within ones' Group. In the end, everyone who has a job earns an additional Wage of $1.00, and everyone who has no job earns a "Wage" of $0.00. Total Profit (per Round) is the Wage MINUS the cost of social Investment made.

Note for any given single Round it is possible that your screen will show a negative Profit for that individual Round. This can occur if/when you end up without a job and you invested some amount in networking. However, since your take-home pay from today's experiment will be based on the sum Profit of six randomly chosen Rounds, it is very unlikely that this sum would be negative. However, in the very rare case that your sum Profit over the six Rounds were negative, the experimenter would round this negative Profit up to $0, and you would receive $10 (show-up fee and completion fee).

For each Round, you will have 30 seconds to read the current Round and submit a selection. Once all Group members have made their selections, the Round is run by the computer system, generating results. You will then have 30 seconds to review the results of that Round. The history of prior Rounds' results does not affect future computer results; each Round is *fully independent*. Between each round, a history screen will appear for 10 seconds showing your choices and the results from all prior Rounds.

3   *Job Losses, Job Offers, Job Search*

Although everyone starts each Round with a job, there is a chance you will lose your "job" via a *job loss*. For example, if the job loss rate were 20%, this would mean a 20% probability that you will lose your job in that Round. Simultaneously, there's also a chance that you will receive a direct *job offer*. For instance, if the direct job offer rate were 20%, this would mean a 20% probability that you will receive a direct job offer.

The job offers are totally *independent* of the job losses. Thus some people might receive a direct job offer even though they have not lost their job; this would be called a "redundant" or extra job offer. Likewise, some people who lost their jobs may not receive a direct job offer. Other times, people with job losses receive an offsetting direct job offer and automatically accept it.

The job loss rates and job offer rates will vary during the different Rounds of the experiment between 0% and 100%, often at the levels of 10% (low), 50% (medium) and 90% (high). Sometimes these rates will be known (i.e., posted), and other times these rates will be unknown (i.e., not posted). Unless noted differently, these rates will be the same among all participants. Importantly, the job-loss outcomes and job-offer outcomes vary amongst participants. That is, just because you lost your job, this does not mean that everyone else lost his/her job, and just because you received a direct job offer, this does not mean that everyone else received a direct job offer.

In this experiment, the employer/firm you work for just has the role of randomly creating job losses and/or job offers to you and the other participants. There is no other role for the employer/firm here.

4   Hypothetical example

Consider the following simplified *hypothetical* visual example with 10 people (numbered 1 to 10), separated into two Groups of 5 people, which sketches out many of the main concepts. First, a collection of links, representing a social network, is formed based on everyones' choice of investment level; then there are some random job losses and job offers (with job offers occurring *independent* of job losses); then there is some use of the social network. Then in the end some people are employed, and some people are unemployed (in the below example, just one person is unemployed).
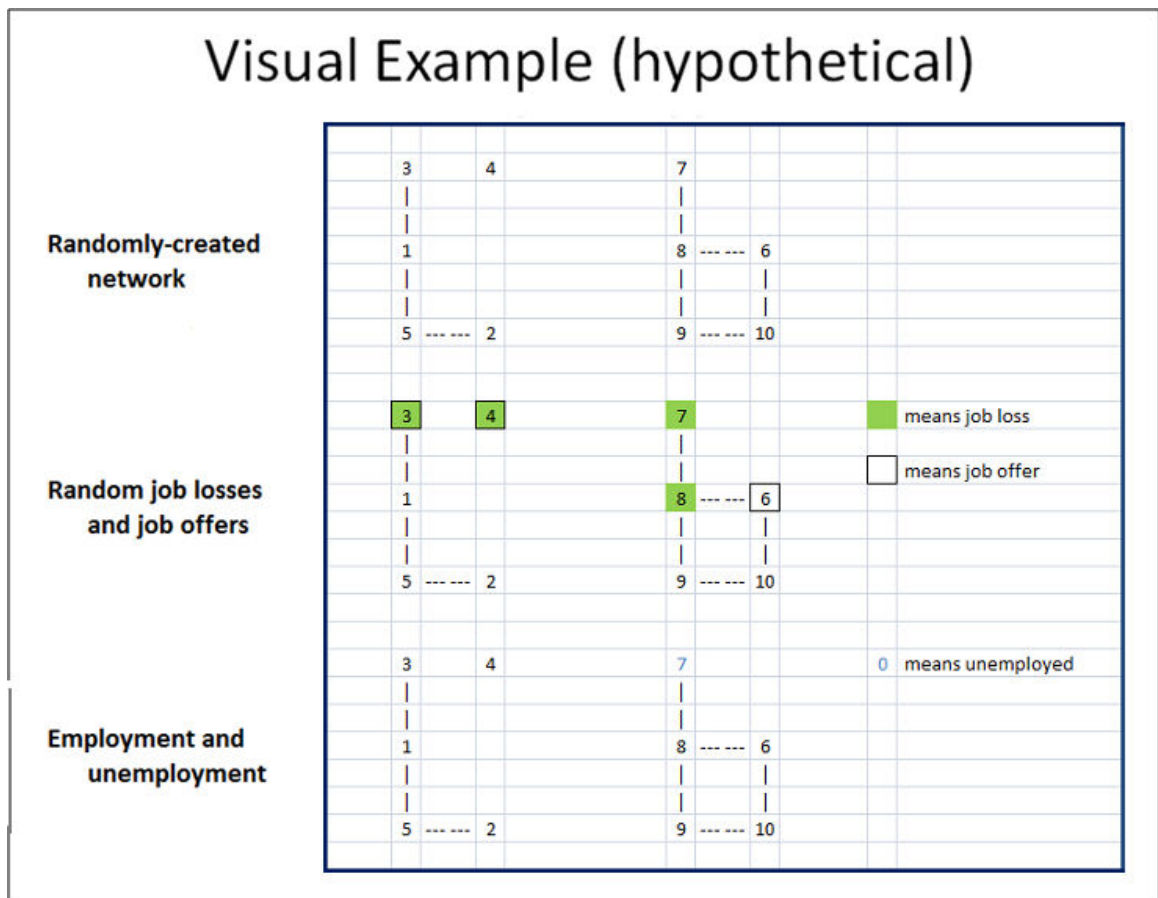
Figure 3: Hypothetical Example

Breaking things down by person: Persons 1, 2, 5, 9, 10 neither lost their job nor received a job offer. Persons 3, 4, 7, 8 lost their jobs. Persons 3, 4, 6 received job offers. For Persons 3 and 4, the job offer received replaced the job lost. For person 6, the job offer received was "redundant," since Person 6 had not lost his/her job. Person 8 was able to obtain an indirect job offer from Person 6. However, Person 7 did not receive any job offer to counter his/her lost job. As a result, Person 7 was unemployed.

This example will become clearer as you read the following sections with additional information.

5   Network Links and Neighbors

You will always be in a random Group of 5 other participants. The Groups are re-created randomly prior to the start of each Round. You and other Group members may affect each others' outcomes depending on how much is invested in the social network, and, consequently, how many links there are among you. If a "link" exists between you and

another person, then you are called "neighbors," and, as a result, there is a chance that a job offer could be forwarded between you.
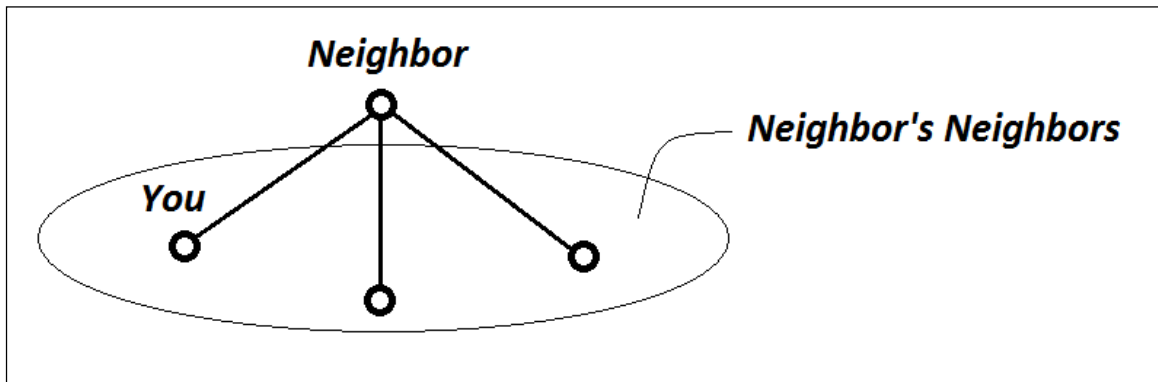
Figure 1: You, Example Neighbor, Example Neighbor's Neighbors

Note there is no link "direction" here. If a link exists between you and another person, then this link exists equally from you to him/her, and from him/her to you. The number of neighbors and links in the network matter because they affect your likelihood of receiving job offers forwarded over the social network.

All else being equal, the more neighbors you have, the greater the chance that an indirect job offer will be forwarded to you. But, importantly, the more neighbors that one of your neighbors has, the smaller the chance that this neighbor would forward a job offer to you. The reason for this is that each 1 redundant indirect job offer will automatically be forwarded to just 1 randomly-selected neighbor lacking a job, not necessarily to all neighbors in need of jobs. When a given neighbor has a lot of neighbors, this means there is a lower chance that you would be the person to receive any of his/her redundant job offers through the network.

Specifically, If you are the only neighbor that your neighbor has, then you would certainly be forwarded any redundant job offer that neighbor may have. In contrast, if you are one of two (three) [four] neighbors that your neighbor has, there would be a 50% (33.3%) [25%] chance that you would be forwarded any redundant job offer that neighbor may have. Although having more neighbors/links means you have more potential sources of jobs, if those sources themselves have a lot of neighbors, then these sources may be less reliable, since some of what these sources obtain may be passed to their other neighbors.

Finally, we note that indirect job offers can only be forwarded by your immediate neighbors, not from your "second-level" neighbors, i.e., not from neighbors of neighbors. If none of one's neighbors are in need of a redundant job offer, then the redundant job offer is simply lost and not utilized.

274

<u>6</u>   <u>Likelihood of Unemployment</u>

After the random job losses and direct job offers occur, there are <u>four possible</u> situations that you could be in, depicted in the below 2x2 grid:

		Get Direct Job Offer?	
		No	**Yes**
Lose Job?	**No**	**(1)** *Employed,* Status quo. You have no redundant job offer to forward on network	**(2)** *Employed,* You forward your redundant job offer on network to someone else (if connected)
	Yes	**(3)** *Unemployed,* Maybe can receive a forwarded job offer from network	**(4)** *Employed,* Your loss and offer cancel out. You have no redundant job offer to forward on network

Figure 2: Four Possibilities

As described below, if you are in the bottom-left square, **(3)**, you are <u>unemployed</u>, and you would need a job offer from the network (if available) in order to be employed for this Round. Below is more information about the four possible situations.

(1) If you have not lost your job, and not received a direct job offer, then of course you are still employed, and no jobs would be forwarded to anyone.

(2) If you have not lost your job, then receiving a direct job offer would be "redundant" for you, and in that case, your redundant direct job offer would automatically be forwarded to a randomly selected neighbor lacking a job (if any) for his/her employment.

(3) If you have lost your job and not received a direct job offer, and if any of your neighbors have received redundant job offers, then there's a chance you might receive an <u>indirect</u> job offer from these neighbors for employment.

(4) If you have lost your job, and receive a direct job offer, the two cancel each other out, and you will have employment. [The computer always will automatically accept any job offer to you.]

If you are in unemployed (box **(3)** above), then you would need a job offer from the network (if available) in order to be employed. The likelihood that you will be in (3), i.e., unemployed and needing a job offer, after the initial job losses and job offers, is simply the likelihood that you lose your job times the likelihood that you do not receive a direct job offer (since the two events are fully independent). And the likelihood that you do not receive a direct job offer is 100% minus the job offer rate. For example, if the job loss

rate were 10% and the job offer rate were 50%, then the likelihood that you would need a job offer is simply 10% (i.e., the job loss rate) times 100%-50% (i.e., 100% minus the job offer rate) =50%, which computes to 5%. Moreover, the likelihood that you do not need a direct job offer is 100% minus the likelihood that you need a job offer, or, in this example, 100% minus 5%, or 95%.

At the start of each round, the likelihood that you will be unemployed (and thus need a job offer), as well the likelihood that you will not be unemployed, is computed and posted on the screen (in blue) for your convenience.

7   Link Formation

Again, neighbors are those other people with whom you share a link. Your neighbors can consist of any of the people in the laboratory room today, who happen to be in your Group of 5 at the time. But all neighbors will remain *anonymous*. You cannot directly pick your neighbors. Instead, you can pick levels of social network investment, just in a generic sense. Higher network investment raises the likelihood that you'll have links to others in the experiment, provided they also invest in the network to some degree. For each Round, the maximum amount of investment units you can choose to purchase is 10, and the costs for each unit will always be posted.

The way to understand these network investments is to think of them as going out to "career nights," intending to meet and socialize with unknown other job seekers (*not* with employers) and to collect their business cards. You are not looking to meet any particular job seekers, but only to increase the number of contacts you have with other job seekers overall, since in the future they might be able to call you if you were to lose your job and if they had extra job offer information. The more time you and any other job seekers spend attending the career nights, the greater is the likelihood that you'll meet and form social contacts for the future. But going to job fairs is costly in terms of time, so there are limits to how much we can network versus doing other activities.

Importantly, note the likelihood of becoming a neighbor with someone is irrespective of your physical proximity to them in the room today. Physical distance within the room does not factor in here.

8   Mathematical Derivation

Just for your information (FYI), the next few paragraphs describe the specific mathematical formula used to turn your Group members' Investment choices into the likelihood of there being links created between any given pair of Group members.

Below is a copy of the earlier example shown from Section 4. In that example, *imagine computing the probability that a link will form* between Person 5 and Person 8. We now discuss these link probabilities.
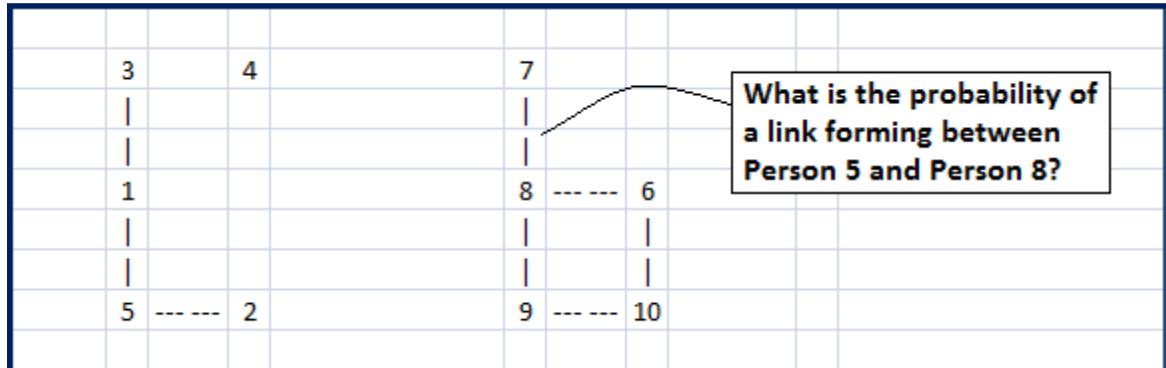
Figure 4: Links Between Group Members

In your Group of 5 people, the probability that there will be a link between you (say, Person A) and any other individual (say, Person B), for a given Round, is computed as:

The product of Person A's investment choice and Person B's investment choice divided by the sum of investment choices of all group members

Or in other words, this probability computation is: [**Mathematical Formula**]

Prob(link between Person A and B exists, given all participants' level of network investment)

$$= \frac{(\text{A's network investment}) \times (\text{B's network investment})}{\text{sum of all 5 group members' network investment}}$$

Equation 1: Probability of Link Formation

You, as person A, have 4 computations like the above, one for each of the other 4 possible people in your group (i.e., the 4 person B's).

Note that if this link-probability computation results in a number *greater than 100% probability* of any link, then in this experiment the probability will simply be capped at 100%. Also, if there were *no network investment* by anyone, so that the denominator were zero, then the probability will simply be set to zero by default.

9   *Example of Computer Screens from the Experiment*

Below (on the next page) are screen-shots from the actual computer screen during the experiment. First is shown the network investment choice screen, and then is shown the network investment confirmation screen.

Your Subject ID is **#1**
You were in Group **1**
Round **1.01**

Job Loss Rate (likelihood of losing job): **25%** = (Job Loss %) X (100% - Job Offer %)

Job Offer Rate (likelihood of getting a job offer): **50%**

Likelihood that you'll need a job: **75%** = 100% - Likelihood that you'll need a job

Likelihood that you'll NOT need a job: **50%**

Wage if you have a Job: **$1.00**

Wage if you do NOT have a Job: **$0.00**

Cost per unit of network investment: **$0.01**

Your investment in social networking

[Acceptable values include: 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]

OK

Screenshot 1: Network Investment Choice

Your Subject ID is **#1**

You were in Group **1**

Round **1.01**

Confirmation Screen

Thank you.

Your chosen network investment is: **5**

Cost per unit of network investment: **$0.01**

<u>Your total investment cost is:</u>   <u>**$0.05**</u>

[OK]

Screenshot 2: Network Investment Confirmation

10   Higher Return from the Network

In the next sequence of Rounds, the situation will be a little different. In particular, the Wage if you receive your job through the network will be $5. However, if you already have a job from a direct job offer then your Wage will still be $1. Similarly, if you do not have a job, your Wage will still be $0. All other aspects of the setup are identical. Likewise, others who receive their only job from the network receive a wage of $5 for that job, or otherwise $1 for a direct-offer job and $0 for no job as before.

In summary, the only difference is that there is now a premium (i.e., higher) Wage of $5 if it turns out that your job came to you from one of your neighbors/links. Note if you already have a direct-offer job and then also receive a job through the network, this direct-offer job holds, and you do not receive that job through the network.

Please recall that your take-home pay from today's experiment is based on the show-up fee, completion fee, and the sum Profit from six random rounds chosen.

11   Yet Higher Return from the Network

In the next sequence of Rounds, the situation will be a little different. In particular, the Wage if you receive your job through the network will be $25. However, if you already have a job from a direct job offer then your Wage will still be $1. Similarly, if you do not have a job, your Wage will still be $0. All other aspects of the setup are identical. Likewise, others who receive their only job from the network receive a wage of $25 for that job, or otherwise $1 for a direct-offer job and $0 for no job as before.

In summary, the only difference is that there is now a premium (i.e., higher) Wage of $25 if it turns out that your job came to you from one of your neighbors/links. Note if you already have a direct-offer job and then also receive a job through the network, this direct-offer job holds, and you do not receive that job through the network.

Please recall that your take-home pay from today's experiment is based on the show-up fee, completion fee, and the sum Profit from six random rounds chosen.

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