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UNIVERSITY OF CALIFORNIA, SAN DIEGO

Networks in Labor Markets and Information

A dissertation submitted in partial satisfaction of the
requirements for the degree of Doctor of Philosophy

in

Economics

by

Ayal Y. Chen-Zion

Committee in charge:

Professor James E. Rauch, Chair
Professor Gordon B. Dahl
Professor Joseph Engelberg
Professor Kevin Lewis
Professor Joel Watson

2016

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The Dissertation of Ayal Y. Chen-Zion is approved and is acceptable in quality and form for publication on microfilm and electronically:

Chair

University of California, San Diego

2016

DEDICATION

For my wife and my parents.
Without you none of this would be possible.

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Chapter 2 is currently being prepared for submission for publication of the material. The dissertation author was a co-author of this paper. Chen-Zion, Ayal; Rauch, James E. “History Dependence in Networks of Close Relationships: Theory, and evidence from cohort attachment in employee entrepreneurship.”

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ABSTRACT OF THE DISSERTATION

Networks in Labor Markets and Information

by

Ayal Y. Chen-Zion

Doctor of Philosophy in Economics

University of California, San Diego, 2016

Professor James E. Rauch, Chair

This dissertation studies the impact that a networked society has on economic behavior in the markets for labor and information. The first chapter examines how former co-workers, and within that hiring-cohort co-workers, influence where a displaced worker is hired. The second chapter develops a theory of network formation that implies a prevalence of starting cohort members in an individuals connections and then tests this prediction in the context of employee entrepreneurship. Finally, the third chapter studies a decentralized market for information where bilateral links form the basis of trade and relates it to the role that intellectual property protection plays in the information age.

Introduction

The following is a more detailed introduction to each chapter.

Connections with former co-workers are important for labor mobility. Co-workers that were hired at the same time, the *hiring-cohort*, enter an existing work landscape together. In Chapter 1, I find that they serve as unique sources of job referral later in life. A simple model of relationship formation from Chapter 2 predicts a tendency for connections to persist over time. This theory implies that a worker's hiring-cohort co-workers are an important source of employment opportunities because they are more likely to have a pre-existing working relationship. I am able to study how hiring-cohort co-workers influence where a displaced worker is hired by using a Brazilian employee-employer dataset. The existence of hiring-cohort co-workers and the quantity of former co-workers at a plant have a significant positive effect on the probability of acquiring a job at that plant, following unemployment. The existence of one hiring-cohort co-worker increases the chance of going to a plant by 3.7-fold which is 2.75 times more than one non-hiring-cohort co-worker. I also address several biases associated with inferred job referral in the existing literature and show that results are robust to placebo tests and controlling for selection on unobservable characteristics (with a peers-of-peers instrument).

In Chapter 2, we develop a model of costly network formation in which agents learn about the quality of their matches. By retaining good connections, agents become increasingly reluctant to form matches of unknown quality, leading their networks to be front-loaded with agents they met near the beginning of their careers. This reluctance naturally gives rise to “cohort attachment”: new agents form links with each other because the agents already there are reluctant to form links with them. We examine the possible influence of membership in the same cohort on which co-workers an employee entrepreneur brings from a parent firm to his spinoff firm. Using matched employer-employee data for Brazil during the period 1995-2001, we find evidence that is consistent with our theory and provides a rich picture of the personnel aspect of firm formation. After controlling for similarity between co-worker and entrepreneur characteristics and for tenure overlap with the entrepreneur, we find that parent firm employees hired in the same first plant and same cohort as the entrepreneur were 21 percent more likely to join him at the spinoff than other parent employees hired in the same first plant.

Finally, in Chapter 3, we study a decentralized market where sellers and prospective buyers of information can negotiate over its price, and the buyers of information cannot commit to not resell it. We study how the potential for resale influences the pricing of information, and the incentives to acquire information when trading frictions are small. We prove that in a no-delay equilibrium, all prices converge to 0, even if the initial seller is an informational monopolist. The seller-optimal equilibrium features delay: the seller is able to sell information at a strictly positive price to a single buyer, but once two players possess information, prices converge to 0. The inability to capture much of the social surplus from selling information results in sellers underinvesting in their technology to acquire information. By contrast, a “patent policy” that permits an informed seller to be the sole seller of information leads to overinvestment in information acquisition. Socially efficient information acquisition emerges under a random patent policy.

Chapter 1

The Beginning of a Beautiful Friendship: The Impact of Hiring-Cohort Connections on Job Referral

1.1 Introduction

A burgeoning industry of firms seek to help job seekers leverage their contacts into a new job. For example, LinkedIn is improving its Recruiter and Referral products to streamline this process (Lunden, 2015). Additionally, firms and policy makers must understand which connections provide the greatest returns to best help their customers and constituents obtain a job at a specific employer. To this end, this paper focuses on job referral among co-workers, because of their established working relationship, and determines how they influence referral destination. The co-workers of particular interest are those who started at the same time at previous jobs - hiring-cohort co-workers. The hiring-cohort is comprised of co-workers from a range of ages, industries and occupations, but the common bond that leads to a connection comes from having to navigate a new environment at the same time. By "going through the fire" together, the hiring-cohort co-workers are shown to be more likely to develop an initial relationship and with persistence in interaction this relationship leads to a more useful referral source for a specific employer in the future. This prediction is validated in the data and suggests that not all co-workers are equally likely to serve as referral sources, even conditional on characteristics. The focus on the hiring-cohort is the main contribution of this paper and has been missing from the previous research discussion of job referral. An additional contribution of this paper is a careful treatment of inferring job referral from job histories and start/end dates. The literature has overstated the connection effect by not accounting for the compatibility of the worker and firm.

Previous research has studied the impact of neighbors, friends and family on employment (Bayer, Ross, and Topa, 2008; Kramarz and Skans, 2014; Schmutte, 2015; Nordman and Pasquier-Doumer, 2015; Gee, Jones, and Burke, forthcoming). Co-workers are of particular interest in labor mobility because their shared experience provides highly relevant information on a job seeker's productivity (Granovetter, 1995; Cingano and Rosolia, 2012; Muendler and Rauch, 2015; Chen-Zion and Rauch, 2016). Recent papers, discussed in Section 1.2, focus on former co-workers as connections for a job referral and study the impact on employment destination and post-referral outcomes (Saygin, Weber, and Weynandt, 2014; Hensvik and Skans, forthcoming; Brown, Setren, and Topa, 2016). In the literature, job referral refers to (a) a worker obtaining any job because of information obtained through connections or (b) a worker obtaining a job at a firm where a referrer is employed. This paper focuses on the latter.

I study how the probability that a displaced worker obtains a job at a particular employer is influenced by a former co-worker being employed there - a connection. Consider two workers who just entered the job market following the same firm closure. They can both potentially go to work at an employer, the first worker used to work with an employee of the potential employer, while the second worker does not know anyone at the potential employer. Assuming that they are identical apart from their connection, the impact of a connection is the increase in likelihood that the connected worker goes to the potential employer relative to the worker with no connection. Multiple job seekers displaced from the same firm closure have differences in connection to a potential employer and thus provide identifying variation for estimation of a connection effect at a worker-potential employer level. Previous work overstates the importance of connections because it does not accurately account for alternative reasons the worker would start at a potential employer. A methodological contribution of this paper is to more rigorously account for these alternatives.

Beyond a more careful treatment of referral, I find that those potential employers with a hiring-cohort co-worker are more likely to be destinations of a job seeker. Theory predicts that the difference in effect is due to hiring-cohort co-workers being more likely than others to have developed a relationship which then persists until the worker needs to look for a job (Chen-Zion and Rauch, 2016). Additionally, the hiring-cohort connections may form a special type of relationship. It is important to note that the literature has studied differences in referral by type of relationship, but tends to focus on characteristics of the agents on either side, like age, or very different types of relationships, like familial versus former co-workers. This is one of the first papers to focus on the characteristics and likelihood of the relationship within a type (former co-workers), namely the difference between co-workers in the hiring-cohort versus those that entered at other times.

Section 1.3 discusses the Brazilian employee-employer dataset, Relação Anual de Informações Sociais (RAIS), that is used to define co-workers and trace labor mobility. Section 1.4 uses a regression framework at a worker-potential employer level to benchmark the results in Brazil against the literature. It improves on previous specifications by restricting the set of co-workers and controlling for compatibility between the worker and potential hiring employer. This paper then diverges from the previous literature to explore the impact of the number of co-workers at the potential hiring employer.

Next, Section 1.5.1 reviews the results of Chen-Zion and Rauch (2016) regarding the importance of hiring-cohort co-workers in network formation. Section 1.5.2 returns to a regression framework and establishes the existence of a significant hiring-cohort co-worker effect. The existence of one hiring-cohort co-worker increases the chance of being hired at a specific plant by 3.7-fold which is 2.75 times more than one non-hiring-cohort co-worker.

The results are extended in Section 1.6 to show that they are robust to multiple identification threats by using placebo sets of former co-workers and potential employers, controlling for alter characteristics and constructing a peers-of-peers instrument.

1.2 Literature

As highlighted in a review article by Ioannides and Loury (2004), the academic study of job referral dates back to Granovetter (1973; 1983; 1995; 2005) and Rees (1966). In his book, "Getting a Job: A Study of Contacts and Careers", Granovetter interviews 282 professional, technical and managerial working men from Newton, Massachusetts with employer changes. 55.7% of his sample use personal connections to find a job, 68.7% of which used a person known from a work environment. These results have been found to be stable and have given rise to an expansive literature on the role of social connections in the labor market. The introduction of large employee-employer datasets and advanced computational techniques have allowed researchers to move beyond small case studies to create a more detailed picture of the relationship between labor mobility and job referral.

One strand of this literature studies the employment outcomes, like wage and tenure, by looking at outcomes for referred, non-referred and referring employees (Hensvik and Skans, forthcoming; Pallais and Sands, forthcoming). Pallais and Sands (forthcoming) find gains in candidate quality from referral, importantly they find referrer-referee teams perform better than other pairings. This is consistent with the theory developed in Chen-Zion and Rauch (2016) where worker specific match quality are a major driver of referrals. To test this model further, in this paper I contribute to a complimentary literature on the inputs into a job referral and how connections influence the acquisition of a referral at a specific employer. For example, Saygin, Weber, and Weynandt (2014) use Austrian employee-employer data to study how an individual's network changes his/her re-employment probability and how having a former co-worker at a specific firm impacts the probability of obtaining a job. They find that being connected to a firm by a historic co-worker more than doubles the chances that the worker is hired.

This finding provides a benchmark for this study of the impact of a connection on referral to a specific employer.

The theoretical literature behind job referral has focused on post-referral outcomes, but of equal importance is the process by which a job seeker receives a referral. Recent evidence supports an important role of learning and a desire to work together as post-referral motivators for referral (Pallais and Sands, forthcoming; Brown, Setren, and Topa, 2016). Chen-Zion and Rauch (2016) develop a model of pre-referral relationship formation to help understand which co-workers an employee would like to work with, it is with this in mind that I turn to the hiring-cohort. The hiring-cohort has been missing from the job referral literature, but the importance of the hiring-cohort in co-worker interaction has been recognized in the sociology literature; hiring-cohort connections naturally occur because of the difficulty of "penetrating established communication networks" (Zenger and Lawrence, 1989). Zenger and Lawrence (1989) find high rates of communication between cohort members across teams. This highlights the fact that the hiring-cohort serves as an observable proxy for a higher likelihood of a relationship in a dataset where individual interaction cannot be observed. The initial connection between cohort members couples with persistence in interaction to yield greater interaction at a later date, or *cohort attachment*. Chen-Zion and Rauch (2016) formalizes this mechanism and show that it is evident in the major decision of who an entrepreneur brings with him to a spinoff firm. This tendency for a cohort connection to influence the employment path is not inherently unique to entrepreneurship. Section 1.5.1 goes over the main components and extensions necessary to study cohort attachment in the job referral context.

1.3 Data: Brazilian Work Histories

This paper's empirical analysis of job referral uses the *Relação Anual de Informações Sociais* (RAIS), an annual administrative census of the Brazilian formal sector labor force conducted by the Ministry of Labor (Ministério de Trabalho, MTE).[1] This paper uses the data from 1994 to 2001. The dataset extends back to 1986, but important variables are missing prior to 1994 so those years are not used in the analysis.[2] Submission of this information is enforced by Brazilian law, under threat of fines. Allocation of workers' government benefits is based upon these records and so there is incentive for workers and firms to report.

The use of an employee-employer dataset provides the distinct advantage of being able to track workers through their job histories and not rely of survey data to construct the set of connections. This can be done because the dataset includes unique identifiers for workers and plants within a firm[3] that can be tracked across time, as well as information on the workers' demographics, occupation[4] , industry, location and month of hiring/leaving.

MTE estimates that roughly 90% of Brazilian employees in the formal sector are covered in RAIS (Muendler, Rauch, and Tocoian, 2012). RAIS does not include the large Brazilian informal sector which constitutes approximately 50% of the population (Henley, Arabsheibani, and Carneiro, 2009). *Unemployment* in this dataset is *unemployment+informal employment*. Formal sector employment is considered preferable to informal employment because of the large benefits that are awarded based on RAIS

[1]This dataset is used under an agreement organized by Marc Muendler, mmuendler@ucsd.edu. Other papers that have used these data include Menezes-Filho, Muendler, and Ramey (2008); Muendler, Rauch, and Tocoian (2012); Muendler and Rauch (2015) and Chen-Zion and Rauch (2016).

[2]Additionally, access to data from 2002-2009 has recently been obtained and will be added in future work. Variation in job referral over time is beyond the scope of this paper, but is studied in-depth by Galenianos (2014).

[3]The plant is the establishment of interest for relationships because that is the level at which relationships are most likely to be formed. The only exception in this paper is that closure is considered at the firm level (see Section 1.3.1 for a more detailed discussion). Most results generalize to using the firm, but some robustness checks cannot be conducted at that level and so those results are not currently reported in the paper. Firm-level results are available upon request from the author.

[4]RAIS has job titles that are matched to three digit group identifier in Brazil's standard occupation classification system Classificação Brasileira de Ocupações (CBO). This paper uses the 1994 CBO system. For more information on the CBO and its relation to international classification systems see Muendler et al. (2004).

reporting. For a more extensive discussion of the choice between the formal and informal sector in Brazil see Menezes-Filho, Muendler, and Ramey (2008); Bosch and Maloney (2010); Bosch and Esteban-Pretel (2012).

I take a number of steps to arrive at a dataset for which the results are meaningful and comparable to other studies of former co-workers and job referral. The universe of employment is restricted to males,[5] working more than 20 hours per week, in job spells lasting more than three months. This rules out transitory employment where workers work at the same plant with a low probability of actually communicating, such as part-time or short-term labor.

The data only includes five of Brazil's 26 states,[6] Ceará, Acre, Santa Catarina, Mato Grosso do Sul, and Espirito Santo. These five states were chosen because they represent different geographic (see Figure 1.E.1) and demographic circumstances in Brazil. Estimates are pooled across states with each state considered in isolation, so obtaining a job outside of the state is not considered. This is justified primarily by computational concerns regarding the time and resources necessary to track and compare job histories among workers.[7] Figure 1.E.3 shows that there is substantial migration in Brazil in 2000, but at relatively low levels in the chosen states. Additionally, the issue of migration is also present in previous results from other countries and so does not take away from the comparison. The states used had total populations of 8.4, 0.7, 6.2, 2.4, and 3.5 million, respectively, in 2010, with corresponding densities of 56.76 , 4.47, 65.27, 6.86, and 76.25 per km^2 (IBGE 2010)[8]. Similar projects have used employee-

[5]Bosch and Maloney (2010) use another Brazilian dataset that measures informal employment, Pesquisa Mensual do Emprego (PME), and suggest that transition probabilities between the formal sector, informal sector and unemployment are considerably different between men and women.

[6]For maps on geographic location, population distribution and migration see Appendix 1.E.

[7]In terms of complexity, matching workers to co-workers is an $O(n^2)$ task. This reason is particularly exacerbated when tracking workers for the peers-of-peers instrument that requires tracking the co-workers of former co-workers, an $O(n^3)$ task.

[8]The Brazilian statistical bureau, Instituto Brasilero de Geografia e Estatística. http://www.ibge.gov.br

employer datasets from European countries like Sweden and Austria (Hensvik and Skans, forthcoming; Saygin, Weber, and Weynandt, 2014), which have comparable populations (densities) of 9.4 (23) and 8.4 (102) million (per km^2) in 2010, respectively (World Bank WDI 2014). This is the first paper to conduct this type of analysis outside of Europe. Given the differences, the consistency of the results with previous studies emphasizes their robustness. Future work may extend this analysis to the entirety of Brazil.

1.3.1 Displaced Workers

Within the universe of workers, the workers of interest are individuals who enter a new job following unemployment from firm closure. Firm closure occurs in year t if the firm last appears in the data in year t. I do not include individual plant closures because they can represent consolidation by the employer and that would overstate the result. Closures represent plausibly exogenous unemployment and prevent issues of selection into job transition with the added benefit of providing a natural set of comparison workers. There is concern that the closure is not exogenous. The solution is to include all workers who were at the closure firm in the last year it appeared in the data, as suggested by Schwerdt (2011). To avoid including small firms that are slowly failing I also require that at least five employees work at the closure in its last year. To address concerns that co-workers from the closure firm select into leaving prior to closure, I restrict connections to co-workers from employment prior to working at the closing firm. This is the first main departure from the previous literature which also includes co-workers from the closure job spell (see Section 1.4 for more information). The sample includes closures from 1998-1999 to allow for a minimum of four years (1994-1998) of work history and two years (2001-1999) to obtain another job. For consistency across workers, I only consider four years of work history prior to the month they left the closure and the first job acquired within two years of leaving the closure. This is similar to the selection procedure in Saygin, Weber, and Weynandt (2014), but they use five years prior and one year after because of a larger panel and greater re-employment rate (possibly because of the lack of a large Austrian informal sector). Each worker leaving a closure is referred to as an *ego*. This terminology is from the sociology literature on networks with a specific individual of interest for the purpose of outcomes and other individuals for the purpose of covariates. These are often called egocentric networks (Marsden, 1990). If an ego is at multiple closures then I only use his observation at the last closure observed in the data. Additionally, if the ego leaves the closure because of death or retirement they are excluded from the sample.

1.3.2 Historic Co-workers

The next important component is the set of co-workers. The first step is to trace the ego back to all plants in his employment history, prior to his employment at the closure firm[9]. Co-workers are those who were at the same plant at the same time and are referred to as *alters*. I restrict connections to those where the ego and alter overlap for more than three months to minimize measurement error of the underlying relationship. The set of alters for a given ego are the ego's *connections*. Those alters at a specific plant when the ego becomes unemployed are the ego's *connection to the plant*. I require that the alter is at the plant at least three months before the closure in order to assure that contemporaneous movement effects do not exist. For the purposes of this paper, those plants where an alter is employed at the time of closure are termed the *alter-plants* of a specific ego. As noted before, plants are considered for relationship formation and referral, while firms (possibly with multiple plants) are considered for closure. Less than 6% of firms have more than two plants in any given year. Within the set of alters, the subset that are hiring-cohort co-workers, or *cohort-alters*, started $+/-2$ months from

[9]This is true for all but the first column in Table 1.4.4 where closure co-workers are included if they are not also egos. See Section 1.4 for a discussion of how this differs from the previous literature.

the ego at the historic plant at which they first worked together. This is done because our universe of employment spells is restricted to those lasting more than three months and so it implies that there is a minimum of one month overlap between the ego and alter.

Figure 1.3.1 depicts the simple case of one closure with two egos. The "treatment" ego has one historic plant and met one alter. At the time of the closure the alter is at a potential hiring plant. The estimate of interest in this paper is the connection effect, or the difference in the chance that the "treatment" ego moves to the potential plant relative to the "control" ego. Each ego serves as a "treatment" ego for plants where they have a connection and a "control" ego for plants where others from the same closure have a connection.

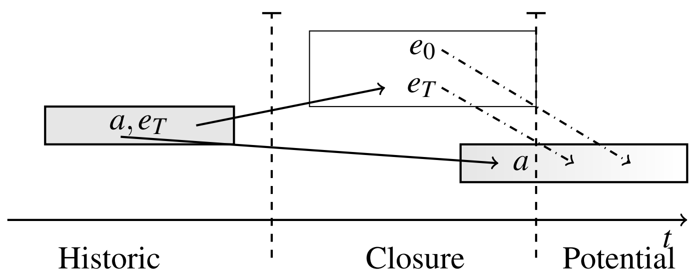


Figure 1.3.1. Finding an Ego's Alters and Potential Plants: Two displaced workers (*egos*) with one potential employers defined relative to a former co-worker (*alter*).

For each closure, plants where at least one ego has an alter are considered the potential destinations plants for an ego, or *potentials*. Egos from the same closure have different sets of alter-plants, but the same set of potential plants. For a specific ego, all alter-plants have at least one alter, but a potential plant can have zero alters if it is the alter-plant of another ego from the same closure. Plants that do not employ any of the egos' alters are not included in the potentials because there is no variation in the variable of interest, the connection, and so the observations would not contribute to the identification of the alter and/or cohort-alter effects on obtaining a job. The use of the ego-potential formulation of the problem was first proposed in Saygin, Weber, and

Weynandt (2014) to study referral to specific destination employers. They estimate the effect from the same identifying variation, but perform a fixed effect transformation to simplify the analysis to the closure-potential level.

Egos who meet the following criteria are the sample population: males, who work more than 20 hours per week for at least three months, leave the closure firm in the closure year and have at least one currently employed alter. The resulting sample is $38,603$ egos at $1,672$ closures with $51,315$ unique potential plants.

The above procedure was based on the sample selection used in the literature, particularly Saygin, Weber, and Weynandt (2014). There are some differences from other papers in the cut-offs used for inclusion, but most dimensions of the selection are represented.[10] This allows for meaningful comparisons to the state of the literature when including previously omitted factors in estimating the impact of a connection, in Section 1.4.

1.3.3 Summary Statistics

Before understanding how an ego's connections relate to their labor market outcomes, it is first necessary to understand the population of *egos, alters, cohort-alters, alter-plants* and *potentials*. In the sample, the mean (median) ego has 253 (16) alters and has worked at 2.18 (2) historic plants. These egos are located at $1,672$ closure firms with each closure having a mean (median) of 23.1 (9) egos and 198.9 (83.5) potential plants (see Table 1.3.1).

As seen in Column (1) of Table 1.3.2, at the time of leaving the closure the egos are young, with less than a high school education and primarily have jobs in the "Manufacturing and Transport" category which includes "workers in industrial production, machine and vehicle operators, and similar workers" (Muendler et al., 2004).

[10] For an extensive comparison of the selection differences between this paper and Saygin, Weber, and Weynandt (2014) see Table 1.A.1.

Table 1.3.1. Ego and Closure Statistics

	Mean	SD	Median
Egos (N=38,603)			
Alters	252.985	967.865	16
Cohort-alters	35.950	118.797	2
Potential Plants	764.621	832.330	443
Alter Plants	23.548	52.085	3
Cohort-alter Plants	5.401	12.587	1
Start at Potential Plant	.257		
... at Alter Plant	.076		
... at Cohort-alter Plant	.053		
Age[1] (Years)	33.372	10.190	32
Average Monthly Wage[1] (Brazilian Reals)	382.161	528.572	232.195
Tenure[1] (Months)	31.790	41.459	18
Historic Plants	2.175	1.106	2
Avg. Historic Plant Size	454.363	1624.810	96
Avg. Tenure at Historic Plants (Months)	34.130	40.449	20
Unemployment Spell (Months)	7.606	6.316	6
Return to a Historic Plant	.021		
Closure Firms (N=1,672)			
Potential Plants	198.903	320.744	83.5
Egos	23.088	52.116	9
Frac. of Egos at Closure starting at any ...			
... Potential Plant	.197	.235	.125
... Alter Plant	.079	.131	.000
... Cohort-alter Plant	.051	.104	.000

[1] At firm closure.

Table 1.3.2. Ego and Potential Characteristics

	Egos	Potentials
	(1)	(2)
Age Breakdown		
18 – 24	.202	.237
25 – 29	.207	.203
30 – 39	.331	.304
40 – 49	.171	.160
50 – 64	.076	.071
≥ 65	.005	.005
Education Breakdown		
Middle School or less	.755	.687
Some High School	.192	.255
Some College	.015	.020
College Degree	.037	.037
Occupation Breakdown		
Scientists and Technicians	.038	.051
Executive and Government	.023	.024
Administrative and Clerical	.125	.144
Commerce	.066	.130
Personal Services	.115	.151
Agriculture	.040	.053
Manufacturing and Transport	.592	.446
Obs	38,603	72,332

The potential characteristics are the average fraction of employees in a category.
The number of potential observations is larger than the 51,315 unique potentials because some potentials are in the sample twice as a destination for a closure in each of the possible closure years (1998-1999)

The egos have an average (median) of 23.55 (3) alter-plants and 8.99 (1) cohort-alter-plants. 25.7% of egos found a job at a potential plant, 7.6% found a job at an alter-plant and 5.3% obtain a job at a cohort-alter-plant. Within the closures the average (median) fraction of egos obtaining a job at a potential plant is 19.7% (12.5%) with 7.9% (0%) obtaining a job at an alter-plant and 5.1% (0%) at a cohort-alter-plant

Of the $51,315$ unique potentials there are $72,332$ potential $\times$ year observations because some are potentials for closures in multiple years (1998-99). Column (2) of Table 1.3.2 presents the mean fraction of employees at the potential in the closure year with a given characteristic. For example, on average 23.7% of each potential is between 18 and 24 years old. The distribution of ages, education and occupation within a potential is similar to that in the ego population. Understanding how the ego compares to the potential plant is important because any similarity can confound the ego's tendency to go to the plant, beyond the referral mechanism. This feature has been largely overlooked and as shown in Section 1.4, it is crucial to an unbiased estimate of the connection effect.

Table 1.3.3. Ego-Potential Statistics

		Alts ≥ 1	Non-Coh. Alts ≥ 1	Coh. Alts ≥ 1
	(1)	(2)	(3)	(4)
Job Acquisition	.0003	.003	.003	.008
Alters ≥ 1	.031	1	1	1
Alters[1]	5.207	5.207	5.917	17.438
	(.082)	(.082)	(.097)	(.357)
Coh. Alters ≥ 1	.007	.229	.092	1.000
Coh. Alters[1]	2.657	2.657	5.445	2.657
	(.033)	(.033)	(.096)	(.033)
Non-Coh. Alters ≥ 1	.026	.849	1.000	.342
Non-Coh. Alters[1]	5.415	5.415	5.415	43.241
	(.090)	(.090)	(.090)	(.964)
% Same Age Group	.230	.244	.244	.249
	(.00003)	(.0002)	(.0002)	(.0003)
% Same Occupation Group	.330	.398	.392	.453
	(.00007)	(.0004)	(.0004)	(.0009)
% Same Education Group	.525	.569	.557	.632
	(.00007)	(.0004)	(.0004)	(.0007)
Same Municipality (Indic)	.415	.519	.523	.521
Potential is Historic Plant (Indic)	.0007	.019	.022	.060
Obs	29,516,677	909,032	771,803	208,501

The summary statistics of the sample of ego-potential characteristics for: the whole sample of ego-potential pairs (Col. 1), the subsets with an alter (Col. 2), non-cohort-alter (Col. 3), and cohort-alter (Col. 4). Standard errors in parentheses.

[1] Conditional on having at least one.

The ego-potential pair is the primary unit of observation. The sample size is large, $29,516,677$, because each of the $38,603$ egos is paired with *all* potential plants from their closure, on average 199, with positive correlation at a closure between the number of egos and potentials. The sample size for a given closure scales quickly in the number of egos because one additional ego adds an observation for the new ego with that ego's alter-plants, all other egos' alter-plants, and for other egos with the new ego's alter-plants. Table 1.3.3 summarizes the main variables of interest in the regression for: the whole sample of ego-potential pairs (Col. 1), subsets with an alter (Col. 2), non-cohort-alter (Col. 3), and cohort-alter (Col. 4). The dependent variable of interest is an indicator for if an ego obtains a job at the specific potential plant. The mean of this variable, .0003, can be interpreted as the chance an ego goes to a specific potential plant. 3.1% of ego-potential pairs have an alter with an average 5.2 alters each, conditional on having at least one. Notice that the set of potential plants is constructed to contain all plants to which egos are connected, but few connections exist. The low rate of alter connections is due to different egos from a closure having divergent job histories and thus different sets of co-workers. Potentials are the union of alter-plants and so the different sets of co-workers result in a low level of alter connection. For example, only $\frac{1}{2}$ of the four observations (two egos $\times$ two potentials) in Figure 1.3.2 have an alter and if a third ego were added with an alter at a third potential then only $\frac{1}{3}$ of the nine observations (three egos $\times$ three potentials) would have an alter. Closures have an average of 23 egos, if each had a unique alter-plant then there would be an alter at $\frac{1}{23}(4.4\%)$ of the 23^2 (529) observations which is comparable to the 3.1% observed in the data. Only 22.6% of ego-potential observations with an alter have more than one, this skewed distribution will play an important role in estimating the impact of a connection in Section 1.4.

The compatibility between the ego and potential is a major factor in labor mobility and largely missed in the previous literature. This bias comes from job referral in large

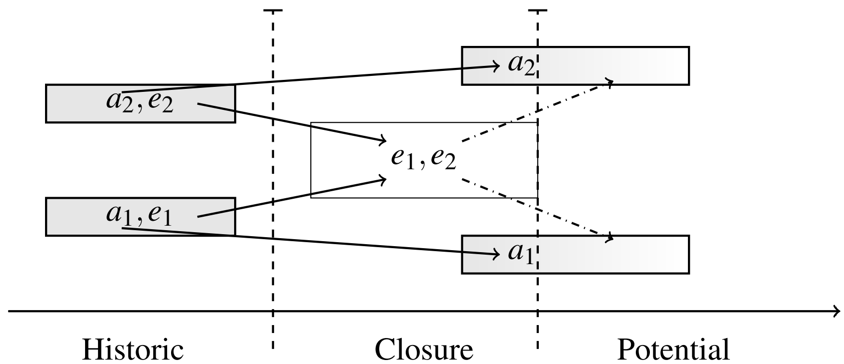


Figure 1.3.2. Sample Size - Two displaced workers (*egos*) with two potential employers defined relative to respective former co-worker (*alters*).

datasets needing to be inferred from labor mobility. The act of moving to a firm where a connection is employed has stood as suggestive evidence for referral because the researcher is unable to observe a job referral. I find this treatment of job referral suspect as there are alternative explanations for mobility that do not center on referral, such as potential plant demand for a specific set of skills or ego comfort with the company culture. This is addressed further in Section 1.4, but for now note that on average 23.0% of a potential plant's employees are in the same age group as the ego, 33.0% are in the same occupation group and 52.5% are in the same education group as the ego.[11] Additionally, 41.5% of potentials are in the same municipality[12] as the ego's location at the closure and 0.07% are also historic plants of the ego. This last form of ego-potential compatibility is important because returning to a historic plant is highly correlated with connection to a plant, yet a job acquisition may be unrelated to referral and actually due to information the ego accessed independently through employment.

Column 2 of Table 1.3.3 shows that when conditioning on the existence of an alter connection these compatibility measures increase. For example, for potentials with

[11]The groups are defined in Table 1.3.2.

[12]The municipality is the smallest administrative unit in Brazil. In 2000, Brazil had 5,507 and the five states used in this analysis had 184 (Ceará), 22 (Acre), 293 (Santa Catarina), 77 (Mato Grosso do Sul), and 77 (Espirito Santo) (IBGE 2000).

an alter 56.9% of the plant's employees are in the same education group as the ego. The chance of an ego obtaining a job at a specific potential also increases to .003 for potentials with an alter. This shows that connection, compatibility and job acquisition are positively correlated and it is unclear if the increase in the chance of getting a job at a plant can be attributed to more connection or more compatibility. To isolate the differential impact of a connection on job referral I move to a regression framework with the ego-potential pair as the unit of observation so that alternate factors, like compatibility, can also be addressed.

1.4 Results: Impact of a Historic Co-worker on Job Referral

The first task is to benchmark results from this setting against the previous literature and address the omitted variables that have been missed in previous analysis. The central result, the importance of hiring-cohort co-workers in job referral, does not depend crucially on these factors, but this section establishes that the effect would be overestimated if not accounting for other factors.

In the following regression framework, the identification of the impact of a connection is coming from multiple egos, i, from the same closure, $c = c(i)$, who can go to the same potential plant f. The variation of interest occurs in the existence and type of connection to the potential plant, f. Recall that i's alter-plants are a subset of the potentials because i is an ego in c.

The regressions are run with ego-potential plant (if) observations, but the ego's connections are defined on the ego-alter level at a fixed time (when i leaves $c(i)$). The time dimension is suppressed because each ego has a unique time that he leaves the closure.

The dependent variable of interest is an indicator for if an ego acquires a job at a potential. This is a binary outcome, but a linear probability model is used for ease of interpretation.[13] This procedure is similar to that of Saygin, Weber, and Weynandt (2014) and so I first conduct a similar baseline regression. Saygin, Weber, and Weynandt (2014) use a fixed effect transformation from Kramarz and Skans (2014) for estimation which reduces the data to closure firm-potential firm observations. This comes at the cost of being able to address some threats to identification that are discussed later in this section.

Benchmark

$$S_{icf} = \alpha + \beta_{alt} \mathbb{1}\{G_{if} \geq 1\} + \theta_{cf} + \varepsilon_{icf} \tag{1.4.1}$$

where

S_{icf} *is an indicator for if ego i acquires a job at plant f following closure c*

G_{if} *is the number of i's alters at plant f at the time that ego i leaves closure c*

$\mathbb{1}\{.\}$ *is an indicator function*

θ_{cf} *is a vector of fixed effects for each closure firm-potential plant pair. The fixed effects capture the culture and demand effects at the potential destination plants as well as the relationship of the closure firm to the potential plant (similarity in industry, tendency for targeting, frequent business partners, etc.).*

Finally, standard errors are clustered at the closure firm level.

The coefficient of interest is β_{alt}, the added probability of going to a specific potential plant given that there exists an alter as depicted in Figure 1.3.1. Saygin, Weber, and Weynandt (2014) find that a connection doubles the chance of being hired at a particular firm and while the estimation techniques and datasets are different I find, similarly, that having a connection to a plant increase the probability of being hired by

[13]For a discussion on the use of the linear probability model for binary outcomes see Wooldridge (2001) Section 15.2.

the potential plant 3.3-fold ($\frac{.0010}{.0003}$), see Column (1) in Table 1.4.4.

Table 1.4.4. Ego-Potential Job Acquisition

	Base	Non-Clos.	Ego FE	Compatibility	Size
	(1)	(2)	(3)	(4)	(5)
Non-Ego Alters ≥ 1	.0010				
	(.0001)***				
Alters ≥ 1		.0012	.0013	.0009	.0004
		(.0001)***	(.0001)***	(.0001)***	(.00009)***
(Log) Alters					.0022
					(.0003)***
% Same Age Group				.0001	.0001
				(.00002)***	(.00002)***
% Same Occupation Grp.				.0003	.0003
				(.00004)***	(.00004)***
% Same Education Group				.00008	.00008
				(.00002)***	(.00002)***
Same Municipality (Indic)				.0012	.0012
				(.0005)***	(.0005)***
Potential is Hist. Pl. (Indic)				.0192	.0143
				(.0019)***	(.0019)***
Obs.	29,705,613	29,516,789	29,516,677	29,516,677	29,516,677
Mean Dep.	.0003	.0003	.0003	.0003	.0003
R^2	.2696	.2403	.2432	.2438	.244
Closure $\times$ Potential (FE)	336,597	332,590	332,565	332,565	332,565
Egos (FE)	-	-	38,603	38,603	38,603
Closures (cluster)	1,724	1,697	1,672	1,672	1,672

Note: Standard errors clustered at the closure level. All columns contain closure firm $\times$ potential plant fixed effects. Columns (3)-(5) also contain ego fixed effects. The dependent variable is an indicator for an ego's job acquisition at the potential plant.

Previous papers do not include egos from the same closure in each others' network because of the concern of simultaneous mobility. There is also a fundamental concern that alters who left the closure firm before the closure year serve more as competition than as a source of referral. This is partially mitigated by requiring that alters have a tenure of at least three months at the potential plant, but a more robust method is to not use any alters first met by the ego at the closure firm. The closure firm alters may select into leaving prior to the closure year. Column (2) of Table 1.4.4 replaces the definition of alters from the literature with the main definition of alter for this paper by restricting attention to alters that were met prior to the ego's tenure at the closure firm. This distinction better reflects the desire to have identifying variation from differences in the job history between egos from the same closure. If alters from the closure were the only connections used then the identifying variation for connection would just rely on differences in tenure at the closure which is more susceptible to critiques surrounding endogenous mobility.[14] Restricting to this subset of alters results in a smaller sample because we lose some potential plants that only employ closure alters and so no longer have identifying variation in the connection. Additionally, the estimated coefficient is slightly larger, implying a 4-fold increase from a connection. The next departure from the previous literature is to introduce ego fixed effects.

Ego Fixed Effects

$$S_{icf} = \alpha + \beta_{alt} \mathbb{1}\{G_{if} \geq 1\} + \phi_i + \theta_{cf} + \varepsilon_{icf} \tag{1.4.2}$$

where ϕ_i is a vector of fixed effects for each ego that captures characteristics and idiosyncratic job search behavior.[15]

The purpose of the ego fixed effect is to account for characteristics of the displaced worker that do not vary between the potential plants. The most obvious potential threat is the total number of alters and alter-plants. These characteristics will be influenced by the ego's turnover frequency, employer history and hiring practices at historic employers and are crucial to labor market outcomes, but confound any estimation of a connection effect. An ego fixed effect is able to robustly control for differences between egos in their labor market experience. Additionally, an ego's observable characteristics at the time of leaving the closure, like age, schooling, etc, are crucial to referral because they impact the jobs available to the ego and are also absorbed in the fixed effect. Finally, unobserved characteristics, like the ego's personality and ability to have a meaningful relationship

[14]Thanks to Marc Muendler for this insightful point.

[15]The Stata command `reghdfe` is used throughout this paper because of its ability to accurately estimate a model with two high dimensional fixed effects (Correia, 2015).

with a co-worker, are also absorbed.

Effectively, including the ego fixed effects reduces the variation in the connection effect to be identified off of the difference between the connection variable and the average connection rate of the ego, $\mathbb{1}\{G_{if} \geq 1\} - \overline{[\mathbb{1}\{G_{if} \geq 1\}]}_i$, and differences in this demeaned variable across egos within the same potential. The fact that Column (3) of Table 1.4.4 is little changed from Column (2) lends credibility to previous estimates and suggests that variation in inherent characteristics of the egos within a potential is minimal and/or has little impact on differences in referral outcomes.[16]

The two sets of fixed effects account for similarities between the closure and destination plant and the ego's idiosyncratic characteristics, but not the similarity between ego i and the potential hiring plant f. Without relying on a connection, it is plausible that f targets individuals like i, or i is more likely to look to plant f, if f has more employees like i. Additionally, aspects of f such as how it relates to i's labor market experience are important. It is necessary to control for observable compatibility between the ego and potential. Targeting on unobservable characteristics is addressed in Section 1.6.

Compatibility

$$S_{icf} = \alpha + \beta_{alt} \mathbb{1}\{G_{if} \geq 1\} + \delta H_{if} + \phi_i + \theta_{cf} + \varepsilon_{icf} \tag{1.4.3}$$

where H_{if} are measures of compatibility:

- *the percentage of the potential in the same occupation, age, and education group*[17] *as the ego*

[16]Most of the remaining results in the paper are robust to the inclusion of the closure alters and/or the ego fixed effect. Results without either of these are omitted for purposes of exposition and are available from the author by request.

[17]The groups are defined in Table 1.3.2.

- *and indicators for if the ego worked at the closure in the same municipality as the potential*[18] *and if the ego has ever worked at the potential plant in the sample period.*

As expected, in Column (4) of Table 1.4.4 the inclusion of the compatibility controls decreases the estimate of the connection effect because it accounts for mobility that is not truly associated with connection. This decrease is largely driven by the inclusion of an indicator for the potential plant also being a historic plant, plausibly because of plant specific human capital. Previous work controlled for specific characteristics of the ego and potential plant independently, but did not address these baseline compatibilities (Saygin, Weber, and Weynandt, 2014; Hensvik and Skans, forthcoming; Kramarz and Skans, 2014). This effect is non-negligible which suggests that previous work has suffered from bias due to the omitted compatibility controls, most importantly if the ego has ever worked at the potential plant.

Correctly accounting for the characteristics of the ego and compatibility between the ego and potential increases confidence that the estimate is reflecting a more accurate impact of a connection on the probability of being hired. To understand the referral mechanism it is important to explore variation between connections.

One source of variation in connection that is often overlooked is the number of connections to a potential plant. This is important because multiple alters at a plant could have complementary effects on referral and/or the number of alters at a firm is correlated with the number of those alters that the ego has a strong working relationship with. The latter point is especially important because when referral is inferred from mobility there is no assurance of a "true" relationship between the ego and alter. The chance of a relationship given one alter is substantially different from the chance of a relationship given five. To understand this variability I now introduce a control for

[18] Each closure firm can have multiple municipalities and so this is not collinear with the fixed effects.

the (log) number of alters that an ego has at a specific potential. Given that $\log(0)$ is undefined I set the log number of alters to 0 if there are no alters. This can be interpreted as an interaction between the indicator and the log term. The addition of the log term changes the interpretation of β_{alt} from the impact of going from no alters to any alters to now represent the impact of going from no alters to one alter, while the log term captures the impact of increases in the number of alters.

Number of Alters

$$S_{icf} = \alpha + \beta_{alt}\mathbb{1}\{G_{if} \geq 1\} + \beta_{log}\log(G_{if}) \times \mathbb{1}\{G_{if} \geq 1\} + \delta H_{if} + \phi_i + \theta_{cf} + \varepsilon_{icf} \tag{1.4.4}$$

When the (log) number of alters is introduced the result is no longer comparable to most of the previous literature, but can be summarized as a 10% increase in the number of alters increasing the chance of job acquisition by $0.0022\ln(1.1) = 0.0002$. More importantly, after controlling for the number of alters Column (5) shows that the impact of only having one alter (the majority of connections) is much lower ($.0004 + .0022\ln(1) = .0004$). This effect is a third the size of the estimate that is directly comparable to the previous literature, from Columns (1)-(3). The previous literature's overestimate of the connection effect on obtaining a job at a specific employer is due to the lack of compatibility controls and not controlling for the number of alters.

1.5 Hiring-Cohort: Relationships with some co-workers are more likely than others

I now turn to the central point of the paper and focus on the added impact of the hiring-cohort co-workers. As developed in Chen-Zion and Rauch (2016), theory predicts that cohort-alters are more likely to have had a working relationship with the ego and so are more likely to provide a meaningful connection to a potential workplace. I begin with a quick overview of the theory and then turn to specifications that include the cohort effect.

1.5.1 Theory of Hiring-Cohort Attachment

Chen-Zion and Rauch (2016) model matches between workers within a firm, much like Jovanovic (1979) models workers and firms matching in the labor market. Well-matched workers become members of each others' networks (stay together), and poorly matched workers avoid each other in the future (separate). The model allows matches with any number of other agents, up to the limit of all the agents in the firm, but with a convex cost. The ego has an optimal number or relationships and fills them with well-matched workers before attempting to find new alters to work with.

Proposition 1.5.1 (Chen-Zion and Rauch 2016)**.** *Egos become monotonically less open over time to meeting alters of unknown match quality.*

This occurs because the ego's network degree increases monotonically with time as he acquires more high quality connections whereas his optimally chosen capacity for work relationships remains unchanged.

This leads to cohort attachment because when the ego's cohort enters the incumbent workers all have established relationships, and are less open to forming new relationships, while the fellow entrants all have no connections and so are especially likely to match with each other. This gives rise to an ego developing a working relationship with others from his/her cohort that continues over time. Those that the ego matched with initially, and found to be of high quality, remain in the network indefinitely if the relationship quality remains known.

The takeaway is that persistence in interaction leads to the cohort-alters being a large portion of the ego's network of work relationships. The importance of the work connections is that the persistence relies on having a good relationship. This good relationship might change slightly over time (captured by knowledge loss in Chen-Zion and Rauch (2016)), but it also translates from one firm to the next. If an alter and ego were to stop working together the knowledge of their good relationship would persist with each.

When the ego leaves the firm the job search process begins. The model for job referral that motivates the following analysis is one in which the hiring manager only acts on positive referrals from their employees/colleagues and where a worker makes a referral to the hiring manager so that they can benefit from renewing their positive work relationship.

The fact that relationships persist and cohort-alters are more likely to have had relationships means that the ego is likely to end up at a firm where said cohort-alters are currently employed because the cohort-alters recommended them to the hiring manager.

The predictions outlined above do not have magnitudes so it is important to empirically test if cohort attachment is meaningfully present in the job acquisition process. To test this I return to the regression specification of Table 1.4.4 Column (5) to assess the marginal contribution of a cohort-alter.

1.5.2 Results

The summary statistics in Table 1.3.3 show that of the 3.1% of observations with at least one alter 22.9% (84.9%) have at least one (non-)cohort-alter. These classifications are not mutually exclusive because potential plants with two alters could have both a cohort and a non-cohort alter. As highlighted in Section 1.3, the chance of obtaining a job at a specific potential increases (.003 to .008) for observations with a cohort-alter, but this occurs with a simultaneous increase in the number of alters (conditional on positive 5.2 to 17.4) and compatibility between the ego and potential (e.g. the fraction in the same education group as the ego: 56.9% to 63.2%). As before, to separate these simultaneous effects I return back to the regression specification. In Table 1.5.5, I decompose the alters by their cohort status and study the impact of the potential plant having cohort-alters and non-cohort-alters.

Hiring-Cohort

$$\begin{aligned} S_{icf} = & \alpha + \beta_{coh} \mathbb{1}\{C_{if} \geq 1\} + \beta_{logcoh} \log(C_{if}) \times \mathbb{1}\{C_{if} \geq 1\} \\ & + \beta_{noncoh} \mathbb{1}\{G_{if} - C_{if} \geq 1\} + \beta_{lognoncoh} \log(G_{if} - C_{if}) \times \mathbb{1}\{G_{if} - C_{if} \geq 1\} \\ & + \delta H_{if} + \phi_i + \theta_{cf} + \varepsilon_{icf} \end{aligned} \tag{1.5.5}$$

where C_{if} is the number of i's cohort-alters at plant f at the time that ego i leaves closure c.

Table 1.5.5. Cohort vs. Non-Cohort

	(1)
Coh. Alters ≥ 1	.0011 (.0002)***
(Log) Coh. Alters	.0016 (.0008)*
Non-Coh. Alters ≥ 1	.0004 (.0001)***
(Log) Non-Coh. Alters	.0015 (.0003)***
Obs.	29,516,677
R^2	.244
Closure $\times$ Potential (FE)	332,565
Egos (FE)	38,603
Closures (cluster)	1,672

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.

The theory predicts this difference between cohort and non-cohort alters to be due to the higher likelihood that the cohort-alter has an existing relationship with the ego. This is seen in the results with one non-cohort-alter still increases the chance of obtaining a job by 1.3-fold ($\frac{.0004}{.0003}$) while one cohort-alter increases it by 3.7-fold ($\frac{.0011}{.0003}$) making a cohort-alter a 2.75 ($= \frac{.0011}{.0004}$) times better connection for obtaining a job, see Table 1.5.5. Beyond the impact of the first cohort or non-cohort alter, additional alters have a larger impact if they are cohort-alter. The second cohort-alter has 1.1 ($= \frac{.0016 \ln(2)}{.0015 \ln(2)}$) times the impact of the second non-cohort-alter. This difference between the cohort- and non-cohort-alters is the core conceptual contribution of this paper: not all connections have an equal chance of being meaningful relationships. The results are consistent with the theory which predicts that cohort-alters are more likely to initially work together and thus still have a relationship later in life. The effect of a connection can be driven heavily by the circumstances in which the relationship arose, such as starting at a job together, and not just characteristics of the agents on each side of the connection. Additionally, the results are also consistent with cohort-alters having a unique type of relationship with the ego and while this is not a prediction of the theory it highlights another reason cohort-alters might be important. The next goal of the paper is to verify that there are not alternative mechanisms driving the connection and/or cohort effects.[19]

1.6 Robustness to Alternative Explanations

The following verify that the previous results are coming from the impact of a connection, and not unobservable characteristics correlated with hiring, by using (i) placebo histories (Section 1.6.1), (ii) placebo destinations (Section 1.6.2) (iii) alter characteristics (Section 1.6.3), and (iv) instruments for connection (Section 1.6.4).

[19]Heterogeneous effects by closure firm characteristics are beyond the scope of this paper and are available by request from the author.

1.6.1 Placebo Histories

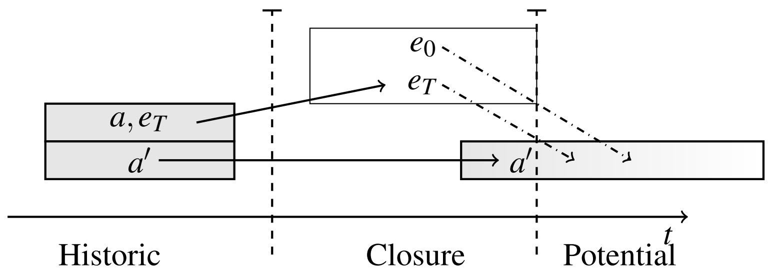


Figure 1.6.3. Placebo from Other Plants of Historic Firms - Two displaced workers (*egos*) and a potential employers defined relative to placebo co-worker (*placebo alter*), see Section 1.6.1.

The first test uses placebo histories for the ego to establish that contemporaneous employment is meaningful.[20] Recall that the alters were defined as being employed at the same historic plant as the ego. For this sample, the placebo history assigns the ego the same employment durations at historic firms, but at other plants (see Figure 1.6.3). See Section 1.3 for details on how alters are selected given this placebo history. The placebo alters are those that were at the historic firms at the same time as the ego, but in a different plant than the ego.[21] Additionally, only alters that are not in the true network are considered for the placebo network. The sample where this placebo is meaningful is limited because it is only applicable to egos who have worked at historic plants in multi-plant firms. The set of potential plants is constructed in the same way as the set of potential plants in the baseline specification, but using placebo alters in place of true alters. The set of potentials is different because all the egos have new sets of plants connected by placebo alters resulting in fewer ego-potential observations.

Column (1) of Table 1.6.6 reproduces the results from Table 1.5.5 for the subset of

[20]For another use of a similar test to study the employment outcomes of referred and non-referred employees see Hensvik and Skans (forthcoming).

[21]See Table 1.C.2 for a summary of the egos and closures in the placebo sample; Table 1.C.3 for summary statistics of the ego-potential observations; and Table 1.C.4 for a comparison of the placebo alters and cohort-alters.

Table 1.6.6. Placebo History

	True Hist.	Plac. Hist.
	(1)	(2)
Coh. Alters ≥ 1	.0011	-.00002
	(.0002)***	(.0001)
(Log) Coh. Alters	.0026	.00005
	(.0009)***	(.0004)
Non-Coh. Alters ≥ 1	.0002	.00002
	(.0001)*	(.00006)
(Log) Non-Coh. Alters	.0016	.0002
	(.0004)***	(.0002)
Obs.	9,734,045	8,723,467
R^2	.2535	.2439
Closure $\times$ Potential (FE)	283,647	241,190
Egos (FE)	11,822	11,793
Closures (cluster)	921	910

Note: Standard errors clustered at the closure level. All columns contain closure$\times$potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.

egos that have placebo histories so that they are comparable to the placebo test. Column (2) of Table 1.6.6 runs the placebo regressions using parallel history alters in place of true alters. The difference in the number of closures and egos stem from the loss of some egos when the closure $\times$ potential fixed effects or ego fixed effects are identified off of one observation. This loss of singletons is standard in the literature because it allows for an efficiency gain in estimating the connection effect.

Comparing Columns (1) and (2) of Table 1.6.6 the lack of significance in the placebo is evidence for contemporaneous employment being important to the accumulation of network connections and their value in job referral.

Table 1.6.7. Placebo Potential Plants

	True Dest.	Plac. Dest.
	(1)	(2)
Coh. Alters ≥ 1	.0010	.0005
	(.0004)**	(.0005)
(Log) Coh. Alters	.0042	-.0011
	(.0018)**	(.0020)
Non-Coh. Alters ≥ 1	.0001	-.0005
	(.0002)	(.0008)
(Log) Non-Coh. Alters	.0017	-.0008
	(.0008)**	(.0011)
Obs.	5,533,532	5,533,532
R^2	.209	.3035

Sample restricted to those potential plants with other plants in the same firm X year, but a different municipality.
Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.

1.6.2 Placebo Potential Plants

The next test is identical to the baseline specification, but with the dependent variable replaced by an indicator for the ego obtaining a job at a different plant within the same firm of a potential plant, see Figure 1.6.4. If the connection effect is a proxy for firm demand then it should predict job acquisition at other plants of the firm where the ego and alter would not work together, but if the connection is meaningful then it should have a greater impact on the plant where alters are located. I place the added restriction that the other plant must also be in a different municipality from the potential plant. The restriction strengthens the placebo. If the other plant is in the same municipality as the potential plant then there is still a chance that the ego and alter would interact on a regular basis and so the connection effect should still exist.

To make this test more meaningful I restrict attention to potential plants within multi-plant firms that have plants in multiple municipalities. Column (1) of Table 1.6.7

shows that the baseline cohort results still hold for this sub-sample with non-cohort alters becoming insignificant, but maintaining the expected sign. In Column (2) the dependent variable is replaced by an indicator for going to another plant of the potential in a different municipality and all coefficients become insignificant. This is what would be expected in a model where relationships are important and referral takes place to take advantage of developed working relationship.

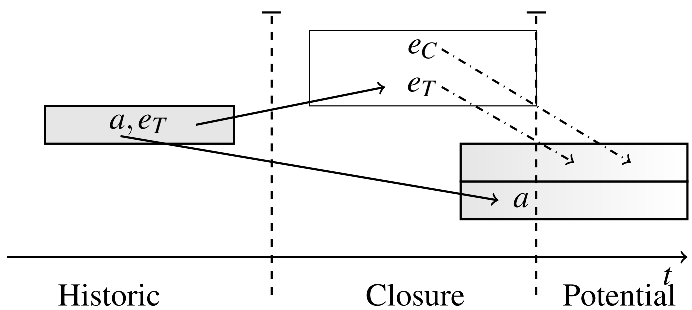


Figure 1.6.4. Other Plant of Potential Plant's Firm - Two displaced workers (*egos*) and placebo potential employer defined relative to co-worker (*alter*), see Section 1.6.2.

1.6.3 Alter Characteristics

There is a concern that the cohort effect is masking the impact of alters of a different type. For example, the overlap in job histories between the ego and alter is directly related to the amount of interaction they had in previous jobs and could drive the cohort effect. Additionally, referral can come from alters who are of a similar age as the ego and correlation between the age of cohort-alters would cause an overestimate of the cohort effect.

First, Table 1.6.8 introduces controls for the characteristics of the alters at the time of closure. In Column (2) the average tenure characteristics of the alters at the potential plant are added to the baseline specification along with controls for the existence of alters of a specific age, education or occupation group (6, 4 and 7 groups, respectively). The regression coefficients for the existence of an alter in a specific group are presented in

Table 1.6.8. Alters' Characteristics

		Char.	Homophily
	(1)	(2)	(3)
Coh. Alters ≥ 1	.0011	.0009	.0008
	(.0002)***	(.0005)**	(.0004)*
(Log) Coh. Alters	.0016	.0010	.0011
	(.0008)*	(.0008)	(.0008)
Non-Coh. Alters ≥ 1	.0004	.0006	.0005
	(.0001)***	(.0005)	(.0005)
(Log) Non-Coh. Alters	.0015	1.00e-05	.00002
	(.0003)***	(.0005)	(.0005)
(Log) Avg Tenure (Months)		-.0002	-.0002
		(.0001)*	(.0001)*
(Log) Avg Total Overlap (Months)		-1.00e-05	-.00002
		(.0001)	(.0001)
(Log) Avg Separation (Months)		-.0005	-.0005
		(.0002)***	(.0002)**
Alt.'s in Same Age Grp ≥ 1			.0004
			(.0001)***
Alt.'s in Same Edu. Grp ≥ 1			.0004
			(.0001)***
Alt.'s in Same Occ. Grp ≥ 1			.0007
			(.0002)***
Obs.	29,516,677	29,516,677	29,516,677
R^2	.244	.244	.2441

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.
-Starting in Column (2) the specifications include alter categorical characteristic controls. See Appendix Table 1.C.5 for the coefficients.

Appendix Table 1.C.5. These groups are not mutually exclusive within a type because there two groups could be included corresponding to two alters at the potential. The tenure characteristics are the (log) average tenure of the alters at the potential plant, the (log) average time that the ego overlapped with the alters[22] and (log) average time since the ego worked with the alter. These continuous measures are the average across all

[22]The overlap is measured in job× months so that overlapping in multiple jobs simultaneously is double counted. This choice does not influence the results.

alters that the ego knows at the potential, but if the potential only has one alter than it is the tenure characteristic of that alter. For ego-potentials with an alter, the average tenure at the potential is 29.3 months, the average overlap is 23.8 months and the average separation is 32.3 months Of the tenure characteristics the only one that significantly impacts job acquisition at the employer is the average time since the alters worked with the ego. As would be expected in a model of network formation, and as found in Chen-Zion and Rauch (2016), a longer separation means that there is less likely to be a maintained relationship and so the probability of getting a job referral is lower. As opposed to the continuous variables, the group indicator will be one if *any* of the alters at the potential are in the group which parallels the cohort-alter variable. The group characteristics of the alters are important to control for because they can bias the relationships that an ego forms and the model of cohort attachment is based on a model of unbiased network formation. The cohort effect is little changed by including all of these potential confounding variables which reinforces the unique role that the cohort-alters play in job referral to a specific employer.

Controlling for the characteristics of the alters is important and the ego fixed effects effectively control for the ego characteristics. This decomposition of job referral based on the job seeker characteristics and referrer characteristics is understood. For example, there are a number of papers studying job referral within minority groups, with the assumption that there is likely to be more interaction both on and off work (Dustmann et al., forthcoming; Kerr and Mandorff, 2015). This paper is taking a complementary perspective and seeking to understand how differences in the *the likelihood of a meaningful relationship* impact referral. This concept is distinct from much of the other job referral literature which might focus on a broad category of relationships, like familial, with minimal comparison to vastly different types of relationships, like co-workers. While interesting, the benefit of understanding these difference has limited implications because the conversion of workplace relationships to familial relationships is not a policy relevant action. In comparison, the result of studying differences among co-worker relationships could yield implications for hiring policies.

If the focus is on the relationship, then beyond controlling for the characteristics of the alters it is also important to control for how similar the ego and alters are along observable dimensions. This is because homophily, the tendency of agents to be more likely to interact with others with similar observable traits, is a known phenomenon (McPherson, Smith-Lovin, and Cook, 2001). In Column (3) I add additional controls for homophily between the ego and alters at the potential: an indicator for the existence of an alter in the ego's age, occupation and education groups. For ego-potentials with alters the fraction with at least one alter in the ego's age, occupation and education group is 35.9%, 45.0% and 61.5%, respectively. The resulting homophily effects are significant, but do not substantially change the cohort or (log) number of alters effects. The differences in the homophily effects reflect meaningful differences in job referral. Most importantly, if an alter is in the same occupation group as the ego he/she would be most able to assess the ego's skills in the field. Even with this proxy for common skills the cohort effect remains significant which highlights that the impact of a relationship transcends observable categories.

1.6.4 Instrument for Alters' Location

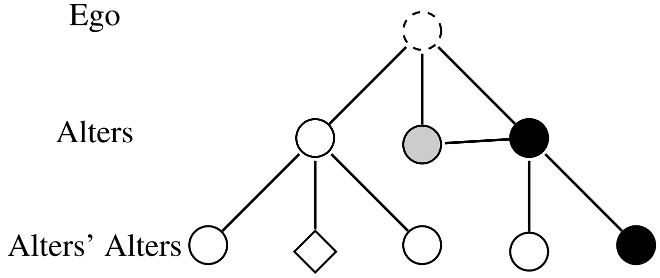
When considering a peer or network effects model, as this paper does, there are multiple sources of endogeneity that the literature has recognized as potentially concerning. All of these sources focus on how the existence of a connection W_{if} ([cohort-alters, non-cohort-alters] $\times$ [≥ 1, log]) relates to the acquisition of a job. The first concern is that agents are simultaneously influencing each others' choices. This has been termed the reflection problem and it is avoided by focusing on the alters' predetermined locations at the time of closure. Ego-ego co-movement is also mitigated because the *Closure X Potential* fixed effects and clustering absorb the impact of other egos from the same closure considering the same potential plant.

The remaining endogeneity is between the location of alters and the destination of an ego. For example, the potential plant could be targeting individuals with similar historic plants and hire the alter before the ego. In the preferred specification, Table 1.5.5, I control for some observable characteristics that are contributing to this effect. To control for the unobservable selection I can use an instrument for the location of an ego's alters at the time of closure. This instrument needs to isolate the impact of an alter separately from the impact of the historic plant and not be correlated with the ego's job acquisition at the plant.

The literature on network effects suggests a peers-of-peers instrument as a natural candidate. This means using the location of the alters' alters as instruments for the location of the alters (Bramoullé, Djebbari, and Fortin, 2009; De Giorgi, Pellizzari, and Redaelli, 2010). This instrument is a network analog to the use of a time-lag as an instrument, like Altonji and Card (1991).

An alter's alter is a worker that is an alter of one of the ego's alters, but not an alter himself. Alter's alters are restricted to those that the alters met before starting at the employer where they are located at the time of the ego's closure. If an alter's alters were included from that final job spell then they would artificially predict the location of the alter and would not be informative. This is similar to the earlier restriction that closure firm alters are not used, but done for a different reason. This instrument is modelled after De Giorgi, Pellizzari, and Redaelli (2010) who study a student's choice of college major relative to the choice of their peers. Their instrument is the fraction of unique excluded peers-of-peers (equivalent to alters' alters) choosing a major.

Figure 1.6.5 displays a simple case of one ego with three alters. In this example



Firm	Alt	Alt Alt
Black	1	1
White	1	3
Grey	1	0
Diamond	0	1

Figure 1.6.5. Alters and Alters' Alters

each alter is located at a distinct potential plant: white, grey, and black. There is also another potential plant, diamond, where another ego from the same closure has an alter. The figure tabulates the number of alters and alters' alters at each of those four plants. Note that there are no alters' alters at the grey plant because the ego is connected to the only individual at the grey plant.

Table 1.6.9. Alters' Statistics

	Frac. w/ ≥ 1	Count[1]
Coh. Alts' Coh. Alts ≥ 1	.047	7.059
Coh. Alts' Non-Coh. Alts ≥ 1	.083	15.866
Non-Coh. Alts' Coh. Alts ≥ 1	.099	9.895
Non-Coh. Alts' Non-Coh. Alts ≥ 1	.155	23.523
Obs w/ Alters (N=909,032)	Mean	
Alter's Tenure (Months)	29.332	
Total Overlap (Months)	23.798	
Separation (Months)	32.274	
Alt.'s in Same Age Grp ≥ 1	.359	
Alt.'s in Same Occ. Grp ≥ 1	.450	
Alt.'s in Same Edu. Grp ≥ 1	.615	

Obs. 29,516,677
[1] Conditional on having at least one.

For the four endogenous variables, W_{if} ([cohort-alters, non-cohort-alters] $\times$ [$\geq$ 1, log]), I use eight instruments Z_{if} ([cohort-alters' cohort-alters, cohort-alters' non-cohort-alters, non-cohort-alters' cohort-alters, non-cohort-alters' non-cohort-alters] $\times$ [$\geq$ 1, log]). Table 1.6.9 summarizes the fraction of observations with at least one of each type of alters' alter and the mean number of that type, given there exists at least one. For example,15.5% of potential plants have a non-cohort alter's non-cohort alter, with an average of 23.5, if there is at least one. The instrumental variable coefficients are estimated using the two-step feasible generalized method of moments (IV-GMM) because it is more efficient than the standard two-stage least squares when the number of instruments is greater than the number of endogenous variables[23]. This efficiency gain is achieved by weighting the moment conditions, for more information on the rationale and implementation see Baum, Schaffer, Stillman, et al. (2003). The assumptions necessary for the instrumental variable to solve the endogeneity are that the instruments must be relevant ($Cov(W_{if}, Z_{if}) \neq 0$) and valid ($Cov(Z_{if}, \varepsilon_{icf}) = 0$).

Given the existence of a peer effect, an alter's alter impacts an alter and thus the locations of the alters' alters are relevant instruments for the location of alters. Instrument validity is more suspect, the necessary exclusion restriction implies that the set of alters' alters only impact an ego through the set of alters.

The motivation for accepting the exclusion restriction is that conditional on observable characteristics alters' alters are randomly assigned. This is plausible if you consider that many factors in hiring and firing led to the ego meeting the alters and not the alters' alters and you assume them to be randomly distributed. The largest concerns are (1) other avenues by which the alters' alters are influencing the ego and (2) the location of the alters' alters still being endogenous.

One case of the first concern is that alter-A's alter may influence the employment destinations of another alter, beyond alter-A, who in turn influences the ego's destination. This has been addressed by using the *set* of alters' alters and the *set* of alters, so that the avenue of concern is within the instrumentation and not an alternative avenue. In

[23]The results do not change qualitatively with standard two-stage least squares, but are less precise and therefore not significant for all specifications and variables.

fact, this allows for many multi-dimensional relationships between the alters' alters' and alters' labor movements without threatening the instrument validity.

To partially address the second, recall that one concern is that the potential plant is specifically targeting workers from a specific historic plant at a specific time and thus I am unable to separate the connection between an ego and alter from their shared work history. The assumption of validity can be cast as assuming that the potential plant can only target a specific job history, conditional on the included covariates, or cannot target at all. In this way the alters' alters cannot be endogenous. If the potential plant is indeed targeting the full set of historic plants and times then there is less concern that the connection to the potential plant is endogenous to the ego's job history, which means that the instrument is not necessary.

Ultimately, the above reasoning is suggestive and is subject to many of the critiques that have been brought against the use of time-lags as instruments. The following results are complements to the main specification and the consistency with previous results serves as supporting evidence.

The results of the first stage, Table 1.6.10 Columns $(1)-(4)$, show that the instruments are indeed predictive of the existence of a cohort-alter, alter and the number of alters and are primarily of the anticipated sign. Column (5) presents the reduced form estimates.

The Kleibergen-Paap F-statistic for the estimation, which is the best summary of the first stage in the IV-GMM setting, is highly significant at 75.08 (Table 1.6.11) and thus provides substantial support for the relevance of the instruments.

The second stage estimates (Table 1.6.11 Column (2)) are larger than the OLS estimates. Notably, the marginal impact of cohort-alters on job acquisition is 3.4 times larger than the OLS estimate, equivalent to a 12.3-fold ($\frac{.0037}{.0003}$) increase from the mean. The estimated effect of the number of cohort alters is also larger. Additionally, the

Table 1.6.10. Instrumental Variable First-stage and Reduced Form

	Coh. Alts ≥ 1	(Log) Coh. Alts	Non-Coh. Alts ≥ 1	(Log) Non -Coh. Alts	Reduced[1]
	(1)	(2)	(3)	(4)	(5)
Coh. Alts'	-.0046	-.0116	-.0019	-.0124	-.00004
Coh. Alts ≥ 1	(.0009)***	(.0005)***	(.0018)	(.0013)***	(.00003)
(Log) ...	.0537	.0448	.0130	.0339	.0004
	(.0016)***	(.0028)***	(.0025)***	(.0061)***	(.0001)***
Coh. Alts'	.0016	-.0034	-.0064	-.0030	-3.00e-06
Non-Coh. Alts ≥ 1	(.0006)***	(.0003)***	(.0019)***	(.0011)***	(.00003)
(Log) ..	.0134	.0028	.0113	.0263	.00003
	(.0008)***	(.0010)***	(.0013)***	(.0027)***	(.00005)
Non-Coh. Alts'	-.0062	-.0041	-.0078	-.0246	.00003
Coh. Alts ≥ 1	(.0006)***	(.0004)***	(.0029)***	(.0008)***	(.00003)
(Log) ..	.0184	.0188	.0766	.1153	.0002
	(.0009)***	(.0010)***	(.0015)***	(.0035)***	(.00008)***
Non-Coh. Alts'	-.0004	.0001	-.0087	-.0033	.00009
Non-Coh. Alts ≥ 1	(.0002)*	(.0002)	(.0019)***	(.0007)***	(.00003)***
(Log) ..	-.0009	-.0060	.0246	-.0142	-.00003
	(.0005)*	(.0004)***	(.0019)***	(.0018)***	(.00004)
Obs.	29,516,677	29,516,677	29,516,677	29,516,677	29,516,677
Mean Dep.	.0071	.0018	.0261	.0083	.0003
R^2	.2181	.3793	.3316	.4691	.2438

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.
[1] The dependent variable is an indicator for an ego's job acquisition at the potential plant.

estimated impact of the non-cohort alters is larger for the first connection, but insignificant for the number of non-cohort alters. The IV results imply that the existence of one hiring-cohort co-worker at a plant has 1.481 ($= \frac{.0037}{.0025}$) times the impact of one non-hiring-cohort co-worker at that plant.

Intuition regarding the factors influencing job referral suggests that the OLS estimates are biased upward because the connection effect is capturing an alternative reason for obtaining the job. This has been seen to be true in Section 1.4 when adding the compatibility controls. Interestingly, the IV analysis shows that the OLS estimate of the cohort-alter effect appears to be biased downward. After controlling for compatibility,

Table 1.6.11. Instrumental Variable

	OLS	IV-GMM
	(1)	(2)
Coh. Alters ≥ 1	.0011	.0037
	(.0002)***	(.0015)**
(Log) Coh. Alters	.0016	.0044
	(.0008)*	(.0026)*
Non-Coh. Alters ≥ 1	.0004	.0025
	(.0001)***	(.0007)***
(Log) Non-Coh. Alters	.0015	-.0016
	(.0003)***	(.0011)
Obs.	29,516,677	29,516,677
R^2	.244	.2436
K-P F (weak) id		75.0848

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.

the bias of the OLS is $\frac{Cov(W_{if},\varepsilon_{icf})}{Var(W_{if})}$. The large size of the bias is plausibly due to the small variance of the four endogenous variables, which are .007, .0184, .025, and .0184 in order of listing in the regression tables.

Another reason for the larger estimates in the IV specification relates to its interpretation as a local average treatment effect (LATE). The logic is that the IV estimate reflects the referral effect for those ego-potential pairs where alters' alters have a meaningful impact on the chance an alter is present. Suppose that hiring managers are making choices between going to the market for labor and using employees (alters' alters) for references as modelled in some papers, such as Galenianos (2014), differentially within a plant. The unobserved choice would not be incorporated in the closure×potential fixed effects because it will be done on a job-by-job basis and so the LATE would be isolating the impact of alters on the probability of starting at plants that used referrals to hire said alters. If this is the case then it is not surprising that the referral estimates are larger in the IV because of correlation in the choice of using referrals.

Another alternative is that some alters have unobserved sociability and were more likely to use a referral to get a job at the potential. This unobserved sociability would result in the LATE isolating the impact of social alters on the probability of starting at the plant where they work. If this is the case then it is not surprising that the referral estimates are larger in the IV because of unobserved alter sociability.

Finally, there is some concern that the instrumental variable specification with the (log) number of alters are identified only off of the few observations with multiple alters at a potential plant. To address this concern Appendix Table 1.D.2 presents the OLS and IV estimates without the (log) alters variables and it remains consistent with the above results, but this comes at the cost of not addressing the correlation between the existence of a cohort-alter and the number of alters and so this is not the preferred specification. The IV results are certainly complements to the main specification and the consistency with previous results serves as supporting evidence.

1.7 Conclusion

In this paper, I robustly estimated the impact that a former co-worker has on the chance that an individual becomes hired at a specific plant. I found that the hiring-cohort effect is larger than the impact of other non-hiring-cohort connections. The existence of one hiring-cohort co-worker increases the chance of going to a plant by 3.7-fold which is 2.75 times more than one non-hiring-cohort co-worker. I also address several biases associated with inferred job referral in the existing literature and show that results are robust to placebo tests and controlling for selection on unobservable characteristics (with a peers-of-peers instrument).

Establishing the existence of a referral effect is the first step toward potential welfare comparisons from cohort hiring policies. Future work can study the impact of hiring-cohort workers and characteristics on the *quality* of the employment outcomes. For example, previous literature has looked at the impact of co-worker connections on unemployment duration, turnover and wages (Cingano and Rosolia, 2012; Hensvik and Skans, forthcoming; Brown, Setren, and Topa, 2016). The addition of the hiring-cohort analysis to these research agendas and other improvements could provide a more accurate estimate of the welfare benefits of job referral networks.

1.7.1 Acknowledgements

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Chapter 1 is currently being prepared for submission for publication of the material. The dissertation author was the sole author of this paper. Chen-Zion, Ayal. “The Beginning of a Beautiful Friendship: The Impact of Hiring-Cohort Connections on Job Referral.”

Appendix - Chapter 1

1.A Sample Selection

Table 1.A.1. Selection Comparison

Dimension	Saygin et al WP	This paper
Closure		
	1980-2007 Austria	1998-1999 Brazil (Ceará, Acre, Santa Catarina, Mato Grosso) do Sul, Espirito Santo)
Distinguish Exit by	worker-flow approach (Fink et al., 2010)	last year observed in data
Period of Firm Exit	Quarter	Year
Min. Num. Employees in last per.	5	5
Ego		
	Blue or white collar workers, 20-55	Males, ≥ 20 hrs/week
	At closure in the period of firm exit	
	?	Not leaving for death or retirement
Tenure at closure	> 1 yr	> 3 months
Alters	-	> 1 employed alter
Re-employment censored at...	1 yr	2 yrs
Location of re-employment	same country as closure	same state as closure
Alter		
	?	Males, ≥ 20 hrs/week
Time Since last Co-worked	≤ 5 years	≤ 4 years
Overlap	> 30 days	> 3 months
If..	ego's hist. firm has ≤ 3000	ego's plant
Excluding..	egos from the same closure	alt.+egos from the closure firm
Potential		
Location of alters..	firm in closure qtr.	pl. in month ego leaves closure
Minimum tenure of alter	?	3 months

1.B Alter Characteristics

Table 1.B.1. Summary Statistics: Alters and Cohort-Alters

	Alts	Non-Coh Alts	Coh Alts
	(1)	(2)	(3)
Alter's Avg. Monthly Wage (at Closure)	477.836	493.987	356.877
	(.254)***	(.277)***	(.547)***
Alter's Tenure (Months)	81.692	86.582	45.073
	(.036)***	(.039)***	(.062)***
Total Overlap (Months)	39.674	41.055	29.332
	(.025)***	(.027)***	(.061)***
Separation (Months)	26.983	26.937	27.327
	(.006)***	(.007)***	(.017)***
Age Breakdown			
18 – 24	.103	.096	.152
25 – 29	.191	.187	.222
30 – 39	.388	.390	.371
40 – 49	.220	.226	.176
50 – 64	.090	.093	.071
$\geq$ 65	.006	.007	.004
Occupation Breakdown			
Scientists and Technicians	.084	.089	.049
Government	.023	.024	.013
Administrative	.165	.166	.155
Commerce	.029	.028	.032
Tourism	.140	.135	.178
Agriculture	.023	.019	.049
Manufacturing	.515	.515	.517
Education Breakdown			
Middle School or less	.580	.570	.659
Some High School	.267	.269	.247
Some College	.016	.016	.011
College Degree	.137	.145	.083
Obs	4,590,984	4,050,179	540,805

Summary of characteristics of all alters (Col 1), non-cohort-alters (Col 2), and cohort-alters (Col 3) of the egos in the sample.

1.C Summary Statistics for Robustness Checks

Table 1.C.1. Other Plant Statistics

		Alts ≥ 1	Coh Alts ≥ 1
	(1)	(2)	(3)
Job Acquisition	.0004	.004	.009
	(8.26e-06)	(.0002)	(.0005)
... at Pl. of Pot. Firm in Other Muni.	.001	.004	.004
	(1.00e-05)	(.0002)	(.0003)
Coh. Alters ≥ 1	.007	.106	1.000
	(.00004)	(.0008)	
Coh. Alters	3.106	6.057	3.106
	(.062)	(.159)	(.062)
Non-Coh. Alters ≥ 1	.027	1.000	.382
	(.00007)		(.002)
Non-Coh. Alters	7.280	7.280	54.973
	(.205)	(.205)	(1.889)
Obs	5,533,532	148,283	41,239

Summary of ego-potential job acquisition and connection with potentials in multi-plant firms with at least one plant in a different municipality. "... at Pl. of Pot. Firm in Other Muni." is an indicator for the ego obtaining a job at a plant within the same potential firm, but a different municipality.

[1] Conditional on having at least one.

Table 1.C.2. Ego and Closure Statistics - Placebo History

	mean	sd	median
Egos (N=11,793)			
Potential Plants	739.716	644.270	578
Alter Plants	43.041	93.270	6
Cohort-alter Plants	9.091	24.900	1
Start at Potential Plant	.220		
... at Alter Plant	.040		
... at Cohort-alter Plan	.012		
Age[1] (Years)	33.302	9.506	32
Average Monthly Wage[1] (Brazilian Reals)	457.558	646.763	260.842
Tenure[1] (Months)	32.715	40.553	19
Num. Historic Plants	2.573	1.163	2
Avg. Historic Plant Size	313.141	588.420	130.75
Avg. Tenure at Historic Plants (Months)	35.744	39.292	22.25
Unemployment Spell (Months)	7.249	6.312	5
Return to a Historic Plant (Indic)	.022		
Closures (N=910)			
Potential Plants	265.044	357.209	136.5
Egos	13.014	37.020	4
Fraction of closure starting at Potential Plant	.123	.203	
... at Alter Plant	.048	.122	
... at Cohort-alter Plant	.012	.056	

[1] At firm closure.

Table 1.C.3. Placebo History Statistics

	(1)
Job Acquisition	.0003
Coh. Alters ≥ 1	.012
Coh. Alters[1]	2.139
	(.019)
Closest Alter $[-6,-2)$ m	.005
... $(+2,+6]$ m	.005
Non-Coh. Alters ≥ 1	.051
Non-Coh. Alters[1]	3.841
	(.058)
Obs	8,723,467

Placebo sample generated by re-coding historic tenure to other plants of historic firm.
[1] Conditional on having at least one.

Table 1.C.4. Alters and Cohort-Alters - Placebo History

	Alts	Non-Coh Alts	Coh Alts
	(1)	(2)	(3)
Age Breakdown			
18 – 24	.139	.130	.202
25 – 29	.208	.206	.219
30 – 39	.367	.374	.317
40 – 49	.201	.205	.168
50 – 64	.078	.077	.082
≥ 65	.005	.005	.005
Occupation Breakdown			
Scientists and Technicians	.058	.062	.028
Government	.075	.083	.020
Administrative	.127	.131	.097
Commerce	.061	.062	.055
Tourism	.085	.083	.097
Agriculture	.123	.110	.217
Manufacturing	.469	.467	.484
Education Breakdown			
Middle School or less	.687	.672	.798
Some High School	.228	.237	.159
Some College	.023	.025	.012
College Degree	.062	.066	.030
Obs	1,895,658	1,671,758	223,900

Summary of characteristics of all placebo history alters (Col 1), non-cohort-alters (Col 2), and cohort-alters (Col 3) of the egos in the sample.

Table 1.C.5. Alters' Characteristics (Ctn.)

		Char.	Homophily
	(1)	(2)	(3)
Alters in $18-24 \geq 1$		.0017 (.0005)***	.0016 (.0005)***
$25-29$		.0014 (.0004)***	.0013 (.0004)***
$30-39$		.0013 (.0004)***	.0011 (.0004)***
$40-49$		.0014 (.0004)***	.0013 (.0004)***
$50-64$		.0019 (.0005)***	.0018 (.0006)***
≥ 65		.0027 (.0023)	.0027 (.0023)
Alters in Scientists and Technicians ≥ 1		.0002 (.0006)	.0002 (.0006)
Government		.0006 (.0007)	.0006 (.0007)
Administrative		.0006 (.0005)	.0005 (.0005)
Commerce		.0011 (.0007)	.0011 (.0007)
Tourism		.0007 (.0006)	.0006 (.0006)
Agriculture		.0025 (.0010)**	.0025 (.0011)**
Manufacturing		.0015 (.0006)**	.0011 (.0006)*
Alters with Middle School or less ≥ 1		-.0005 (.0006)	-.0007 (.0006)
Some High School		-.0003 (.0005)	-.0004 (.0005)
Some College		-.0004 (.0008)	-.0003 (.0008)
College Degree		-.0007 (.0006)	-.0008 (.0006)
Obs.	29,516,677	29,516,677	29,516,677
R^2	.244	.244	.2441

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.
See Table 1.6.8 for main coefficients.

1.D IV Related Results

Table 1.D.1. Instrumental Variable First-stage and Reduced Form (No Size)

	Coh. Alts ≥ 1	Non-Coh. Alts ≥ 1	Reduced[1]
	(1)	(2)	(3)
Coh. Alts' Coh. Alts ≥ 1	.0339	.0368	.0002
	(.0020)***	(.0039)***	(.00004)***
Coh. Alts' Non-Coh. Alts ≥ 1	.0171	.0153	.00009
	(.0012)***	(.0026)***	(.00003)***
Non-Coh. Alts' Coh. Alts ≥ 1	.0047	.0461	.0001
	(.0008)***	(.0051)***	(.00003)***
Non-Coh. Alts' Non-Coh. Alts ≥ 1	.0030	.0161	.0001
	(.0004)***	(.0025)***	(.00002)***
Obs.	29,516,677	29,516,677	29,516,677
Mean Dep.	.0071	.0261	.0003
R^2	.1773	.2846	.2438

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.
[1] The dependent variable is an indicator for an ego's job acquisition at the potential plant.

Table 1.D.2. Instrumental Variable (No Size)

	OLS	IV-GMM
	(1)	(2)
Coh. Alters ≥ 1	.0018	.0031
	(.0002)***	(.0013)**
Non-Coh. Alters ≥ 1	.0008	.0034
	(.0001)***	(.0006)***
Obs.	29,516,677	29,516,677
R^2	.2439	.2434
K-P F (weak) id		94.5418

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown. The dependent variable is an indicator for an ego's job acquisition at the potential plant.

1.E Maps

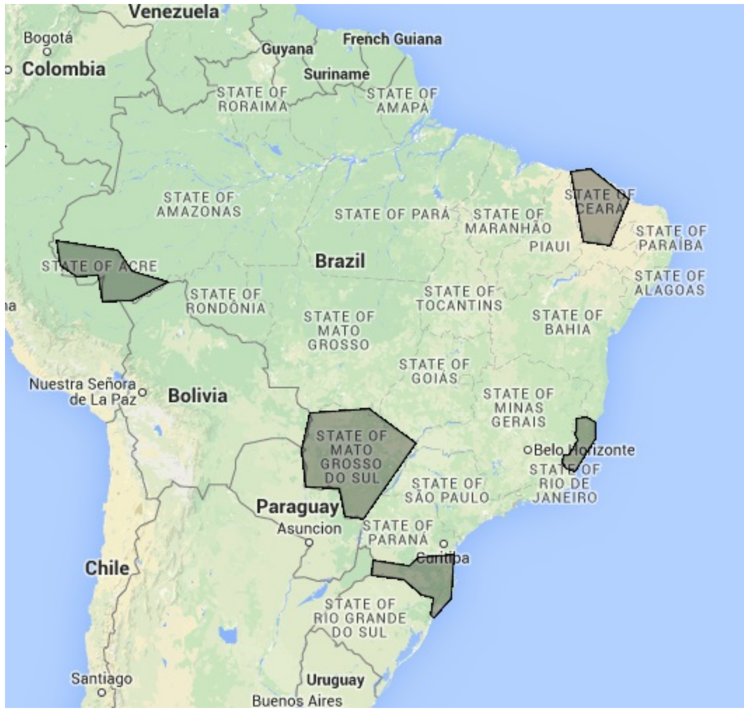

Figure 1.E.1. Brazilian State Coverage - Source: Brazil. Map. Google Maps. 17 August 2014.

Figure 1.E.2. Distribution of Urban Population 2000 - Source: IBGE 2000

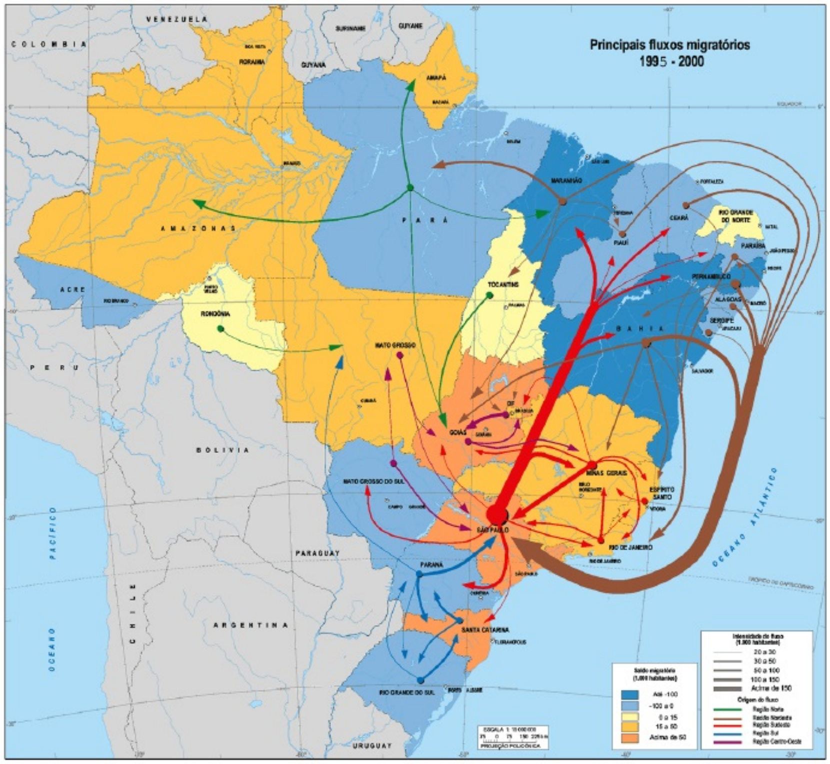

Figure 1.E.3. Migration 2000 - Source: IBGE 2000

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Chapter 2

History Dependence in Networks of Close Relationships: Theory, and evidence from cohort attachment in employee entrepreneurship

2.1 Introduction

People form close social and work relationships inside organizations such as firms and schools. These networks influence how happy and productive they are in the organizations. A distinguishing feature of close relationships is that they require significant time and energy. In this paper we argue that these relationships are also persistent. We show how this persistence of close relationships, in combination with their time-intensity, shapes the way agents form their networks of close relationships and the resulting patterns of history dependence in these networks. Moreover, we provide evidence that these relationships continue to have value even outside their original organizational contexts.

In our model agents learn whether they get along well or work productively together by trying to do so. If they discover they are well matched, they continue to socialize or work collaboratively in the future, given the opportunities. Denoting a focal agent by ego and designating the others in the organization as alters, we consider the set of alters with whom ego has learned he is well matched to constitute his network of close relationships. Ego can expand this network by trying out relationships with alters of unknown match quality and learning with which new alters match quality is good. Adding members to his network becomes increasingly costly, however, because close interaction with each one eventually interferes with close interaction with the others, given limited time and energy. Considering an ego entering a new environment, he will be most open to trying out relationships at the beginning, and less open later when his network is growing large. Agents' networks thus tend to be front-loaded with people they met near the beginning of their organizational careers. As relationships decay over time, this front-loading erodes as the oldest relationships are replaced by recent ones, leading to a U-shaped pattern of history dependence for the networks of agents with careers of moderate length.

Now consider a group of agents each of whom joins an organization at close to the same time. They find that the agents already there are not very open to trying out new relationships, so the agents in the new cohort try out relationships with each other. A pattern of network links (close relationships) forms within the organization in which within-cohort links are overrepresented. Our model thus gives rise to predictions about the cross-section pattern of network links within an organization as well as predictions regarding how individual networks evolve over time.

We will give the name "cohort attachment" to the tendency for within-cohort links to be overrepresented within an organization. The concept is recognized in sociology, though the phrase "cohort attachment" is not used. Wagner, Pfeffer, and O'Reilly III (1984, p. 76) write, "Thus, because of the effects of free communication capacity and interest in forming relationships, persons who enter [the organization] at roughly the same time are more likely to communicate with each other than with those who entered either much earlier or later." This idea is used by Zenger and Lawrence (1989) to examine the impact of tenure similarity (equivalent to time-of-entry similarity) on subsequent communication. They find that tenure similarity strongly predicts the frequency with which engineers and engineering managers in the research division of a medium-sized U.S. electronics firm communicate outside of their project groups. We were able to find one example of the use of the concept of cohort attachment in economics.[1] Bandiera, Barankay, and Rasul (2008, Table 4) find that "same arrival date" is a strong predictor of friendship among college students working on seasonal contracts picking fruit on a UK farm, controlling for a wide range of ascriptive characteristics and potential correlates such as same living site. They go on to use this indicator as a "plausibly

[1]Because it is useless to search for the phrase "cohort attachment," it is entirely possible that we missed many other examples.

exogenous" measure of network links when analyzing the impact of network links on worker productivity.

An advantage of the prediction of cohort attachment over the other predictions of our model is that it can be tested without detailed, retrospective surveys of the agents in an organization, making it feasible to use data from many organizations. It is simple to extend our model to allow members of ego's network formed within an organization who are subsequently split across many organizations to be his "contacts." The desire of contacts to renew their successful working relationships leads to job referrals. In a companion paper, Chen-Zion (2015) revisits this canonical application of network models, and finds that presence of a hiring-cohort co-worker from a previous job is a much better predictor of the plant in which a laid-off worker gets his new job than presence of a previous co-worker who was not in his hiring cohort. His use of a peers-of-peers instrumentation strategy, pioneered by Bramoullé, Djebbari, and Fortin (2009) and De Giorgi, Pellizzari, and Redaelli (2010), casts doubt on the alternative explanation that firm hiring cohort is a proxy for specific skills sought by the new employer.

The papers cited above provide evidence that belonging to the same hiring cohort (simply "cohort" hereafter) affects with whom agents communicate, with whom they form short-term friendships, and whom they recommend to their bosses. It would be interesting to know whether these relationships formed by historical accident also influence decisions where the stakes are higher. In this paper we will examine whether membership in the same cohort of an existing firm affects which co-workers an employee entrepreneur brings with him to a new firm. The entrepreneur wants someone who has the right skills for the job he has in mind, of course. But he may also care about having established a smooth work relationship with this person, rather than risk having to deal with a poor working relationship in the stressful, mistake-prone environment of a new firm. For his part, the employee (typically) leaves an existing job rather than unemployment. Note that this decision by the entrepreneur and worker concerns cooperation in a new endeavor outside an organization rather than a continuing endeavor within an organization.[2]

We build on the work of Muendler, Rauch, and Tocoian (2012) who use a linked employee-employer data base for Brazil to identify employee spinoff firms during the period 1995-2001. They find that roughly one-sixth of new firms in Brazil's formal sector during this period are "manager spinoffs." These are new firms for which the top employee holds the occupational classification "director" or "manager" and previously worked for an existing ("parent") firm in the same 4-digit industry. These firms also had a legal form such that they could not be owned by their parent firms, or they did not take more than 70 percent of the employees from any one parent plant, so they are unlikely to be employer-initiated divestitures. Typically these director/managers "took with them" other employees from the parent firm.

We find that parent firm employees hired in the same first plant and same cohort as the future director/manager were 21 percent more likely to join him at the spinoff than other parent employees hired in the same first plant. This estimate controls for employee tenure and length of overlap with the future director/manager, which both our theory and alternative explanations predict to be important determinants of the probability that the employee will join the spinoff firm. We find evidence of network decay in that the impact of same cohort is found to decrease with the length of separation of the employee from the director/manager when the former leaves the parent firm before the latter. Addition of a broad range of observed measures of similarity between employees and the director/manager, from age to industry classification, decreases the same cohort effect only slightly. Nevertheless, our findings can be rationalized in terms of same cohort as a proxy for skills desired by the spinoff firm, and unlike in Chen-Zion (2015) we have

[2]The same is true for the job referrals studied by Chen-Zion (2015) since they are made to the plants in which the referrers are now working.

no instrumental variable strategy. We can safely say only that our results are consistent with a role for historically accidental relationships in higher stakes economic decisions than previously studied. We hope these results are suggestive enough to encourage further research into our model of history dependence in network formation in general and cohort attachment in particular.

Our work is closely related to, and has implications for, the peer effects literature. Both are concerned with networks formed as a result of being in the same place at the same time.[3] The current state of the art in the peer effects literature is to examine peer groups created by random assignment (see Sacerdote 2014 for a survey). Typically random assignment occurs at the beginning of the agents' tenure in an organization. A popular example is random assignment of college freshmen to dorm rooms. The alters to which ego is randomly assigned are then found to influence a wide range of his behaviors, from binge drinking to buying a new car. The results of our model suggest that this influence would be much weaker if the random assignments occurred at the ends instead of the beginnings of organizational careers, because egos will be less open to establishing new relationships with the alters to whom they have been assigned. At the same time, persistence of close relationships suggests that it would be worth pursuing follow-up studies of the influence of randomly assigned peers.

In the next section we develop our basic model of network formation and history dependence with a fixed set of agents. In Section 2.3 we extend our model to allow periodic entry of cohorts of agents and develop predictions for cohort attachment. A further extension to contacts and job referrals is in Section 2.4. Our data on employee entrepreneurs and their coworkers are described in Section 2.5. We examine the determinants of whether the coworkers join the entrepreneurs at their spinoff firms in Section

[3]We believe that belonging to the same workplace cohort is a much more ubiquitous instance of "same place at the same time" than others covered in this literature.

2.6. Section 2.7 concludes.

2.2 The Model with a Fixed Set of Agents

We will consider the formation of personal networks by agents within an organization. We will call this organization a firm with a view to our later empirical application. However, we believe that our model applies to network formation in other institutional settings as well.

A key inspiration for our model is Jovanovic (1979). In his model, one worker meets with one firm, and the pair learn about the quality of their match. Roughly speaking, if they learn that the quality of their match is good, they stay together, and if they learn that the quality of their match is bad, they separate. In our model, matches are between workers (agents) within a firm. Well matched agents become members of each others' networks (stay together), and poorly matched agents avoid each other in the future (separate). Different from Jovanovic (1979), an agent can in principle form matches with any number of other agents, up to the limit of all the agents in the firm.

In this section we will assume that all agents begin their careers in the firm in the same initial period $t = 0$, and that there is no exit from the firm. We will follow the evolution of their networks over time $t = \{0, 1, 2, \dots\}$. We will assume these agents are symmetric and form a continuum of size N. The continuum assumption allows us to avoid integer problems. We will ignore agents outside the boundary of the firm.

In every period, risk-neutral agents engage in pairwise work relationships or matches.[4]

Assumption 2.A. *Every match is one of two types determined by the surplus it yields to the matched parties in the period in which it occurs: high quality yielding y_H or low*

[4] We believe that work relationships are ubiquitous even where employees appear to work in isolation, as in a typical cubicle environment, for example. Employees find others with whom they work well solving non-routine problems or fill in for each other.

quality yielding y_L $(y_H > y_L > 0)$.[5] *The unconditional probability that a match is high quality is* $p \in (0,1)$.

The match surplus can be thought of as net of any benefit derived by the firm.

Assumption 2.B. *Every match is of equal value to both parties, i.e., the matched parties divide the surplus equally.*

When the context is appropriate, it is possible to interpret this assumption as the outcome of Nash bargaining with a disagreement point of $(0,0)$. For example, we could suppose that if the matched parties cannot agree on who deserves how much credit, they cannot turn in their project to their boss to get paid. In other contexts the benefits of the match are non-monetary, so we are effectively assuming that the "technology of friendship" divides the surplus equally.

Assumptions 2.A and 2.B imply that, in the period in which the match occurs, each agent receives $\frac{y_H}{2}$ when the match is high quality and $\frac{y_L}{2}$ when the match is low quality. We assume that all matches contribute equally, regardless of type, to an agent's time and energy cost. Recalling that every agent is symmetric, let z_t be the total number of matches formed by an agent in period t:

Assumption 2.C. *The cost to an agent of forming* z_t *matches is* $c(z_t)$, *where* $c(0) = 0$, $c'(z) > 0$, $c''(z) > 0$ *and* $\lim_{z\to\infty} c'(z) = \infty$.

We assume $c''(z) > 0$ because, as the number of work relationships grows, the agent gets tired, has scheduling conflicts, etc.

Agents learn their match qualities with other agents by experience. We also allow for the possibility that their knowledge becomes obsolete:

[5] This follows the Moscarini (2005) simplification of Jovanovic (1979).

Assumption 2.D. *At the end of every period, the qualities of all unknown matches formed in that period are revealed. At the beginning of every period, with probability δ a known match quality returns to unknown, where $\delta \in [0,1]$.*

Obsolescence of knowledge could be caused by otherwise unmodeled "drift" in the capabilities and preferences of agents, so that some who formerly knew they worked well or poorly together now no longer know.

Let us call the agent on whose decisions we are focusing ego and all other agents alters. In each period t, ego inherits from the previous period knowledge that allows him to partition alters into three sets: alters with whom he knows he is well matched, alters with whom his match quality is unknown, and alters with whom he knows he is poorly matched. We call the set of alters with whom he knows he is well matched at the end of the period his **network** and denote its size or **degree** by n. We denote the size of the set of alters unknown to ego by u. The decisions that each agent needs to make in any period are how many matches z_t to form and with whom. Clearly he prefers to match with alters within his network before trying matches with unknown alters, and prefers trying matches with unknown alters before matching with alters with whom he knows he is poorly matched. We can then consider three cases: i) $z_t \leq (1-\delta)n_{t-1}$; ii) $(1-\delta)n_{t-1} < z_t \leq (1-\delta)n_{t-1} + u_t$, where u_t is the number of unknown alters after the share δ of known match qualities has returned to unknown; and iii) $z_t > (1-\delta)n_{t-1} + u_t$. We rule out case iii) by imposing an additional condition on the cost function, derived in Appendix 2.A and expressed in terms of the model parameters, that prevents the number of matches ego desires to form from exceeding $(1-\delta)n_{t-1} + u_t$ in equilibrium. We will show below that case i) never obtains. Therefore, at the margin, ego always matches with an unknown alter (case ii). Inframarginally, ego matches with any alter within his network with probability one.[6]

[6] Note that ego's desire to match with alters in his network is always reciprocated.

We denote by x_t the number of matches ego chooses to form in period t with alters of unknown match quality. He meets x_t alters uniformly at random, and then incurs matching costs $c(z_t) = c(x_t + (1-\delta)n_{t-1})$. At the end of the period match qualities are revealed and surplus is divided. Ego's total per-period payoff is thus given by the sum of his payoffs from matching within his network and matching outside his network less his matching costs,

$$(1-\delta)n_{t-1}\frac{y_H}{2} + x_t\frac{py_H + (1-p)y_L}{2} - c(x_t + (1-\delta)n_{t-1}).$$

His network degree evolves according to

$$n_t = (1-\delta)n_{t-1} + px_t. \tag{2.2.1}$$

We assume that ego maximizes the discounted sum of his per-period payoffs. His value function is then given by

$$V(n_{t-1}) = \max_{x_t}\{(1-\delta)n_{t-1}\frac{y_H}{2} + x_t\frac{py_H + (1-p)y_L}{2} - c(x_t + (1-\delta)n_{t-1}) + \beta V(n_t)\}, \tag{2.2.2}$$

where β is the constant discount factor.

The first-order condition yields

$$\frac{py_H + (1-p)y_L}{2} + \beta V'(n_t)p = c'(x_t^* + (1-\delta)n_{t-1}).$$

Note that

$$V'(n_{t-1}) = (1-\delta)\frac{y_H}{2} - (1-\delta)c'(x_t^* + (1-\delta)n_{t-1}) + \beta V'(n_t)(1-\delta)$$
$$+ \left[\frac{py_H + (1-p)y_L}{2} + \beta V'(n_t)p - c'(x_t^* + (1-\delta)n_{t-1})\right]\frac{\partial x_t^*}{\partial n_{t-1}}.$$

The coefficient on $\frac{\partial x_t^*}{\partial n_{t-1}}$ equals zero by the first order condition. We also use the first-order condition to substitute for $c'(x_t^* + (1-\delta)n_{t-1})$, obtaining

$$V'(n_{t-1}) = (1-\delta)\frac{y_H}{2} - (1-\delta)\left[\frac{py_H + (1-p)y_L}{2} + \beta pV'(n_t)\right] + \beta V'(n_t)(1-\delta)$$
$$= (1-\delta)(1-p)\frac{y_H - y_L}{2} + \beta(1-\delta)(1-p)V'(n_t).$$

This is a linear difference equation for $V'(n_t)$, which admits a constant solution

$$V'(n_{t-1}) = V'(n_t) = \frac{(1-\delta)(1-p)}{1-\beta(1-\delta)(1-p)}\frac{y_H - y_L}{2}.$$

The constant solution is the only solution that satisfies the transversality condition.[7] We can substitute it back into the first-order condition to obtain

$$\frac{py_H + (1-p)y_L}{2} + \beta p\frac{(1-\delta)(1-p)}{1-\beta(1-\delta)(1-p)}\frac{y_H - y_L}{2} = c'(x_t + (1-\delta)n_{t-1}) \equiv c'(z^*). \tag{2.2.3}$$

We see from equation (2.2.3) that ego forms a constant total number of matches z^* in every period.[8] Equation (2.2.4) then yields the number of random matches that ego

[7] We can show that $V'(n_t)$ grows at rate $[\beta(1-p)(1-\delta)]^{-1} > 1$ unless it is constant. But by the transversality condition, $\beta^t V'(n_t)$ must be bounded, and since $\beta \times [\beta(1-p)(1-\delta)]^{-1} = [(1-p)(1-\delta)]^{-1} > 1$, this is impossible. Hence the only possibility is $V'(n) =$ constant.

[8] The additional condition on the cost function that rules out case iii) above also ensures the existence of a z^* that solves equation (2.2.3).

forms in any period:

$$x_t = z^* - (1-\delta)n_{t-1}. \tag{2.2.4}$$

We can substitute equation (2.2.4) into equation (2.2.1), yielding

$$n_t = pz^* + (1-p)(1-\delta)n_{t-1}.$$

We can then derive the complete time paths for network degree[9] and for the number of random matches ego forms in each period:

$$n_t = \sum_{\tau=0}^{t}(1-p)^{\tau}(1-\delta)^{\tau}pz^* \qquad x_t = z^* - (1-\delta)\sum_{\tau=0}^{t-1}(1-p)^{\tau}(1-\delta)^{\tau}pz^*. \tag{2.2.5}$$

Note that the expression for n_t gives the value of network degree at the end of the period. In particular, for $t = 0$ the expression yields $n_0 = pz^*$, but the value of network degree at the beginning of period 0 is zero, which also implies $x_0 = z^*$.

As $t \to \infty$, network degree and the number of matches of unknown quality ego forms approach their steady state values:

$$n_t \to \bar{n} = \frac{p}{[\delta + p(1-\delta)]}z^* \qquad x_t \to \bar{x} = \frac{\delta}{[\delta + p(1-\delta)]}z^*. \tag{2.2.6}$$

We see from equations (2.2.5) and (2.2.6) that n_t increases monotonically from zero to its steady state value, which never exceeds z^*. It follows that case i) above ($z_t \leq (1-\delta)n_{t-1}$) never obtains. Note that steady state network degree increases with the probability of a good match and decreases with the rate of network decay. If the network does not decay ($\delta = 0$), then in the limit all matches are within network and random matches drop to

[9] Our model implies that network degree is the same for all agents in any period. In a future draft we will introduce heterogeneity in network degree through heterogeneity in cost functions.

zero. Our results in section 2.6 suggest that network decay is empirically important.

Inspection of equation (2.2.5) establishes our first proposition:

Proposition 2.2.1. *Ego becomes monotonically less open over time to meeting alters of unknown match quality.*

This occurs because ego's network degree increases monotonically with time whereas his optimally chosen capacity for work relationships remains unchanged.

Clearly ego's network is valuable to him, in that the same number of work relationships without a network yields less benefit. We can compute the value of a network of degree n_{t-1} explicitly by comparing $V(n_{t-1})$ to $V(0)$. We have

$$V(n_{t-1}) = \sum_{\tau=t}^{\infty} \beta^{\tau-t}[(1-\delta)n_{\tau-1}\frac{y_H}{2} + x_\tau^* \frac{py_H + (1-p)y_L}{2} - c(x_\tau^* + (1-\delta)n_{\tau-1})].$$

Substituting equation (2.2.4) into this expression yields

$$V(n_{t-1}) = \sum_{\tau=0}^{\infty} \beta^{\tau}\{(1-p)(1-\delta)\frac{(y_H - y_L)}{2} n_{(t+\tau)-1}(n_{t-1}) \\ + z^* \frac{py_H + (1-p)y_L}{2} - c(z^*)\}, \quad (2.2.7)$$

where $n_{(t+\tau)-1}(n_{t-1}) = n_{t-1}$ for $\tau = 0$ and

$$n_{(t+\tau)-1}(n_{t-1}) = (1-p)^\tau (1-\delta)^\tau n_{t-1} + \sum_{\theta=0}^{\tau-1} (1-p)^\theta (1-\delta)^\theta p z^* \text{ for } \tau > 0.$$

We can then use equation (2.2.7) to obtain

$$\begin{aligned} V(n_{t-1}) - V(0) &= (1-p)(1-\delta)\frac{(y_H - y_L)}{2}\sum_{\tau=0}^{\infty}\beta^{\tau}\{n_{(t+\tau)-1}(n_{t-1}) - n_{(t+\tau)-1}(0)\} \\ &= (1-p)(1-\delta)\frac{(y_H - y_L)}{2}\sum_{\tau=0}^{\infty}\beta^{\tau}\{(1-p)^{\tau}(1-\delta)^{\tau}n_{t-1}\} \\ &= \frac{(1-p)(1-\delta)}{1-\beta(1-p)(1-\delta)}\frac{(y_H - y_L)}{2}n_{t-1}. \end{aligned}$$

Inspection of this expression establishes:

Proposition 2.2.2. *The value of ego's network is increasing in (last period's) network degree n_{t-1}, decreasing in the rate of network decay δ, decreasing in the probability of a good match p, decreasing in the rate at which future payoffs are discounted (increasing in β), and increasing in the difference between good and bad match values $y_H - y_L$.*

Since n_{t-1} is monotonically increasing with time, we have the following corollary:

Corollary 2.2.1. *The value of ego's network is monotonically increasing with his tenure at the firm.*

This will be important in our empirical work when we consider the probability that a worker leaves his parent firm for an employee spinoff firm.

We conclude this section with our results on history dependence. In our model an ego with tenure t looking at his network retrospectively will see that he met the alters at various times t'. We denote the number of matches that were formed in t' that are still in ego's network at the end of t by $n_t(t') = px_{t'}$ if $t = t'$ and $(1-\delta)^{t-t'}px_{t'}$ if $t > t'$.

Definition. ***History dependence*** $HD_t(t') \equiv \frac{n_t(t')}{n_t}$*, the probability that a member of ego's network in t resulted from a random meeting from a given previous period t'.*

Substituting for $x_{t'}$ in the expression for $n_t(t')$ using equation (2.2.4) yields $HD_t(t') =$

$\frac{(1-\delta)^{t-t'} p[z^* - (1-\delta) n_{t'-1}]}{n_t}$. Note that if $\delta = 1$, $HD_t(t') = 0$ for $t > t'$: if match quality does not persist, there is no history dependence.

We see that the past time period t' has two counteracting influences on our measure of history dependence. On the one hand, since $n_{t'-1}$ increases with t', $HD_t(t')$ tends to decrease with t', reflecting the "front-loading" of agents' networks caused by persistence of relationships and time constraints as discussed above. On the other hand, since $(1-\delta)^{t-t'}$ increases with t', $HD_t(t')$ tends to increase with t', showing how exponential decay of network relationships tends to establish a more conventional pattern of history dependence where more recent meetings are more influential. We also see that $HD_t(t')$ is decreasing in t, so the longer is an agent's tenure in an organization the less is the influence on his network of meetings from any particular time in the past.

The influences of t' and t on our measure of history dependence can be summarized in the following proposition:

Proposition 2.2.3. *Assume $p > \frac{\delta}{(1-\delta)}$. For $\delta > 0$, there exists a $\underline{t}' \geq 1$ such that $HD_t(t')$ is monotonically decreasing in t' for $t' < \underline{t}'$ and monotonically increasing in t' for $t' > \underline{t}'$. Moreover, there exists a $\underline{t} > \underline{t}'$ such that $HD_t(0) > HD_t(t)$ for $t < \underline{t}$ and $HD_t(0) < HD_t(t)$ for $t > \underline{t}$.*

Proof. Substituting $n_{t'-1}$ and n_t into the definition of $HD_t(t')$:

$$HD_t(t') = \frac{(1-\delta)^{t-t'}p[z^* - (1-\delta)\sum_{\tau=0}^{t'-1}(1-p)^\tau(1-\delta)^\tau pz^*]}{\sum_{\tau=0}^{t}(1-p)^\tau(1-\delta)^\tau pz^*}$$
$$HD_t(t') = \frac{(1-\delta)^{t-t'}[1 - p(1-\delta)\sum_{\tau=0}^{t'-1}(1-p)^\tau(1-\delta)^\tau]}{\sum_{\tau=0}^{t}(1-p)^\tau(1-\delta)^\tau}$$
$$HD_t(t') = \frac{(1-\delta)^{t-t'}[1 - p(1-\delta)\frac{1-(1-p)^{t'}(1-\delta)^{t'}}{1-(1-p)(1-\delta)}]}{\frac{1-(1-p)^{t+1}(1-\delta)^{t+1}}{1-(1-p)(1-\delta)}}$$
$$HD_t(t') = \frac{(1-\delta)^{t-t'}[\delta + p(1-\delta) - p(1-\delta)[1-(1-p)^{t'}(1-\delta)^{t'}]]}{1-(1-p)^{t+1}(1-\delta)^{t+1}}$$
$$HD_t(t') = \underbrace{\frac{(1-\delta)^t}{1-(1-p)^{t+1}(1-\delta)^{t+1}}}_{A}[(1-\delta)^{-t'}\delta + (1-\delta)p(1-p)^{t'}] \qquad (2.2.8)$$

Inspection of equation (2.2.8) shows that $HD_t(t')$ is increasing in t' for t' sufficiently large. Straightforward computation shows that $HD_t(0) > HD_t(1)$ given $p > \frac{\delta}{(1-\delta)}$. Moreover, if we treat t' as continuous and differentiate $HD_t(t')$ twice with respect to t', we obtain $A[(1-\delta)^{-t'}\delta[\ln(1-\delta)]^2 + (1-\delta)p(1-p)^{t'}[\ln(1-p)]^2] > 0$. Thus $HD_t(t')$ is strictly convex in continuous t' and has a global minimum, and in discrete time reaches a minimum for some $\underline{t}' \geq 1$.

It follows from the first part of the proposition that $HD_t(0) > HD_t(t)$ for $t < \underline{t}'$, hence $\underline{t} > \underline{t}'$. Next, we can use equation (2.2.8) to show that the inequality $HD_t(0) < HD_t(t)$ reduces to $\delta + (1-\delta)p < (1-\delta)^{-t}\delta + (1-\delta)p(1-p)^t$. From the first part of the proposition the right-hand side of this inequality is monotonically increasing in t for $t > \underline{t}'$. Since, in fact, the right-hand side of this inequality increases without bound in t, the existence of a $\underline{t}$ as described in the second part of the proposition follows. □

Proposition 2.2.3 shows that when an agent's tenure in an organization is sufficiently short ($t \leq \underline{t}'$), representation of alters in his network is least influenced by his most recent meetings and most influenced by his very first meetings. With longer tenure

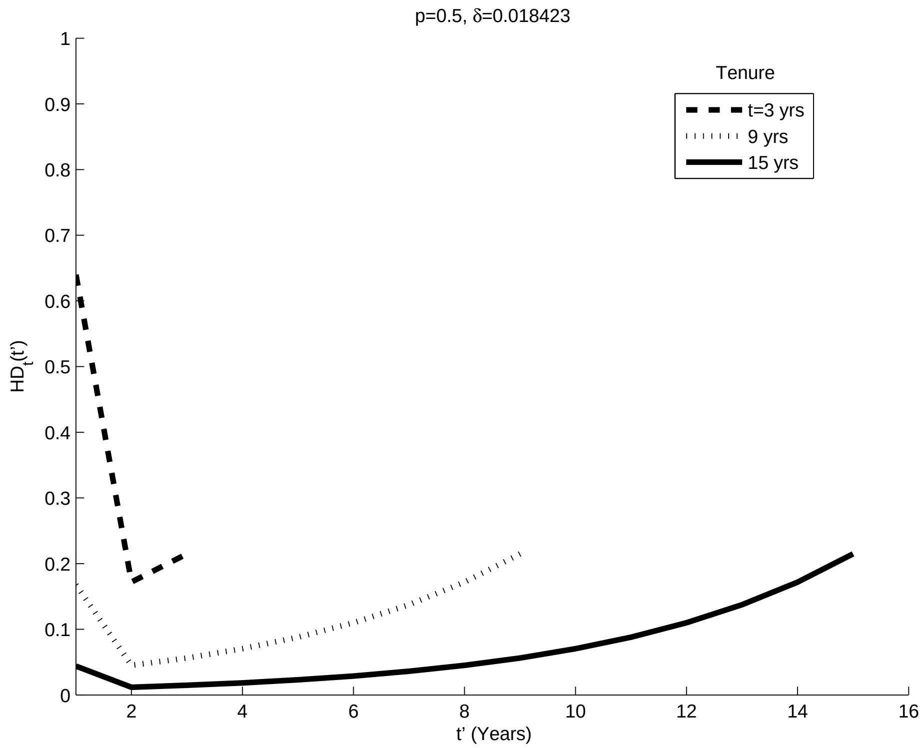

Figure 2.2.1. History Dependence (over t')

($t > \underline{t}'$), the share of alters resulting from his most recent meetings increases relative to less recent meetings, creating a U-shaped pattern of history dependence where ego's network is dominated by alters he met at the beginning and most recent periods of his organizational career. Eventually ($t > \underline{t}$), the influence of the distant past diminishes sufficiently that the most recent meetings account for the largest share of alters of any period.

It is informative to consider two special cases.

Example 1: $\delta = 0$. We have $n_t(t') = pz^*[1 - \sum_{\tau=0}^{t'-1}(1-p)^\tau p] = pz^*[1 - 1 + (1-p)^{t'}] = pz^*(1-p)^{t'}$. That is, as we move from the past toward the present, $HD_t(t')$ decreases at rate $(1-p)$.

Example 2: $\delta > 0$, T large so that $n_T \approx \bar{n}$. In this case $\bar{x} = \frac{\delta \bar{n}}{p}$, $HD_T(T) \approx \frac{p\bar{x}}{\bar{n}} = \delta$, and $HD_T(t') \approx \delta(1-\delta)^{T-t'}$. That is, as we move t' from the present toward the past,

$HD_T(t')$ decreases at rate $(1-\delta)$.

The second example shows that, for any positive rate of network decay, a conventional pattern of network history dependence will be established if a sufficient amount of time passes. For relatively short time horizons or small rates of network decay, the greatest representation in ego's network will be from alters he met early in his career at the firm.

Figure 2.2.1 calculates the time pattern of history dependence for various lengths of ego tenure at the firm, where time is measured in years to build intuition. The calculation assumes an even bet that matches are of high quality ($p = 0.5$) and a 20 percent rate of network decay per year ($\delta \approx 0.018$, where the underlying periods are months as in our data). At three years of tenure, which is in between the median and mean for the employee entrepreneurs in our data, more than 60 percent of ego's network consists of alters he met in his first year at the firm. We also see that the U-shaped pattern of history dependence already appears, with greater representation of alters met during ego's third year at the firm than during his second. At nine years of tenure, representation of alters met during ego's most recent year at the firm finally surpasses representation of alters met during his first year. After fifteen years of tenure ego's pattern of history dependence is dominated by network decay.

2.3 Cohort Entry

In real firms, agents do not all enter (or exit) at the same time. In this section we turn this complicating fact to our advantage by using it as a way to develop predictions from our model that can be tested using publicly available data. In particular, although we cannot see in what periods ego meets randomly with which alters, we can see in which period ego and alters entered the firm together. In that period, ego and alters are both maximally open to matches of unknown quality, hence likely to form matches with each other.

We now begin to develop this intuition more formally. Denote by a superscript c the time period or *cohort* in which an agent entered the firm with N^c denoting the size of the cohort. Let $\mathscr{C}_t$ be the collection of cohorts in period t and let $N_t = \sum_{c \in \mathscr{C}_t} N^c$ be the total number of agents in a period t.

Adding a cohort structure to a firm does not change equation (2.2.5), except that we must now write n_t^c and x_t^c because period t will correspond to different lengths of tenure for different cohorts c. For example, $x_c^c = z^*$, but $x_c^{c-1} = z^* - (1-\delta)pz^*$. Now consider the fraction of alters from his own cohort with whom ego has random meetings in period c, i.e., the probability that ego will have a random meeting with a given alter from his own cohort when they both enter the firm. This will be proportional to the product $(x_c^c)(x_c^c) = (z^*)^2$. In contrast, the probabilities that ego will have random meetings with alters from cohorts $c-1$ (in period c) and $c+1$ (in period $c+1$), respectively, are proportional to $(x_c^c)(x_c^{c-1}) = (x_{c+1}^c)(x_{c+1}^{c+1}) = (z^*)^2[1-(1-\delta)p]$. In turn, the probability that a given alter becomes a member of ego's network at the end of a period (and remains a member in the future) is directly proportional to the probability that ego randomly met with that alter in that period.

Using this reasoning, we develop the idea that, in any period following ego's entry, an alter from ego's own cohort is more likely to be a member of ego's network than an alter from any other cohort. We call this *cohort attachment*. If cohort attachment obtains, then if an employee entrepreneur is more likely to take members of his network with him to his new firm, he will be more likely to take with him members of his own cohort.[10]

Let $P_t^c(c')$ be the probability that a given alter in cohort c' is in the network of a

[10]One might argue that an employee entrepreneur is also more likely to take with him co-workers of unknown match quality than co-workers known to be of low match quality, which would work against taking members of his own cohort. Co-workers of unknown match quality, however, have no advantage over workers from outside the employee entrepreneur's parent firm.

given ego in cohort c at the end of period t, and let L_t^c be the number of matches formed in period t by agents whose match quality is unknown to a given ego in cohort c. Noting that $P_t^c(c')$ equals p times the probability that a given alter in cohort c' is of known match quality to a given ego in cohort c at the end of period t, we have

$$P_t^c(c') = \begin{cases} 0 & \text{if} \quad t < \max\{c, c'\} \\ (1-\delta)P_{t-1}^c(c') + [1-(1-\delta)\frac{P_{t-1}^c(c')}{p}]px_t^c\frac{x_t^{c'}}{L_t^c} & \text{if} \quad t \geq \max\{c, c'\} \end{cases} \tag{2.3.9}$$

$$L_t^c = \begin{cases} \sum_{c' \in \mathscr{C}_c} N^{c'} x_c^{c'} & \text{if} \quad t = c \\ \sum_{c' \in \mathscr{C}_t} N^{c'} [1-(1-\delta)\frac{P_{t-1}^c(c')}{p}]x_t^{c'} & \text{if} \quad t > c \end{cases} \tag{2.3.10}$$

Equations (2.3.9) and (2.3.10) provide recursive solutions for $P_t^c(c')$ and L_t^c. We can use these solutions to quantify cohort attachment.

Definition. *Ego displays cohort attachment relative to agents in cohort c' if the probability that a member of his cohort is in his network is greater than the probability that a member of cohort c' is in his network. The **strength** of cohort attachment is given by the difference between these probabilities, i.e.,*

$$CA_t^c(c') \equiv P_t^c(c) - P_t^c(c').$$

The strength of cohort attachment at the end of the cohort entry period relative to any incumbent cohort $\hat{c} < c$ takes a particularly simple form:

$$CA_c^c(\hat{c}) = pz^* \frac{z^* - x_c^{\hat{c}}}{L_c^c}, \tag{2.3.11}$$

where $CA_c^c(\hat{c}) > 0$ since $x_c^{\hat{c}} < z^*$ by equation (2.2.5). We can build on this result to prove that there is cohort attachment relative to any incumbent cohort in all periods $t \geq c$.

Proposition 2.3.4. $CA_t^c(\hat{c}) = P_t^c(c) - P_t^c(\hat{c}) > 0$*: Ego displays cohort attachment relative to any incumbent cohort* $\hat{c} \in \mathscr{C}_{c-1}$.

Proof. The proof proceeds by induction. For the base case $t = c$, we have $CA_c^c(\hat{c}) > 0$ by equation (2.3.11). For the inductive step for period $t > c$, compute $CA_t^c(\hat{c})$ as

$$(1-\delta)[P_{t-1}^c(c) - P_{t-1}^c(\hat{c})] + [1-(1-\delta)\frac{P_{t-1}^c(c)}{p}]px_t^c\frac{x_t^c}{L_t^c} - [1-(1-\delta)\frac{P_{t-1}^c(\hat{c})}{p}]px_t^c\frac{x_t^{\hat{c}}}{L_t^c}.$$

Let $k_c = (1-\delta)\frac{P_{t-1}^c(c)}{p}$, $k_{\hat{c}} = (1-\delta)\frac{P_{t-1}^c(\hat{c})}{p}$, $m_c = x_t^c\frac{x_t^c}{L_t^c}$ and $m_{\hat{c}} = x_t^c\frac{x_t^{\hat{c}}}{L_t^c}$. Note that $0 < k_{\hat{c}} < k_c < 1$ by the inductive hypothesis. Additionally, $0 < m_{\hat{c}} < m_c < 1$ because $x_t^c > x_t^{\hat{c}}$ for all t by equation 2.2.5. Substituting in $k_c, k_{\hat{c}}, m_c$ and $m_{\hat{c}}$, we have

$$p\{(k_c - k_{\hat{c}}) + [(1-k_c)m_c - (1-k_{\hat{c}})m_{\hat{c}}]\} = p\{(1-m_c)(k_c - k_{\hat{c}}) + (1-k_{\hat{c}})(m_c - m_{\hat{c}})\} > 0.$$

□

It follows from the proof of Proposition 2.3.4 that ego displays cohort attachment relative to a population-weighted average of incumbent cohorts. This can be important for empirical application.[11] Another empirical application could be to the density of the network of links between all agents in a firm, which we would predict to be greater within ego's cohort than between ego's cohort and any incumbent cohort.

One might think that the strength of cohort attachment for ego relative to cohorts that arrive after his cohort would be greater than relative to incumbent cohorts, because ego has had less time to meet with members of later cohorts. In fact, we cannot show that in general ego's cohort attachment relative to later cohorts is positive, let alone compare

[11] It should also be noted for empirical application that many production processes encourage entrants to a firm to meet with members of incumbent cohorts for training purposes. If these meetings result in increased representation of incumbent cohorts in ego's network, they make it less likely we will find empirical support for Proposition 2.3.4. Such meetings may not yield information regarding whether the parties work well together as colleagues, however.

its magnitude with cohort attachment relative to incumbent cohorts. Note that ego is an incumbent relative to new cohorts. The same reduced openness to uncertain meetings that makes ego less likely to meet with members of a new cohort than he was to meet with members of his own cohort affects all incumbents. With fewer total meetings available, the probability of meeting with any given new arrival increases. If a new cohort is small, it absorbs few meetings of the new arrivals and thus does not offset their greater chance of meeting with ego.

In Appendix 2.B, we calculate the strength of cohort attachment of ego relative to a later cohort in a three cohort firm in which ego's cohort is sandwiched in between an incumbent cohort and a later cohort. The calculation uses the same values of p and δ as in Figure 2.2.1 in the previous section and the mean values of cohort sizes from the data used in our application to employee entrepreneurship below (see Table 2.5.2). The strength of ego's cohort attachment relative to the later cohort is positive. In the calculation we also varied the size of the later cohort and found that the strength of cohort attachment relative to the later cohort was increasing in the size of the later cohort, consistent with the intuition above.

An important issue that arises in empirical application is that some agents separate from the firm. Assume that ego cannot meet with an agent who is no longer with the firm, and hence cannot learn his match quality if it is unknown. In this case it follows from Assumption 2.D that the probability that an agent is in ego's network falls at rate $1-\delta$ for every period he is separated from the firm. Proposition 2.3.5 then follows immediately from the definition of the strength of cohort attachment:

Proposition 2.3.5. *Ego's strength of cohort attachment to agents who have separated from the firm decreases at rate $1-\delta$ per period. That is, considering an agent in cohort c and an agent in cohort c' who separate from the firm at the end of period t, cohort attachment is given by $CA^c_{t+\tau}(c') = (1-\delta)^\tau CA^c_t(c')$.*

Finally, it can be shown using Equations (2.3.9) and (2.3.10) that if any incumbent cohort or ego's cohort is large enough, $P_t^c(c')$ goes to zero for any cohort c' (including ego's cohort). It follows from the definition of the strength of cohort attachment that it must also go to zero. In our empirical investigation we will therefore look for evidence that cohort attachment decreases with firm size in the period of ego's entry.

2.4 Contacts and Job Referral

Job referrals are the canonical application of network models in economics (e.g., Calvo-Armengol and Jackson, 2004). A small but growing empirical literature specifically analyzes job referrals to ego from alters he met in previous employment (Cingano and Rosolia, 2012; Saygin, Weber, and Weynandt, 2014; Chen-Zion, 2016).[12] This indicates the importance of exactly the kind of history-dependent network formation we emphasize in this paper. However, a job referral necessarily connects an ego outside a firm to alters inside the firm, whereas our model has focused entirely on network formation and operation within a firm (or, more broadly, within any one organization).

Let us extend our model to include many firms, finite in number. We assume that an agent can be employed by at most one firm in any period. An agent who does not work for any firm in a given period is unemployed in that period. Agents can move between firms or between unemployment and firms. Firms can form or dissolve.

We will call agents the *contacts* of ego if they were in ego's networks in previous firms but are not in his network in his current firm (if he is employed). A contact is different from an alter in ego's network in his current firm because, in the current period, ego cannot form a match with him. Ego therefore neither derives value nor incurs costs from the contacts in his network in the current period. We assume that, like other network

[12]There is a much broader job referral literature, which covers all types of connections between egos and alters rather than focusing on those formed through previous work at a common employer. For surveys see Ioannides and Loury (2004) and Topa (2011).

relationships, contacts return to unknown match quality at a constant exogenous rate every period. It seems reasonable to assume that the rate of contact decay is greater than the rate of network decay, but this is not necessary.

We only consider referrals of unemployed agents to firms.[13] Still more narrowly, we only consider referrals of egos who are unemployed because their previous firms dissolved. We do this to match the small empirical literature cited above. By focusing on egos whose firms have closed, these papers avoid the selection bias that would arise from studying egos who have been laid off from thriving firms.

Now consider a firm that wishes to hire workers from the pool of unemployed. We take the number of workers it wants to hire as exogenous. Consistent with the referral literature, we assume an information structure such that the firm only knows of contacts that are brought to its attention by its current employees. In particular, the firm is unaware of contacts that may exist between the unemployed workers themselves. If the firm knew of such contacts, it might want to hire a "ready-made" network of unemployed workers.

In this situation, the interests of the firm's employees and the firm are clearly aligned. The employees want the firm to be aware of their contacts among the unemployed, and the firm wants to hire the unemployed workers with the greatest mass of contacts among its employees.

To begin, we assume that unemployed workers are simply endowed with contacts at firms that are hiring, postponing consideration of how those contacts originated. We denote the mass of contacts of unemployed worker i at firm j by $m_{ij} \in [0, \bar{n}]$. Firms will rank the unemployed workers by m_{ij} and hire until all vacancies are filled.[14] Hence, the

[13]Referrals of employed agents, and job-to-job transitions more generally, bring up interesting additional issues that we hope to address in future work.

[14]We assume that, when these workers are matched with their contacts, none of the networks of their contacts is pushed above size $\bar{n}$. If the firm exhausts all unemployed workers with $m_{ij} > 0$ without filling all its vacancies, we assume it chooses randomly among the remaining workers. In a richer model unemployed workers could be distinguished not only by m_{ij} but also by some ε_{ij} that is independent of m_{ij}. ε_{ij} could, for example, reflect idiosyncratic firm-specific training costs.

probability that unemployed worker i is hired by firm j is increasing in m_{ij}.

Only the direct contacts of an unemployed worker can generate a referral. However, with multiple rounds of referrals, ego's contacts may receive referrals, and then refer ego in turn. In this case ego is affected by alters with more than one degree of separation. In our model, we have suppressed consideration of this dimension of egocentric networks in order to concentrate on the time dimension. That is, in the model of the previous sections ego does not care about the networks of his network members. In the extended model of this section, if there are multiple rounds of referrals ego will in general be affected by the contacts of his network members, and may therefore care about their networks as well. In the remainder of this section, we will show how, under certain assumptions, two rounds of referrals can be incorporated into our model of endogenous network formation. Ego will therefore be affected by contacts separated by two degrees. This can be important in empirical application, particularly if use of "peers-of-peers" instruments is desirable.

Let us divide the firms in our extended model into first-generation, second-generation, and third-generation firms. First-generation firms will hire unemployed workers based on referrals, second-generation firms will create the egocentric networks of interest, and (some) third-generation firms will dissolve into the pool of unemployed workers from which the first-generation firms will hire. In any period in which there is referral-based hiring, the expected mass of hires is equal across the first-generation firms, but hiring is distributed unevenly across them ex post. At $t = 1$, there exist only the first-generation firms. We assume that, prior to period 1, the first-generation firms reach steady state, meaning that all employees have networks of size $\hat{n}$. We expect that $\hat{n} > \bar{n}$ because network members may later prove useful as contacts, increasing the incentives for egos to accumulate networks.

During periods $t \in [2, T]$, second-generation firms emerge, which consist of successive cohorts of masses of workers hired away from first-generation firms such that each leaves behind a fraction α of his network. Now consider the process of network formation in the second-generation firms. By assumption, all workers in second-generation firms are symmetric with respect to contacts: each has $\alpha\hat{n}$ contacts at one first-generation firm.[15] Does ego care if a given member of his network has a larger network himself (e.g., is from an earlier cohort), and therefore has more indirect contacts? No, because contacts separated from ego's network member by two degrees are separated from ego by three degrees, and therefore cannot affect ego given only two rounds of referrals.

Finally, during periods $t \in [3,T]$ third-generation firms emerge, which consist of successive cohorts of randomly drawn masses of workers hired away from second-generation firms. Although workers in third-generation firms have contacts in second- as well as first-generation firms, this does not affect the process of network formation because only first-generation firms will hire based on referrals. At the end of periods T and $T+1$ some third-generation firms close, creating pools of unemployed workers. Each unemployed worker has a set of direct contacts at one first-generation firm and a set of indirect contacts to multiple first-generation firms through contacts made at a second-generation firm. Of course, unemployed workers also have indirect contacts to first-generation firms through contacts made at third-generation firms. Empirically, indirect referrals running through co-workers at third-generation firms are suspect. What we observe is successive hiring from the same closed firm, which may occur because the

[15]However, consider an alter from the same first generation firm as ego. The indirect contacts potentially acquired by meeting this alter cannot be of help to ego if he is unemployed and his first-generation firm is not hiring, unlike the indirect contacts of any other alter. Thus ego avoids meeting with unknown alters from his first generation firm, just as he avoids meeting with any alters known to be bad matches. Ego may also move to the second-generation firm with network members from his first generation firm. In this case ego starts with $n > 0$ rather than $n = 0$ at the second-generation firm, assuming that the higher expected match value with a network member dominates the benefit of better indirect contacts with an unknown alter.

hiring firm is targeting former workers at the third-generation firm for a specific kind of experience obtained there, rather than because the earlier hires refer the later hires. Absent this concern, we could do away with third-generation firms and consider indirect referrals of workers through co-workers at closed second-generation firms.

We focus on workers who became unemployed at the end of $T+1$ and whose first-generation firms are not hiring in $T+2$. Some of their contacts from second-generation firms may have been hired in $T+1$. In $T+2$, those contacts will refer them in turn. Ultimately, then, some unemployed workers will be hired by first-generation firms at which they never worked as the indirect result of referrals by workers they never met. Their probabilities of being hired by first-generation firms will be increasing in the masses of second-generation firm contacts that were hired by the first-generation firms in $T+1$.

Figure 2.4.2 illustrates indirect referral of ego e by alters a_2 through ego's contacts a. Firms 1A and 1B are the first-generation firms that respectively employ the referring alters and ego; Firm 2 is the second-generation firm at which alters and ego meet; and Firms 3A and 3B are the third-generation firms that ultimately close and respectively leave alters and ego unemployed. The mass of alters a consists of those agents who leave Firm 1A and ultimately return through referral after having become ego's contacts. They are a subset of the agents who leave Firm 1A and join ego at Firm 2. The mass of alters a_2 consists of the members of the networks of a who never leave Firm 1A and survive decay to remain their contacts.[16] Over time ego progresses upward in the figure, ultimately reaching Firm 1A as the result of a causal chain initiated by a_2.

[16]In empirical practice, a_2 could be working at any firm, so a do not have to be referred to their former employer.

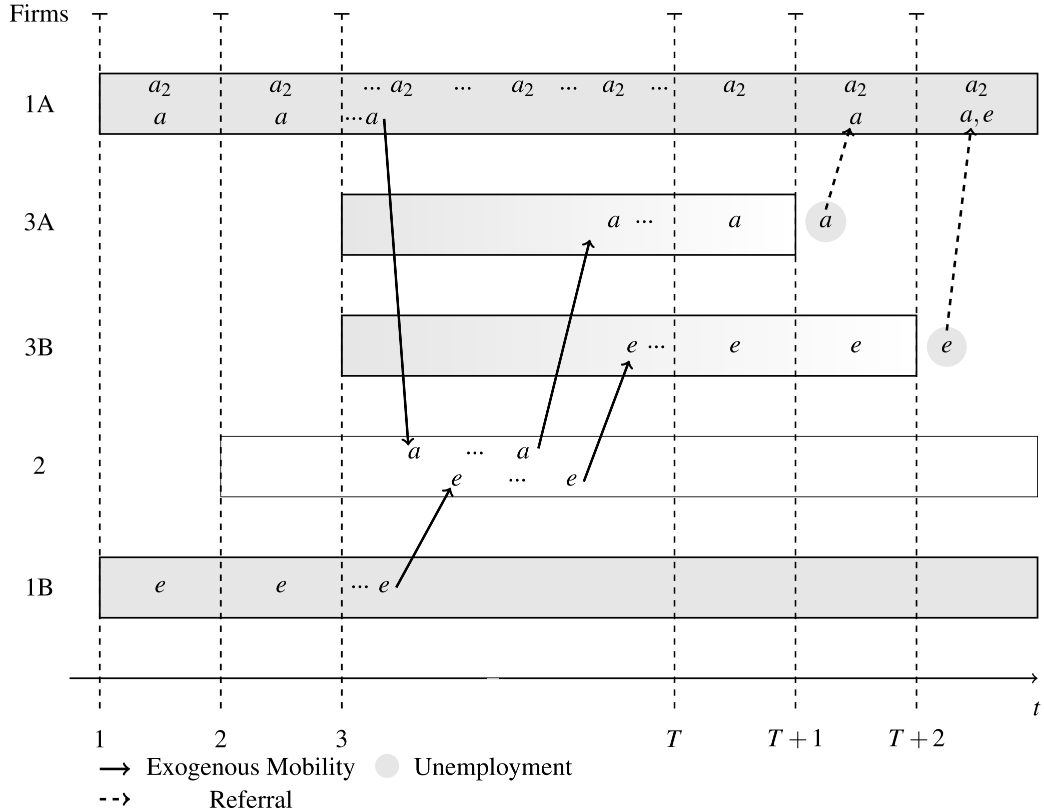

Figure 2.4.2. Ego is indirectly referred by a_2 through his contacts a

2.5 Data and Summary Statistics

Our data derive from the linked employer-employee records RAIS (*Relação Anual de Informações Sociais* of the Brazilian labor ministry *MTE*), which record comprehensive individual employee information on occupations, demographic characteristics and earnings, along with employer identifiers. By Brazilian law, every private or public-sector employer must report this information every year.[17] De Negri et al. (1998)

[17]RAIS primarily provides information to a federal wage supplement program (*Abono Salarial*), by which every employee with formal employment during the calendar year receives the equivalent of a monthly minimum wage. RAIS records are then shared across government agencies. An employer's failure to report complete workforce information can, in principle, result in fines proportional to the workforce size, but fines are rarely issued. In practice, employees and employers have strong incentives to ascertain complete RAIS records because payment of the annual public wage supplement is exclusively

compare labor force information in RAIS to that in a main Brazilian household survey (PNAD) and conclude that, when comparable, RAIS delivers qualitatively similar results to those in the national household survey. Menezes-Filho, Muendler, and Ramey (2008) apply the Abowd et al. (2001) earnings-estimation methodology to Brazil and show that labor-market outcomes from RAIS broadly resemble those in France and the United States, even after controlling for selection into formal employment, except for unusually high returns to high school and college education and to experience among males.

A job observation in RAIS is identified by the employee ID, the employer's tax ID (CNPJ), and dates of job accession and separation. To avoid double-counting employees at new firms, we keep only one observation for each employer-employee pair, choosing the job with the earliest hiring date. If the employee has two jobs at the firm starting in the same month, we keep the highest paying one. The rules on tax ID assignments make it possible to identify new firms (the first eight digits of the tax ID) and new plants within firms (the last six digits of the tax ID). Our pristine RAIS records include 71.1 million employees (with 556.3 million job spells) at 5.52 million plants in 3.75 million firms over the sixteen-year period 1986-2001 in any sector of the economy. We limit our attention to the years 1995-2001 and use the period 1986-1994 in RAIS to ensure that firms we label as new in 1995-2001 have not operated before. Moreover, RAIS does not specify the legal form of firms until 1995, information that is needed to carefully identify employee spinoffs as described below. During this 7-year period, 1.54 million new firms and 2.17 million plants entered (of which 581 thousand new plants were created within incumbent firms). Muendler, Rauch, and Tocoian (2012, hereafter MRT) present further details on the data source and its application to employee spinoffs.

By 1995 macroeconomic stabilization had succeeded in Brazil. The Plano

based on RAIS. The ministry of labor estimates that well above 90 percent of all formally employed individuals in Brazil are covered in RAIS throughout the 1990s.

Real from August 1994 had brought inflation down to single-digit rates. Fernando Henrique Cardoso, who had enacted the Plano Real as Minister of Finance, became president, signalling a period of financial calm and fiscal austerity. Apart from a large exchange-rate devaluation in early 1999 and a subsequent switch from exchange-rate to inflation-targeting at the central bank, macroeconomic conditions remained relatively stable throughout the period.

In order to test our predictions it is crucial that we successfully identify employee spinoff firms and their parents. MRT use two alternative criteria and show the robustness of results under either criterion. For their first employee spinoff definition, they restrict their attention to new firms with at least one employee recorded as "director" or "manager",[18] and use the criterion that if the top paid director (or top paid manager if there is no director) previously worked for an existing firm in the same 4-digit CNAE industry,[19] the new firm is an employee spinoff and the existing firm is its parent. However, if this new firm absorbed at least seventy percent of the workers in one of the parent's plants and has a legal form such that it could be owned by the parent, MRT classify it as a divestiture (an employer-initiated spinoff) rather than an employee spinoff.[20] MRT find that the performance of spinoffs is superior to new firms without parents but inferior to divestitures. In particular, size at entry is larger among employee spinoffs than among new firms without parents but smaller than among divestitures, and subsequent exit rates (controlling for size at entry) for employee spinoffs are smaller than for new firms without parents but larger than for divestitures. We will use MRT's criteria to distinguish employee spinoffs from new firms without parents and from divestitures. By these

[18]Occupational classifications in RAIS follow the CBO (Classificao Brasileira de Ocupaes), which had more than 350 categories during the period 1995-2001.

[19]During our sample period, sectors are reported under the CNAE four-digit classification (Classificao Nacional de Atividade Econmica) for 564 industries in the RAIS universe, spanning all sectors of the economy. The level of detail is roughly comparable to the NAICS 2007 five-digit level.

[20]A new firm that has a legal form such that it could be owned by the parent but that absorbed less than 70 percent of workers from a parent plant is classified as a spinoff.

criteria, 16.9 percent of new firms in Brazil's domestically-owned private sector (that is, excluding firms with state or foreign ownership) in the period 1995-2001 with a recorded director or manager are employee spinoffs.

Our analysis is centered on the network in the parent firm of the employee who will become the top paid director (or top paid manager if there is no director) of the employee spinoff firm. Hereafter we will refer to that employee as the "director/manager."[21] If the director/manager recruits any of his co-workers at the parent firm to join him at his new firm, all else equal he will recruit co-workers in his network. Our theory predicts that members of his cohort at the parent firm will be disproportionately represented in his network, hence members of his cohort at the parent firm will be disproportionately represented among the co-workers he recruits to his new firm.

We consider two different approaches to defining the universe of parent co-workers who could be in the director/manager's network. The less restrictive approach includes all co-workers who were employed at the parent firm after 1993 and before the year that the director/manager founds the spinoff, where co-worker is defined as any worker whose job tenure overlaps that of the director/manager by at least one month.[22] By the time the spinoff firm is founded, many of these employees would have left the parent firm for other formal sector jobs, the informal sector, or unemployment. We call this sample of workers ALL. The more restrictive approach only includes employees who were co-workers of the director/manager in the month he left the parent firm, so

[21]A weakness of our data is that we do not know whether the director/manager has an ownership stake in his new firm, hence he cannot be unambiguously labelled the "entrepreneur." Unobserved owners may have picked all other new employees for their new firm and then picked the director/manager to lead them, drawing on the knowledge of customers, suppliers and technology he accumulated at the parent. If the true owner(s) does not internalize any psychic benefits the director/manager might obtain from working with employees with whom he is well matched, we are less likely to find evidence for cohort attachment in the choice of co-workers (if any) that join the director/manager at the new firm.

[22]Before 1994 RAIS does not include a worker's industry classification (or municipality), which is an important control variable in the analysis of the next section of our paper. If the director/manager leaves the parent firm in the same year he founds the spinoff, his co-workers in that year are included.

we call this sample LVMONTH. Our results tend to be the same regardless of which sample we use, despite the fact that the ALL sample contains 92 percent more workers (3,254,089 compared to 1,691,272 in the LVMONTH sample). To save space we only report results for the ALL sample, citing any qualitative differences for the LVMONTH sample in footnotes and showing our final specifications using the LVMONTH sample in Appendix 2.C. The chief advantage of the ALL sample is that it gives us more data with which to estimate the effects of separation, which will include network decay according to our theory, whereas the LVMONTH sample yields substantially higher values of R^2.[23]

In the analysis of the next section, our dependent variable will be an indicator that equals one if a parent-firm employee accompanied the director/manager to the employee spinoff firm, and zero otherwise. We will include spinoff firm fixed effects to account for the overall attractiveness of the spinoff relative to the parent.[24] We drop spinoff firms to which the director/manager moved without any co-workers, for which the dependent variable is identically zero.[25] This leaves 6,094 employee spinoff firms from 6,033 director/managers and 5,718 parent firms for the ALL sample.

We define a same cohort indicator equal to one for any co-worker whose starting month at the parent firm is within two months of the future director/manager's starting month, and zero otherwise. The two-month cohort window is determined by our decision (following MRT) to save only job spells of three months or longer. The minimum length of three months was chosen to ensure that a worker considered to have been employed at a firm actually spent a substantial amount of time there, as opposed to the end of one

[23]If we include in the ALL sample parent firm workers who arrive and leave before the director/manager is hired, our results in Section 2.6 are qualitatively unchanged, though we need to change the specifications including the log months of overlap variable to instead include an indicator for whether overlap is positive and the interaction between that indicator and log months of overlap.

[24]Fixed effects account for factors such as director/manager characteristics and parent firm quality at the time of spinoff. Spinoff firm fixed effects rather than director/manager fixed effects are used because there are some director/managers who found multiple spinoffs.

[25]These are the firms for which the scenario in which unobserved owners picked all other employees for their new firm and then picked the director/manager to lead them is most likely.

month and the beginning of the next. A two-month cohort window then ensures that any worker counted as a member of the director/manager's hiring cohort overlaps with him for at least one month. For 92.6 percent of the spinoff firms in the ALL sample, there is at least one parent firm employee in the director/manager's cohort by this definition.

When a parent firm has multiple plants, we expect the process of network formation we model in Section 2.2 to occur primarily within a plant rather than between plants. We therefore distinguish parent firm workers who are in the same initial plants as the future director/managers from all other parent firm workers in the descriptive statistics reported in Table 2.5.1 and in the regressions in the next section of our paper.[26] Henceforward we refer to the former workers as "same plant workers" and the latter workers as "other plant workers." We see that the mean probability that a same plant worker will join the director/manager at his spinoff is ten percent, compared to one percent for other plant workers. Because there are more than two and a half times as many other plant workers, however, they account for 20.8 percent of all parent firm co-workers who join director/managers at their spinoffs. Eleven percent of same plant workers were in the director/manager's cohort, compared to six percent of other plant workers. The industry breakdown shows that a much higher proportion of same plant workers than other plant workers were in the manufacturing sector and in manufacturing and transport occupations, which is consistent with their lower education levels and lower female share. Comparing future director/managers to parent workers in their plants or others, we see that director/managers tend to be older and more educated, as we would expect. Future director/managers were also far more likely to have held that same occupation (within the "Executive and Government" group) in the parent firms than were their co-workers, with

[26]We choose workers in the same initial plants rather than same final plants because our theory predicts that the future director/managers are most open to forming links when they first join the parent firms. We will control for working in the same final plants as the director/managers starting with Table 2.6.6 below.

potential implications for cohort attachment that we will explore in the next section.[27]

In Table 2.5.2 we provide some summary statistics relating to the process of employee spinoff formation from the point of view of the future director/managers. When the director/manager is hired, the mean (median) number of same plant co-workers (inclusive of his hiring cohort) is 81 (14).[28] For multi-plant parents, the mean (median) number in other plants is 656 (36). When the director/manager leaves the parent firm to found a spinoff, his mean (median) tenure at the parent is 40 (29) months. The mean (median) number of workers at his spinoff is 52 (16), of whom a mean (median) of 35.7 (33.3) percent have been recruited from the parent firm. As a preliminary test of the cohort attachment hypothesis, we can ask whether the members of the director/managers' cohorts were overrepresented among the workers who joined them at the spinoff firms. First consider same plant workers. At least one such worker was in the "founding team" for 5,685 of the 6,094 spinoff firms. For these spinoff firms, at the times the director/managers left the parent firms the share of same plant workers who were also in the director/managers' cohorts was 20.3 percent on average.[29] These cohort workers accounted for an average of 22.4 percent of the same plant workers in the founding teams. A paired t-test of whether the 2.1 percent difference in means is positive is statistically significant at the one percent level. Turning to other plant workers, at least one such worker was in the founding team for 1,367 of the 2,442 spinoff firms that had multi-plant parents. For these spinoff firms, the average share of other plant workers in the director/managers' cohorts at the parent firms was 9.2 percent at the times the director/managers left the parent firms. These cohort workers accounted for 7.5 percent

[27] All worker characteristics are recorded in the year the spinoff was formed or the last year the worker was employed at the parent firm, whichever comes earlier.

[28] These numbers exclude the 12 percent of spinoff firms for which the director/manager had no incumbent or cohort workers in his first plant at the parent firm.

[29] The reason this number exceeds the corresponding 11 percent reported in Table 2.5.1 is that Table 2.5.1 gives more weight to larger parent firms.

of the other plant workers in the founding teams on average. A paired t-test of whether the -1.7 percent difference in means is positive is not statistically significant.

2.6 Application to Cohort Attachment in Employee Entrepreneurship

In this section we report regressions in which the dependent variable is an indicator for whether a parent firm worker joins the director/manager at his spinoff firm. We introduce explanatory variables suggested by our theory in Tables 2.6.4 and 2.6.5. Potentially confounding explanatory variables are introduced in Tables 2.6.6 and 2.6.7. The means by same versus other plants for all of these variables not previously summarized are given in Table 2.6.3.

As we discussed in the previous section, we expect the explanatory variables relating to meetings between the worker and director/manager at the parent firm to have more impact for same plant workers than for other plant workers. We therefore include an interaction term with the indicator for different first plant for each of these variables. In each table we report the coefficients on the listed variables in columns labeled "base#," where # is the 1st, 2nd, etc. specification in the table, and we report the sums of these coefficients with the coefficients on the interaction terms in columns labeled "other#." (We report the coefficients on the interaction terms for the final specifications in columns labeled "otherX#" in Appendix Tables 2.A.1 and 2.A.3.) We continue this procedure for the potentially confounding variables for consistency, without the expectation that their effects will be weaker for other plant workers. All regressions also include: a constant term; worker age, education, gender, nationality, occupation, industry, and state at the time the worker leaves the parent; the interactions between all of these and an indicator for whether the worker was in a different first plant than the director/manager; and spinoff firm fixed effects.

Our use of the linear probability model facilitates interpretation and is in line with much of the current literature. However, we will introduce several explanatory variables measured in months, and extreme values of these variables will clearly lead to predicted values of the dependent variable outside the interval [0,1]. We will therefore explore other estimation strategies such as logit in a future draft.[30]

Table 2.6.4 addresses our predictions that workers in the same cohort as the future director/manager are more likely to join him at his spinoff firm, and that the impact of same cohort will weaken with time for workers who separate from the parent firm before the director/manager does. We defer to the end of this section any distinction between the impact of same cohort relative to incumbent versus later cohort workers. The first specification in Table 2.6.4 includes only the same cohort indicator, and the second specification adds an indicator for whether the worker separated from the parent firm, the interaction of this indicator with the log of the number of months of separation, and the interactions of both of these variables with the same cohort indicator. Months of separation are measured from the worker's separation from the parent firm to the director/manager's separation from the parent firm.

For same plant workers the coefficient on the same cohort indicator is positive and statistically significant in both specifications but much larger when the separation variables are included. It is interesting to contrast these results with those for the LVMONTH sample, which is conditioned on the workers being at the parent in the month the director/manager left, so that a worker in the LVMONTH sample cannot have been separated from the firm. Appendix Table 2.A.2 shows that, compared to the first specification for the ALL sample, the coefficient on the same cohort indicator for same plant workers more than triples. For other plant workers, the effect of same cohort on the

[30]For a discussion of the pros and cons of the linear probability model, see Wooldridge (2001) Section 15.2.

probability of joining the director/manager at his spinoff is statistically insignificant for the LVMONTH sample and for the second specification for the ALL sample.[31]

The impacts of the separation variables shown in Table 2.6.4, both in levels and interacted with the same cohort indicator, prove very stable in later specifications despite inclusion of variables such as length of worker overlap with the director/manager. We interpret the level effect of the separation indicator as showing that a worker who is a poor fit for the parent firm is also a poor fit for its spinoff,[32] and the level effect of the interaction of this indicator with log months of separation as showing that the longer the separation the more any relevant skills will have deteriorated. These effects are much smaller for other plant workers because skills in other plants are less likely to have been relevant to begin with. Controlling for these level effects, the negative coefficient on the interaction between the same cohort indicator and the length of separation variable for same plant workers shows the weakening of cohort attachment predicted by our theory. We cannot explain why, for other plant workers, the separation indicator and its interaction with log months of separation have statistically significant positive and negative effects, respectively, but note that the sum of these effects evaluated at the mean months of separation for other plant workers (22.74 months) is .0011 and is statistically insignificant.

Our theory suggests that the more opportunities the future director/manager has to meet with workers at the parent firm, the more likely they are to be in his network. We can measure these opportunities by the number of months for which the director/manager and co-worker overlap at the parent firm. The first specification in Table 2.6.5 adds log months of overlap as an explanatory variable. Overlap has a positive and statistically significant

[31] In our final specifications (Table 2.6.7 and Appendix Table 2.A.3) this effect is negative and statistically significant for both samples.

[32] Recall that the spinoff definition that we are using from MRT requires the spinoff to be in the same four-digit industry as the parent.

impact on the probability that a worker joins the director/manager at his spinoff for same plant workers. The impact for other plant workers is an order of magnitude smaller and statistically insignificant. The addition of the overlap variable slightly reduces the coefficient on the same cohort indicator. This is not surprising given that being in the same cohort generates high overlap.

Quite apart from length of overlap with director/manager tenure, length of worker tenure at the parent firm can be expected to have an effect on the worker's probability of joining the director/manager at the spinoff. It is a well-known result in labor economics that the probability that a worker will separate from his employer decreases with his tenure, except for a possible increase at very short tenure lengths (Farber, 1999). Our model is consistent with this result because the value of a worker's network, which he gives up if he leaves for another employer, increases with his tenure at the firm (Corollary 1). If a worker's probability of separation from the parent decreases, so will his probability of joining the spinoff.[33] We therefore add log months of tenure as an additional explanatory variable in the second specification in Table 2.6.5.[34] The effect on the probability that a worker joins the director/manager at his spinoff is negative and statistically significant for same and other plant workers, but about six times larger for the same plant workers. Note that, for workers who arrive at the parent after the director/manager, months of overlap and months of tenure are the same if the director/manager founds his spinoff in the same year he leaves the parent. Hence it is the presence of incumbent workers that allows separate identification of the effects of overlap and tenure in these cases. Taken together, the coefficients on the overlap and tenure variables show that, before the future director/manager arrives, additional months of tenure reduce the

[33]Yet another reason to control for worker tenure is that a worker with longer tenure becomes progressively less open to meeting with workers of unknown match quality, hence less likely to become a member of the network of the future director/manager.

[34]Table 2.6.3 shows, for same plant workers, that average tenure is 48 months, which is 9 months higher than for the future director/managers.

probability that a worker will leave the parent firm for the spinoff, whereas after the director/manager arrives additional months of tenure do not affect this probability for same plant workers: the sum of the coefficients is 0.0015 with a standard error of 0.0016.

The positive coefficient on the same cohort indicator may reflect the influence of similarities between workers hired by a parent firm in the same first plant and at the same time as the future director/manager. Numerous studies show that people tend to form network links with others like themselves (McPherson, Smith-Lovin, and Cook, 2001; Currarini, Jackson, and Pin, 2009). More directly, workers like the director/manager may be the best fits for the spinoff firm. We therefore add to our previous specification a long list of potentially confounding variables of this type: same age group, same education group, same gender, same nationality, same occupation group, and same industry group. Age groups, education groups, and occupation groups are defined as in Table 2.5.1, and industry group is defined at the two-digit CNAE level. A related issue arises because some parent firms are very large, with operations in many states. The future director/manager may not even be aware of most employees not in his locality. Therefore we add a variable for same state. Finally, workers may change plants during their employment with the parent firm, so we include a variable for same last plant. All of these variables are measured for the year(s) the worker and director/manager leave the parent firm, because this is when fit for the spinoff firm is most relevant. Table 2.6.3 lists the four variables relating to worker characteristics not determined by their employment first, followed by the other four variables. The means for all of these variables except same nationality are higher for same plant workers than for other plant workers, and far higher for same state and same last plant, as would be expected.[35]

Table 2.6.6 shows the impacts of the potentially confounding variables on the

[35]Workers are classified by industry in RAIS, not their plants, so workers in the same plant can be classified in different industries.

probability that a parent firm worker joins the future director/manager at his spinoff firm. All statistically significant effects, whether for same or other plant workers, have the expected positive sign. Except for same gender and same nationality, all of these effects are larger for other plant workers, sometimes statistically significantly larger as shown in Appendix Table 2.A.1.[36] Most importantly, inclusion of these potentially confounding variables causes the coefficient on the cohort indicator to decrease only slightly.

In our last main table we examine the robustness of our results to addition of several variables that might explain away some or all of the same cohort effect. First we add an indicator for same previous employer as the future director/manager ("was with dir/man"). This can be thought of as capturing another dimension of potential similarity between a worker and the director/manager, but it could also be the case that a previous co-worker is already in the network of the director/manager. This could account for the cohort effect if the future director/manager arrived at the parent firm with a team from a previous employer, then left with members of the same team. We see from the first two columns of Table 2.6.7 that having the same previous employer as the future director manager increases the probability that a same (other) plant worker will join him at the spinoff firm by 3.7 (6.2) percentage points, but inclusion of this variable reduces the same cohort effect only slightly.

As we saw in Table 2.5.1, 47 percent of future director/managers in the ALL sample were in the "Executives and Government" occupation in their parent firms,[37] compared to two percent of other parent workers in this sample. Perhaps the director/managers had hiring authority at the parent firms, and hired other workers shortly after the parents hired them – indeed, perhaps this was one of the tasks the parent firms hired them to do. If so, it would not be surprising if the director/managers continued to

[36]This statement does not hold for the LVMONTH sample.
[37]The "Executives and Government" group contains most management level positions.

prefer the workers they hired at the parents when they founded their spinoff firms. To check if this is the source of the same cohort effect, we added to the third and fourth columns of Table 2.6.7 an interaction between the same cohort indicator and an indicator for whether the director/manager was an executive. The effect of this interaction is negative for same and other plant workers and statistically significant for the latter workers, though for the LVMONTH sample it is positive for the former workers, negative for the latter, and statistically significant for neither. The coefficient on the same cohort indicator is almost unchanged.

The last concern we address is that same cohort is a proxy for ability. Perhaps the future director/manager emerged from his cohort because it was a collection of especially high ability workers, from whom he then recruited. (This leaves unanswered the question of why the parent firm, which hired the workers to begin with, is unable to retain them.) We do not have a measure of ability in our data, but we can include the worker's (log) wage at the parent as an additional control, which should proxy for ability given that all of the worker's observable characteristics are already included in the regressions. Since wage data are missing for some workers, to avoid dropping observations we add in the fifth and sixth columns of Table 2.6.7 an indicator for whether the data are present and its interaction with the worker's log wage at the parent. The effect of this interaction is negative (positive) and statistically insignificant (significant) for same (other) plant workers, though for the LVMONTH sample it is positive and statistically insignificant for both groups of workers. The coefficient on the same cohort indicator is unaffected.[38]

In Appendix Tables 2.A.4 and 2.A.5, we explore more speculative elements of

[38]We also tried adding to our final regressions the interaction between our same cohort indicator and the log of director/manager tenure. Subsequent to his entry into the parent firm and formation of his period c cohort attachment, our model predicts two counteracting effects of the length of director/manager tenure on the strength of his cohort attachment in period $t > c$. On the one hand, initial cohort attachment should decay at rate δ. On the other hand, initial cohort attachment may be reinforced over time, at least relative to incumbent cohorts, because workers in the entering cohort remain more open to new meetings relative to incumbent workers. The coefficient on this interaction was statistically insignificant for both samples.

the theory in Section 2.3. The theory suggests (but does not prove) that the strength of cohort attachment will decrease with the number of incumbent workers and the number of cohort workers. In Table 2.A.4 we create two new variables, an indicator for whether any worker is present and an interaction of this indicator with the log of the number of workers in the plant (inclusive of cohort workers) at the time the director/manager was hired, and add the interactions of these two variables with the same cohort indicator to the last specification in Table 2.6.5 and the last specification in Table 2.6.7.[39] For same plant workers the coefficient on the interaction with log plant size is negative as predicted but statistically insignificant. The interaction for log of other plant size has a small positive and statistically significant coefficient.[40] The interaction for presence of any same plant worker has a negative and statistically significant coefficient, though only marginally significant using the last specification in Table 2.6.7, suggesting a "founding cohort" effect: cohort attachment is especially strong for the very first cohort, as would be expected.

As discussed in Section 2.3, cohort attachment may differ relative to incumbent versus later cohorts, and the latter may increase with the size of the later cohort. To explore these possibilities, in Table 2.A.5 we add two variables to the specifications used in Table 2.A.4. The first is an indicator for whether a worker arrives at the parent firm more than two months after the director/manager, and the second is an interaction between that indicator, the log of the number of such workers, and an indicator for whether the number of such workers is positive.[41] Now the coefficient on the same cohort indicator measures the probability that a same cohort worker joins the spinoff

[39] The new variables themselves, as opposed to their interactions with the same cohort indicator, are absorbed into the spinoff fixed effects.

[40] For the LVMONTH sample the coefficient on the interaction with log plant size is negative and statistically significant for same plant workers and statistically insignificant for other plant workers; see Table 2.A.6.

[41] It proved impossible to separately estimate a coefficient on the indicator for whether the number of later cohort workers is positive due to collinearity.

relative to incumbent cohort workers, and the coefficient on the new indicator measures the probability that later cohort workers join the spinoff relative to incumbent cohort workers. A positive coefficient on the new indicator therefore implies that the same cohort effect is *smaller* relative to later than incumbent cohorts, and a positive coefficient on the new interaction term implies that the same cohort effect relative to later cohorts *decreases* with later cohort size. Tables 2.A.5 and 2.A.6 show the results for the ALL and LVMONTH samples, respectively. For the ALL sample the coefficient on the later cohort indicator is negative and insignificant or weakly significant depending on specification; for the LVMONTH sample this coefficient is consistently positive and insignificant. The coefficient on the interaction between later cohort indicator, log of later cohort size, and the indicator for positive later cohort size is consistently negative and insignificant for the ALL sample and negative and highly significant for the LVMONTH sample. Overall, there seems to be insufficient evidence to justify disaggregating the same cohort effect relative to later versus incumbent cohorts, though there is intriguing support for the theory illustrated in Figure 2.A.1.

Returning to Table 2.6.7, we quantitatively evaluate the cohort effect using the coefficient on the same cohort indicator in the first column, before adding the statistically insignificant interaction with the indicator for whether the director/manager was an executive at the parent firm. We can compare this value of 0.038 (with a standard error of 0.009)[42] to the mean probability of 0.18 that a same plant worker who does not separate from the parent firm before the director/manager does will join his spinoff: belonging to the same hiring cohort increases that probability by about 21 percent. According to our theory, this effect indicates that membership in the same hiring cohort at the same plant of the parent firm increases the probability that a worker will be in

[42]The corresponding coefficient for the LVMONTH sample in Table 2.A.3 is 0.021 with a standard error of 0.008.

the future director/manager's network, which in turn has an impact on who joins him at the spinoff firm. Network colleagues are compared to workers of unknown match quality both outside and inside the parent firm. As suggested in our introduction, both director/manager and worker may see substantial value in having established a smooth work relationship, rather than risk having to negotiate a difficult work relationship in the tense, error-prone setting of a new firm.

However, our results for the same cohort indicator can also be rationalized in terms of its being a proxy for unobserved similarity between the worker and director/manager. Months of separation may weaken the cohort effect because they reduce the unobserved similarity. The negative or statistically insignificant impact of same cohort for other plant workers could be due to same cohort not being a proxy for similarity between these workers and the director/manager. The fact that controlling for all the elements of similarity we can observe reduced the coefficient on the same cohort indicator only slightly (Table 2.6.6) casts some doubt on this alternative explanation, but we cannot reject it.

2.7 Conclusion

When chance meetings reveal compatibility, the agents involved have incentives to maintain their relationships. Accumulating relationships becomes increasingly costly, however, causing agents to become less open to chance meetings over time. The interaction of this dynamic with the natural tendency of relationships to decay leads to Proposition 2.2.3 in our paper, describing for an egocentric network in an organization the time pattern of history dependence as a function of ego's tenure in the organization.

We extended our model to allow agents to enter an organization in cohorts, and showed a tendency for members of ego's cohort to be disproportionately represented in his network. In a further extension we allowed members of ego's network who are subsequently split across many organizations to be his “contacts.” The desire of contacts to renew their successful working relationships leads to job referrals. We showed how our model could incorporate indirect referrals through contacts of contacts.

In our empirical work it was convenient for us to focus on the prediction of cohort attachment, the impact of which could be estimated using publicly available data. In the future, surveys of individuals in organizations could map out the times at which they met the alters in their networks and thus directly test Proposition 2.2.3. Data at the firm rather than individual level could also be relevant if the agents in our model were firms instead of individuals, establishing relationships with other firms. Proposition 2.2.3 then suggests, for example, that the networks of young firms would be dominated by the clients and suppliers with which they were matched at startup, whereas the networks of firms that survive to “maturity” would be dominated by more recent clients and suppliers. The generality of our framework should accommodate many applications.

2.7.1 Acknowledgements

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Table 2.5.1. Means for ALL Sample

	Same Plant (1)	Other Plant (2)	Dir/man (3)
Leave for spinoff	.10	.01	
Started within 2 m of Dir/man (Indic)	.11	.06	
Age Breakdown			
18 – 24	.23	.21	.11
25 – 29	.20	.19	.19
30 – 39	.31	.31	.40
40 – 49	.17	.18	.22
50 – 64	.06	.08	.07
≥ 65	.005	.007	.002
Education Breakdown			
Middle School or less	.63	.45	.34
Some High School	.26	.34	.41
Some College	.04	.05	.07
College Degree	.07	.16	.18
Occupation Breakdown			
Scientists and Technicians	.08	.21	.03
Executive and Government	.02	.02	.47
Administrative and Clerical	.22	.22	.16
Commerce	.08	.12	.19
Personal Services	.13	.21	.03
Agriculture	.05	.02	.008
Manufacturing and Transport	.43	.20	.10
Industry Breakdown[1]			
Manufacturing Sector	.30	.12	.21
Service Sector	.63	.67	.74
Primary Sector	.04	.01	.01
Female	.27	.40	.27
Brazilian (Nationality[2])	.9967	.9968	.99
South-east Region[3]	.61	.60	.53
Obs	895,827	2,358,262	6,094

[1] The reported sectors are aggregates of the 2-digit CNAE that is used in the regressions and to calculate "Same Industry": Primary 1-14, Manufacturing 15-37, and Service 40-90.
[2] Other nationalities are not reported in this table, but are included in the regressions.
[3] State indicators are used in the analysis. The South-east region is the aggregate of those indicators for that region (which has the majority of the population): Rio de Janeiro, São Paulo, Minas Gerais and Espirito Santo.

Table 2.5.2. Director/Manager Summary Statistics

	mean	sd	p50	N
	(1)	(2)	(3)	(4)
Init. Pl. Size > 0	.876	.329	1	6,094
Init. Pl. Size[1]	80.553	416.926	14	5,341
Other Init. Pl. Size> 0	.332	.471	0	6,094
Other Init. Pl. Size[1]	656.361	3090.807	36	2,021
Dir/man Tenure	39.601	33.725	29	6,094
Spinoff Firm Size	51.546	203.429	16	6,094
Team Size / Spinoff Firm Size	.357	.251	.333	6,094
Init. Pl. Size prior to entry[1,2]	80.696	425.275	14	4,855
Init. Pl. Cohort Size[1,2]	21.553	64.000	7	5,480
Init. Pl. Entrants > 2 m after entry[1,2]	105.811	438.439	20	5,378

[1] Variable is summarized conditional on positive.
[2] Used in Figure 2.A.1

Table 2.6.3. Means of Additional Variables Used in the Regressions

	Same Plant	Other Plant[2]
	(1)	(2)
Separation>0	.51	.47
Separation[1] (Months)	21.67	22.74
Overlap w/ Dir/man (Months)	23.68	28.60
Tenure (Months)	48.08	67.49
Same Age Bin (Indic)	.24	.24
Same Education Group (Indic)	.38	.36
Same Gender (Indic)	.70	.60
Same Nationality (Indic)	.97	.98
Same Occupation Group (Indic)	.22	.16
Same 2d-Industry Group (Indic)	.97	.80
Same Last Plant[2] (Indic)	.89	.05
Same State[3] (Indic)	.96	.35
Was w/ Dir/man	.04	.02
Avg Monthly Wage >0	.98	.98
Avg Monthly Wage[1]	610.36	648.88
Obs	895,827	2,358,262

[1] Variable is summarized conditional on positive.
[2] 61.4% of parents in the ALL sample have a unique plant.
[3] 84.1% of parents in the ALL sample have a unique state.

Table 2.6.4. Same Cohort Indicator and Separation

	base1	other1	base2	other2
	(1)	(2)	(3)	(4)
Started within 2 m of Dir/man (Indic)	.012	-.004	.062	-.001
	(.005)**	(.001)***	(.009)***	(.002)
Same Coh. X Separation>0			-.027	.010
			(.017)	(.004)**
Same Coh. X (Log) Separation (Months)			-.015	-.003
			(.005)***	(.001)**
Separation>0			-.093	-.011
			(.012)***	(.004)***
(Log) Separation (Months)			-.025	-.006
			(.003)***	(.002)***
Obs.	3,254,089		3,254,089	
R^2	.328		.37	
Mean Dep. variable	.039		.039	
Spinoffs	6,094		6,094	

Note: Standard errors clustered at the closure level. All columns contain closure$\times$potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.6.5. Overlap and Tenure

	base1	other1	base2	other2
	(1)	(2)	(3)	(4)
Started within 2 m of Dir/man (Indic)	.060	-.002	.042	-.007
	(.009)***	(.002)	(.010)***	(.002)***
Same Coh. X Separation> 0	-.027	.009	-.026	.008
	(.017)	(.004)**	(.017)	(.004)**
Same Coh. X (Log) Separation (Months)	-.015	-.003	-.013	-.002
	(.005)***	(.001)**	(.005)***	(.001)
(Log) Overlap w/ Dir/man (Months)	.006	.0009	.032	.006
	(.002)***	(.0006)	(.004)***	(.001)***
(Log) Tenure (Months)			-.031	-.005
			(.004)***	(.001)***
Separation> 0	-.093	-.011	-.103	-.013
	(.012)***	(.004)***	(.012)***	(.004)***
(Log) Separation (Months)	-.024	-.006	-.021	-.005
	(.003)***	(.002)***	(.003)***	(.002)**
Obs.	3,254,089		3,254,089	
R^2	.37		.372	

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.6.6. Controlling for Skill Similarity or Homophily

	base1	other1
	(1)	(2)
Started within 2 m of Dir/man (Indic)	.040	-.005
	(.010)***	(.002)***
Same Coh. X Separation>0	-.027	.009
	(.017)	(.004)**
Same Coh. X (Log) Separation (Months)	-.013	-.002
	(.005)***	(.001)*
(Log) Overlap w/ Dir/man (Months)	.034	.005
	(.004)***	(.001)***
(Log) Tenure (Months)	-.031	-.005
	(.004)***	(.001)***
Separation>0	-.105	-.013
	(.012)***	(.004)***
(Log) Separation (Months)	-.019	-.004
	(.003)***	(.002)**
Same Age Bin (Indic)	-.0008	.002
	(.001)	(.0006)***
Same Education Group (Indic)	-.003	.002
	(.004)	(.0009)**
Same Gender (Indic)	.007	.002
	(.002)***	(.001)
Same Nationality (Indic)	.003	.001
	(.021)	(.023)
Same Occupation Group (Indic)	.002	.004
	(.003)	(.003)
Same 2d-Industry Group (Indic)	.036	.038
	(.013)***	(.015)**
Same Last Plant (Indic)	.049	.079
	(.010)***	(.015)***
Same State (Indic)	.007	.035
	(.020)	(.011)***
Obs.	3,254,089	
R^2	.381	

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.6.7. Robustness Checks

	base1	other1	base2	other2	base3	other3
	(1)	(2)	(3)	(4)	(5)	(6)
Started within 2 m of Dir/man (Indic)	.038 (.009)***	-.006 (.002)***	.040 (.012)***	-.002 (.002)	.040 (.012)***	-.002 (.002)
Same Coh. X Separation>0	-.027 (.016)	.010 (.004)***	-.027 (.016)	.010 (.004)**	-.027 (.016)	.010 (.004)**
Same Coh. X (Log) Separation (Months)	-.013 (.005)***	-.003 (.001)**	-.013 (.005)***	-.002 (.001)*	-.013 (.005)***	-.002 (.001)*
Same Coh. X Dir/man was Executive			-.004 (.010)	-.007 (.002)***	-.004 (.010)	-.007 (.002)***
(Log) Overlap w/ Dir/man (Months)	.033 (.004)***	.004 (.001)***	.033 (.004)***	.004 (.001)***	.033 (.004)***	.004 (.001)***
(Log) Tenure (Months)	-.031 (.004)***	-.005 (.001)***	-.031 (.004)***	-.005 (.001)***	-.031 (.004)***	-.005 (.001)***
Separation>0	-.104 (.012)***	-.013 (.003)***	-.104 (.012)***	-.013 (.003)***	-.104 (.012)***	-.013 (.003)***
(Log) Separation (Months)	-.019 (.003)***	-.004 (.002)**	-.019 (.003)***	-.004 (.002)**	-.019 (.003)***	-.004 (.002)**
Was w/ Dir/man	.037 (.010)***	.062 (.022)***	.037 (.010)***	.062 (.022)***	.037 (.010)***	.062 (.022)***
Avg Monthly Wage >0					.028 (.023)	-.008 (.007)
(Log) Avg Monthly Wage					-.002 (.004)	.002 (.0009)**
Same Age Bin (Indic)	-.0008 (.001)	.002 (.0006)***	-.0008 (.001)	.002 (.0006)***	-.0008 (.001)	.002 (.0006)***
Same Education Group (Indic)	-.004 (.004)	.002 (.0009)**	-.004 (.003)	.002 (.0009)**	-.004 (.003)	.002 (.0009)**
Same Gender (Indic)	.007 (.002)***	.002 (.001)	.007 (.002)***	.002 (.001)	.007 (.002)***	.002 (.001)
Same Nationality (Indic)	.003 (.021)	.001 (.023)	.003 (.021)	.001 (.023)	.003 (.021)	.0004 (.023)
Same Occupation Group (Indic)	.002 (.003)	.004 (.003)	.002 (.003)	.004 (.003)	.002 (.003)	.004 (.003)
Same 2d-Industry Group (Indic)	.037 (.013)***	.038 (.015)**	.037 (.013)***	.038 (.015)**	.036 (.013)***	.038 (.015)**
Same Last Plant (Indic)	.049 (.009)***	.077 (.014)***	.049 (.009)***	.077 (.014)***	.049 (.009)***	.077 (.014)***
Same State (Indic)	.005 (.020)	.035 (.012)***	.005 (.020)	.035 (.012)***	.005 (.020)	.035 (.011)***
Obs.	3,254,089		3,254,089		3,254,089	
R^2	.382		.382		.382	

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Appendix - Chapter 2

2.A Quantity Unknown

In this Appendix we derive a condition on the cost of matching that ensures that agents will not desire to form so many matches that they have to form matches they know to be of low quality. That is, our sufficient condition ensures that in equilibrium there are more agents of unknown match quality to ego than the number of matches he desires to form outside his network.

The supply of agents of unknown match quality to ego at the start of period t, u_t, is $N-(1-\delta)n_{t-1}/p$, where n_{t-1}/p is the number of agents of known match quality to ego at the end of the previous period. The number of matches ego desires to form outside his network at the start of period t, x_t, is given by equation (2.2.4). We can therefore write the condition $u_t > x_t$ as $N-(1-\delta)n_{t-1}/p > z^* - (1-\delta)n_{t-1}$, which we can rearrange to obtain $N > z^* + [(1-p)/p](1-\delta)n_{t-1}$. Since n_t never exceeds its steady state value, for this condition to hold it is sufficient that $N > z^* + [(1-p)/p](1-\delta)\bar{n}$. Substituting in equation (2.2.6), we have

$$N > \{1+\frac{(1-\delta)(1-p)}{\delta+p(1-\delta)}\}z^*, \text{ or } N > \frac{1}{\delta+p(1-\delta)}z^*.$$

The inequality $[\delta+p(1-\delta)]N > z^*$ is implied by

Assumption 2.A. $c'([\delta+p(1-\delta)]N) > \frac{py_H+(1-p)y_L}{2} + \beta p \frac{(1-\delta)(1-p)}{1-\beta(1-\delta)(1-p)} \frac{y_H-y_L}{2}$,

where the right-hand side equals $c'(z^*)$ by equation (2.2.3). Assumption 2.A can be thought of as an addendum to Assumption 2.C in Section 2.2.

2.B Calculation of Cohort Attachment

We present a very stylized calculation of the strength of cohort attachment for ego relative to a later cohort. We assume there are three cohorts in the firm: an incumbent cohort (cohort 1), ego's cohort (cohort 2), and a later cohort (cohort 3). The three cohorts join the firm in consecutive periods, and we evaluate the strength of ego's cohort attachment relative to the later cohort at the end of period 4. In the notation of section 2.3, we compute $CA_4^2(3)$. If we equate periods with years then we are computing the strength of ego's cohort attachment relative to the later cohort after three years of his tenure at the firm, which is in between the median and mean for the director/managers in our data. For the sizes of cohorts 1 and 2 (N_1 and N_2) in the calculation, we use the mean values in our data of pre-cohort plant size and cohort size for the director/manager's plant (see Table 2.5.1). The calculation also assumes an even bet that matches are of high quality ($p = 0.5$) and a 20 percent rate of network decay per year ($\delta = 0.2$). Finally, we assume ego engages in ten matches per period ($z^* = 10$). Merluzzi and Burt (2013) present evidence that the top five relationships capture all that are important in affecting employee performance, so we want to use at least that number.

In Figure 2.A.1 we plot $CA_4^2(3)$ against later cohort size (N_3), marking with a vertical line the mean value in our data of later cohort size for the director/manager's plant. The results that $CA_4^2(3) > 0$ and that $CA_4^2(3)$ increases with N_3 have proven robust to many choices of number of periods and variations in other parameters used in the calculations.

2.C Additional Tables

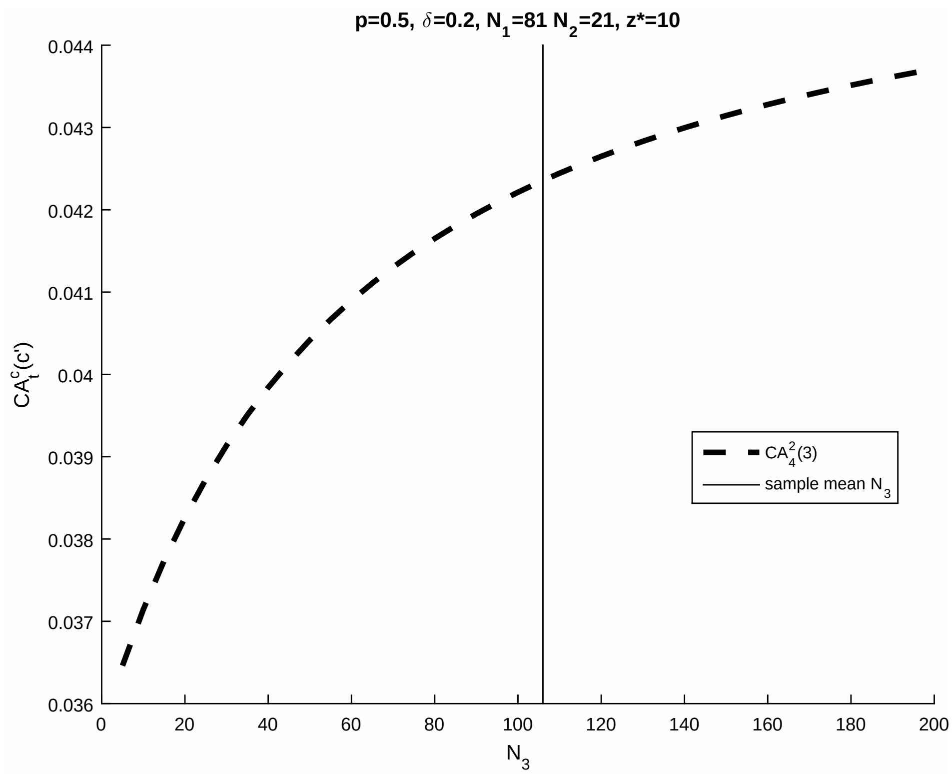

Figure 2.A.1. Cohort Attachment

Table 2.A.1. Robustness Checks: Full Specification

	base1	otherX1	other1	base2	otherX2	other2	base3	otherX3	other3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Started within 2 m of Dir/man (Indic)	.038 (.009)***	-.044 (.010)***	-.006 (.002)***	.040 (.012)***	-.042 (.013)***	-.002 (.002)	.040 (.012)***	-.042 (.013)***	-.002 (.002)
Same Coh. X Separation>0	-.027 (.016)	.037 (.017)**	.010 (.004)***	-.027 (.016)	.036 (.017)**	.010 (.004)**	-.027 (.016)	.036 (.017)**	.010 (.004)**
Same Coh. X (Log) Sep. (Months)	-.013 (.005)***	.010 (.005)**	-.003 (.001)**	-.013 (.005)***	.011 (.005)**	-.002 (.001)*	-.013 (.005)***	.011 (.005)**	-.002 (.001)*
Same Coh. X Dir/man was Exec.				-.004 (.010)	-.004 (.011)	-.007 (.002)***	-.004 (.010)	-.004 (.011)	-.007 (.002)***
(Log) Overlap w/ Dir/man (Months)	.033 (.004)***	-.029 (.004)***	.004 (.001)***	.033 (.004)***	-.029 (.004)***	.004 (.001)***	.033 (.004)***	-.029 (.004)***	.004 (.001)***
(Log) Tenure (Months)	-.031 (.004)***	.026 (.004)***	-.005 (.001)***	-.031 (.004)***	.026 (.004)***	-.005 (.001)***	-.031 (.004)***	.026 (.004)***	-.005 (.001)***
Separation>0	-.104 (.012)***	.092 (.013)***	-.013 (.003)***	-.104 (.012)***	.092 (.013)***	-.013 (.003)***	-.104 (.012)***	.091 (.013)***	-.013 (.003)***
(Log) Separation (Months)	-.019 (.003)***	.015 (.004)***	-.004 (.002)**	-.019 (.003)***	.015 (.004)***	-.004 (.002)**	-.019 (.003)***	.015 (.004)***	-.004 (.002)**
Was w/ Dir/man	.037 (.010)***	.025 (.022)	.062 (.022)***	.037 (.010)***	.025 (.022)	.062 (.022)***	.037 (.010)***	.025 (.022)	.062 (.022)***
Avg Monthly Wage >0							.028 (.023)	-.036 (.023)	-.008 (.007)
(Log) Avg Monthly Wage							-.002 (.004)	.004 (.004)	.002 (.0009)**
Same Age Bin (Indic)	-.0008 (.001)	.002 (.001)*	.002 (.0006)***	-.0008 (.001)	.002 (.001)*	.002 (.0006)***	-.0008 (.001)	.002 (.001)*	.002 (.0006)***
Same Education Group (Indic)	-.004 (.004)	.006 (.004)	.002 (.0009)**	-.004 (.003)	.006 (.004)	.002 (.0009)**	-.004 (.003)	.006 (.004)	.002 (.0009)**
Same Gender (Indic)	.007 (.002)***	-.006 (.003)**	.002 (.001)	.007 (.002)***	-.006 (.003)**	.002 (.001)	.007 (.002)***	-.006 (.003)**	.002 (.001)
Same Nationality (Indic)	.003 (.021)	-.001 (.039)	.001 (.023)	.003 (.021)	-.001 (.039)	.001 (.023)	.003 (.021)	-.002 (.039)	.0004 (.023)
Same Occupation Group (Indic)	.002 (.003)	.003 (.003)	.004 (.003)	.002 (.003)	.003 (.003)	.004 (.003)	.002 (.003)	.003 (.003)	.004 (.003)
Same 2d-Industry Group (Indic)	.037 (.013)***	.001 (.017)	.038 (.015)**	.037 (.013)***	.001 (.017)	.038 (.015)**	.036 (.013)***	.001 (.017)	.038 (.015)**
Same Last Plant (Indic)	.049 (.009)***	.028 (.016)*	.077 (.014)***	.049 (.009)***	.028 (.016)*	.077 (.014)***	.049 (.009)***	.028 (.016)*	.077 (.014)***
Same State (Indic)	.005 (.020)	.029 (.021)	.035 (.012)***	.005 (.020)	.029 (.021)	.035 (.012)***	.005 (.020)	.030 (.021)	.035 (.011)***
Obs.	3,254,089			3,254,089			3,254,089		
R^2	.382			.382			.382		

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.A.2. Same Cohort Indicator, Alternative Sample - Dir/man Leave Month

	base1	otherX1	other1
	(1)	(2)	(3)
Started within 2 m of Dir/man (Indic)	.045 (.007)***	-.044 (.008)***	.001 (.002)
Obs.	1,691,272		
R^2	.528		
Mean Dep. variable	.074		
Spinoffs	5,563		

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.A.3. Robustness Checks: Full Specification, Alternative Sample - Dir/man Leave Month

	base1	otherX1	other1	base2	otherX2	other2	base3	otherX3	other3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Started within 2 m of Dir/man (Indic)	.021	-.030	-.009	.018	-.025	-.007	.017	-.025	-.007
	(.008)***	(.009)***	(.002)***	(.012)	(.014)*	(.003)**	(.012)	(.014)*	(.003)**
Same Coh. X Dir/man was Executive				.007	-.010	-.003	.006	-.010	-.003
				(.015)	(.017)	(.004)	(.015)	(.017)	(.004)
(Log) Overlap w/ Dir/man (Months)	.029	-.020	.008	.029	-.021	.008	.029	-.020	.008
	(.008)***	(.008)**	(.002)***	(.008)***	(.008)**	(.002)***	(.008)***	(.008)**	(.002)***
(Log) Tenure (Months)	-.026	.019	-.007	-.026	.019	-.007	-.027	.020	-.008
	(.008)***	(.008)**	(.002)***	(.008)***	(.008)**	(.002)***	(.007)***	(.007)***	(.002)***
Was w/ Dir/man	.068	.022	.090	.068	.022	.090	.067	.022	.090
	(.016)***	(.035)	(.033)***	(.016)***	(.035)	(.033)***	(.016)***	(.035)	(.033)***
Avg Monthly Wage > 0							.009	-.001	.008
							(.045)	(.047)	(.020)
(Log) Avg Monthly Wage							.008	-.007	.001
							(.007)	(.007)	(.003)
Same Age Bin (Indic)	-.0009	.003	.002	-.0009	.003	.002	-.001	.003	.002
	(.002)	(.003)	(.001)*	(.002)	(.003)	(.001)	(.002)	(.003)	(.001)
Same Education Group (Indic)	.013	-.008	.005	.014	-.008	.005	.013	-.008	.005
	(.010)	(.010)	(.002)**	(.010)	(.010)	(.002)**	(.010)	(.010)	(.002)**
Same Gender (Indic)	.008	-.007	.001	.008	-.007	.001	.008	-.007	.001
	(.004)**	(.004)*	(.002)	(.004)**	(.004)*	(.002)	(.004)**	(.004)*	(.002)
Same Nationality (Indic)	-.049	.073	.024	-.049	.073	.024	-.052	.076	.024
	(.018)***	(.045)	(.032)	(.018)***	(.045)	(.032)	(.019)***	(.045)*	(.032)
Same Occupation Group (Indic)	.008	-.003	.004	.008	-.003	.004	.008	-.004	.004
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Same 2d-Industry Group (Indic)	.096	-.029	.067	.096	-.029	.067	.095	-.028	.067
	(.056)*	(.056)	(.032)**	(.056)*	(.056)	(.032)**	(.056)*	(.056)	(.032)**
Same Last Plant (Indic)	.102	.048	.150	.102	.048	.150	.102	.048	.150
	(.021)***	(.029)*	(.026)***	(.021)***	(.029)*	(.026)***	(.021)***	(.029)*	(.026)***
Same State (Indic)	.089	-.003	.087	.090	-.003	.087	.092	-.005	.087
	(.037)**	(.037)	(.027)***	(.037)**	(.037)	(.027)***	(.037)**	(.038)	(.027)***
Obs.	1,691,272			1,691,272			1,691,272		
R^2	.55			.55			.551		

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.A.4. ALL Sample w/Entry Plant Size

	base1	otherX1	other1	base2	otherX2	other2
	(1)	(2)	(3)	(4)	(5)	(6)
Started within 2 m of Dir/man (Indic)	.133 (.045)***	-.113 (.042)***	.020 (.013)	.119 (.045)***	-.116 (.043)***	.003 (.013)
Same Coh. X Separation> 0	-.026 (.017)	.035 (.017)**	.008 (.004)**	-.027 (.017)	.037 (.017)**	.010 (.004)***
Same Coh. X (Log) Separation (Months)	-.013 (.005)***	.011 (.005)**	-.002 (.001)	-.012 (.005)**	.010 (.005)**	-.002 (.001)*
Same Coh. X Pl./Oth. Pl. Entry Plant Size> 0	-.085 (.043)**	.047 (.040)	-.037 (.015)**	-.074 (.041)*	.057 (.038)	-.017 (.014)
Same Coh. X Pl./Oth. Pl. (Log) Entry Plant Size	-.003 (.002)	.004 (.002)*	.001 (.0007)*	-.002 (.002)	.004 (.002)	.001 (.0007)**
Same Coh. X Dir/man was Executive				-.004 (.010)	-.004 (.011)	-.008 (.002)***
(Log) Overlap w/ Dir/man (Months)	.033 (.004)***	-.027 (.004)***	.006 (.001)***	.034 (.004)***	-.030 (.004)***	.004 (.001)***
(Log) Tenure (Months)	-.031 (.004)***	.027 (.004)***	-.005 (.001)***	-.031 (.004)***	.026 (.004)***	-.005 (.001)***
Separation> 0	-.103 (.012)***	.090 (.013)***	-.013 (.004)***	-.104 (.012)***	.091 (.013)***	-.013 (.003)***
(Log) Separation (Months)	-.021 (.003)***	.017 (.004)***	-.005 (.002)**	-.019 (.003)***	.015 (.004)***	-.004 (.002)**
Was w/ Dir/man				.035 (.010)***	.028 (.022)	.062 (.022)***
Avg Monthly Wage > 0				.027 (.023)	-.035 (.023)	-.008 (.007)
(Log) Avg Monthly Wage				-.002 (.004)	.004 (.004)	.002 (.0009)**
Same Age Bin (Indic)				-.0008 (.001)	.002 (.001)*	.002 (.0006)***
Same Education Group (Indic)				-.004 (.003)	.006 (.004)	.002 (.0009)**
Same Gender (Indic)				.007 (.002)***	-.006 (.003)**	.002 (.001)
Same Nationality (Indic)				.002 (.021)	-.0004 (.038)	.002 (.023)
Same Occupation Group (Indic)				.002 (.003)	.003 (.003)	.004 (.003)
Same 2d-Industry Group (Indic)				.037 (.013)***	.001 (.017)	.038 (.015)**
Same Last Plant (Indic)				.048 (.009)***	.028 (.016)*	.076 (.014)***
Same State (Indic)				.005 (.020)	.030 (.021)	.035 (.011)***
Obs.	3,254,089			3,254,089		
R^2	.373			.383		

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.A.5. ALL Sample w/Post Cohort Size

	base1	otherX1	other1	base2	otherX2	other2
	(1)	(2)	(3)	(4)	(5)	(6)
Started within 2 m of Dir/man (Indic)	.107 (.045)**	-.082 (.043)*	.024 (.013)*	.089 (.047)*	-.081 (.044)*	.009 (.014)
Started > 2 m after Dir/man (Indic)	-.022 (.016)	.038 (.020)*	.016 (.008)**	-.033 (.018)*	.050 (.023)**	.017 (.008)**
Same Coh. X Separation> 0	-.049 (.017)***	.053 (.018)***	.004 (.003)	-.051 (.017)***	.056 (.018)***	.005 (.003)
Newer Coh. X Separation> 0	-.038 (.017)**	.027 (.018)	-.010 (.003)***	-.040 (.017)**	.029 (.017)*	-.011 (.003)***
Same Coh. X (Log) Separation (Months)	-.014 (.006)**	.011 (.006)**	-.002 (.001)**	-.013 (.006)**	.011 (.006)*	-.002 (.001)**
Newer Coh. X (Log) Separation (Months)	-.0006 (.005)	.00003 (.005)	-.0005 (.001)	-.00002 (.005)	.00009 (.005)	.00007 (.001)
Same Coh. X Pl./Oth. Pl. Entry Plant Size> 0	-.077 (.042)*	.044 (.039)	-.033 (.015)**	-.069 (.041)*	.055 (.037)	-.014 (.015)
Same Coh. X Pl./Oth. Pl. (Log) Entry Plant Size	-.003 (.002)	.003 (.002)	.0004 (.0008)	-.002 (.002)	.003 (.002)	.0006 (.0008)
Newer Coh. X Pl./Oth. Pl. (Log) Post-Cohort Plant Size	-.0002 (.003)	-.001 (.004)	-.002 (.0009)*	-.0005 (.003)	-.0008 (.004)	-.001 (.001)
Same Coh. X Dir/man was Executive				.010 (.012)	-.019 (.012)	-.009 (.002)***
Newer Coh. X Dir/man was Executive				.030 (.008)***	-.034 (.008)***	-.004 (.002)*
(Log) Overlap w/ Dir/man (Months)	.043 (.005)***	-.037 (.005)***	.006 (.001)***	.043 (.005)***	-.038 (.005)***	.005 (.001)***
(Log) Tenure (Months)	-.050 (.006)***	.044 (.006)***	-.006 (.001)***	-.048 (.005)***	.042 (.005)***	-.006 (.001)***
Separation> 0	-.083 (.015)***	.075 (.015)***	-.008 (.004)**	-.082 (.014)***	.074 (.015)***	-.008 (.003)**
(Log) Separation (Months)	-.023 (.005)***	.018 (.006)***	-.004 (.002)***	-.021 (.005)***	.016 (.005)***	-.004 (.002)***
Was w/ Dir/man				.033 (.010)***	.029 (.022)	.062 (.022)***
Avg Monthly Wage > 0				.029 (.023)	-.036 (.022)	-.007 (.007)
(Log) Avg Monthly Wage				-.002 (.004)	.004 (.004)	.002 (.0009)**
Same Age Bin (Indic)				-.00007 (.001)	.002 (.001)	.001 (.0006)**
Same Education Group (Indic)				-.003 (.003)	.005 (.004)	.002 (.0009)**
Same Gender (Indic)				.007 (.003)***	-.005 (.003)*	.002 (.001)
Same Nationality (Indic)				.004 (.021)	-.002 (.038)	.001 (.022)
Same Occupation Group (Indic)				.005 (.003)	-.002 (.003)	.003 (.003)
Same 2d-Industry Group (Indic)				.038 (.013)***	-.0002 (.017)	.038 (.015)**
Same Last Plant (Indic)				.047 (.010)***	.029 (.016)*	.077 (.014)***
Same State (Indic)				.007 (.020)	.027 (.021)	.035 (.012)***
Obs.	3,254,089			3,254,089		
R^2	.374			.385		

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

Table 2.A.6. LVMONTH Sample w/Post Cohort Size

	base1	otherX1	other1	base2	otherX2	other2
	(1)	(2)	(3)	(4)	(5)	(6)
Started within 2 m of Dir/man (Indic)	.188 (.064)***	-.103 (.103)	.086 (.088)	.149 (.064)**	-.093 (.091)	.056 (.072)
Started $>$ 2 m after Dir/man (Indic)	.016 (.019)	.001 (.021)	.017 (.009)*	.010 (.019)	.0001 (.022)	.010 (.009)
Same Coh. X Pl./Oth. Pl. Entry Plant Size$>$ 0	-.135 (.062)**	.056 (.101)	-.079 (.088)	-.105 (.057)*	.043 (.087)	-.062 (.073)
Same Coh. X Pl./Oth. Pl. (Log) Entry Plant Size	-.010 (.003)***	.009 (.003)***	-.001 (.001)	-.010 (.003)***	.010 (.003)***	.0003 (.001)
Newer Coh. X Pl./Oth. Pl. (Log) Post-Cohort Plant Size	-.008 (.004)**	.007 (.004)*	-.002 (.001)	-.007 (.003)**	.007 (.004)**	-.0004 (.001)
Same Coh. X Dir/man was Executive				.009 (.015)	-.014 (.017)	-.005 (.004)
Newer Coh. X Dir/man was Executive				.011 (.011)	-.018 (.013)	-.008 (.005)
(Log) Overlap w/ Dir/man (Months)	.032 (.009)***	-.021 (.009)**	.011 (.002)***	.031 (.009)***	-.024 (.009)***	.007 (.002)***
(Log) Tenure (Months)	-.037 (.012)***	.028 (.012)**	-.008 (.002)***	-.036 (.011)***	.029 (.011)**	-.007 (.002)***
Was w/ Dir/man				.060 (.016)***	.031 (.035)	.091 (.033)***
Avg Monthly Wage $>$ 0				.007 (.046)	.002 (.047)	.009 (.020)
(Log) Avg Monthly Wage				.008 (.007)	-.007 (.007)	.001 (.003)
Same Age Bin (Indic)				-.0009 (.002)	.002 (.003)	.001 (.001)
Same Education Group (Indic)				.012 (.010)	-.007 (.010)	.005 (.002)**
Same Gender (Indic)				.008 (.004)**	-.007 (.004)*	.001 (.002)
Same Nationality (Indic)				-.051 (.019)***	.074 (.044)*	.024 (.032)
Same Occupation Group (Indic)				.009 (.006)	-.005 (.006)	.004 (.006)
Same 2d-Industry Group (Indic)				.094 (.056)*	-.027 (.056)	.067 (.032)**
Same Last Plant (Indic)				.098 (.021)***	.051 (.028)*	.149 (.026)***
Same State (Indic)				.095 (.037)***	-.007 (.037)	.087 (.027)***
Obs.	1,691,272			1,691,272		
R^2	.531			.551		

Note: Standard errors clustered at the closure level. All columns contain closure×potential plant and ego fixed effects. Controls for the compatibility between the ego and potential (*% Same Age Group – Potential is Hist. Pl. (Indic)* from Table 1.4.4) are included, but not shown.

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Chapter 3

Reselling Information

3.1 Introduction

We live in an age of data and analytics in which the market for information occupies a central role. But as has been appreciated since at least Arrow (1962), and likely before, selling information is difficult for at least two reasons: it is difficult to prove that one has valuable information without revealing it, and information can be easily replicated and re-sold once it has been acquired. We study the implications of resale on the pricing of information, on the incentives for information acquisition and innovation, and the implications of institutional structures that may control resale. We establish that resale leads to *underinvestment* in the production of information; by contrast, permitting only a single firm to trade in information leads to *overinvestment*. An optimal policy is that which awards monopoly rights to sell information stochastically.

This framework and these results speak to the debate on intellectual property and its implications for innovation. Since at least Schumpeter (1942), monopoly power has been believed to be an important ingredient for innovation. Discussions of economic growth (e.g. Barro and Sala-i-Martin, 1995) note that making ideas freely available is *ex post* efficient but retards a firm's *ex ante* incentives to invest in innovation. Analogously, Grossman and Helpman (1994) argue that innovation may require imperfectly competitive markets so that the initial innovator can capture rents to recover the costs she bears in innovation. We study these tradeoffs using a decentralized bargaining and matching framework where a seller of information may have substantial bargaining power and begin as a monopolist, and buyers and sellers face trading frictions from delaying trade. Buyers of information cannot commit to not reselling the information, nor can a seller commit to not continuing to sell information. We show that this inability to commit leads to information being sold for very low prices, even if a seller has substantial bargaining power and begins as a monopolist, and severely detracts from players' incentives to innovate.

The impact of resale on prices: We consider a market where there are sellers and buyers of information, but to crystallize the key intuitions, suppose for now that there is a single seller of information. This seller, therefore, begins at $t = 0$ as a monopolist. Each buyer has an exogenous value for this information. This information may correspond to learning, for example, some payoff relevant state variable. The seller and each buyer face a trading opportunity at a random time, and when presented with a trading opportunity, the pair negotiate over how much the buyer pays the seller for her information. Once trade occurs, the seller can continue selling information to others, and any buyer can also resell her information. We study prices at the frictionless limit of the market, i.e., when the number of trading opportunities per unit of effective time is converging to ∞.

In this benchmark model—without any IP protection or commitment—prices converge to 0, across all equilibria, as soon as two parties can sell information. The intuition for this result is subtle because it reflects two opposing forces. On the one hand, no seller wishes to lose the opportunity to sell to a buyer, and so competition between sellers naturally dampens the price of information. But on the other hand, our decentralized framework features trading frictions in which each buyer meets at most one seller at any instance, and bears some delay in waiting for the next trading opportunity. Analogous to the Diamond Paradox (Diamond, 1971), one may anticipate that these trading frictions would benefit sellers, particularly if they have a high share of bargaining power. We find that so long as buyers possess a modicum of bargaining power, the competitive effect dwarfs the "Diamond effect" so that prices converge to 0.

The monopolist's ability to capture rents depends solely on how she conducts her first trade, and this corresponds to a question of equilibrium selection. In a "no-delay" equilibrium, she is compelled to sell information cheaply (despite beginning as a monopolist) because each buyer anticipates that he can buy information for low prices once there are two sellers of information. Prices collapse to 0 because of players' inability to commit. In the seller-optimal equilibrium, she sets a high price for her first sale of information—and designates a particular buyer to be her exclusive "first buyer"–and after that first sale, prices converge to 0. In this equilibrium, the seller uses delay as a strategy to extract surplus, but she can do so only from a single buyer. Across equilibria, resale limits the monopolistic seller's ability to capture rents.

The commitment problem: The fundamental challenge encountered by the monopolistic seller is the lack of commitment: neither she nor buyers can commit to not selling to third-parties. The traditional, and most salient, form of commitment to escape this price trap is to award that innovator with exclusive rights to sell information; then necessarily, she can capture much of the social surplus because she no longer needs to compete with others. But other forms of commitment also benefit the innovator: e.g., if she and each buyer can commit to selling information *only once*, then she may capture a substantial fraction of social surplus. Fundamentally, the single innovator is stymied not only by the buyers' ability to resell information but also her own ability to do so. Thus, analogous to the problem of the durable good monopolist described by Coase (1972), the informational good monopolist suffers from her ability to sell information in future periods and her inability to commit to a price.[1]

How to foster socially efficient investments: We use these results to investigate mechanisms to encourage socially efficient investment at an *ex ante* stage. Suppose that k of the n players can choose how much effort to exert to learn the payoff relevant state variable.

[1]The commitment problem that we identify is also similar to the strategic tradeoffs of *bilateral opportunism* studied by Hart and Tirole (1990) and McAfee and Schwartz (1994) where an upstream firm is tempted to contract with several downstream producers, and this temptation, in the absence of commitment, can generate inefficiency.

Naturally, without intellectual property protection, the low prices lead individuals to underinvest relative to social efficiency. But awarding monopoly rights to a single seller of information leads to the opposite conclusion: individuals then overinvest in effort so as to corner the market. A socially efficient level of innovation is supported by either randomizing whether individuals obtain monopoly power, or awarding monopoly rights that expire after a particular duration.

We should highlight that the inefficiency of offering patents or exclusive rights permanently (or for too long) is different from and complements the existing critiques of using patents to incentivize innovation. Existing theories focus on the challenges introduced by "defensive patenting" or "patent trolls" (Boldrin and Levine, 2013; Cohen, Gurun, and Kominers, 2014) as well as quantity distortions that emerge from imperfect competition (Kremer and Williams, 2010). Our analysis highlights that even in a decentralized market that features neither of these issues, one may wish to offer exclusive rights stochastically.

Imitation and first-mover advantage: While we frame the issues here in terms of information sale and resale, our results apply to the commonly studied challenge where a seller can reverse-engineer and imitate the products of its competitor. When imitation is straightforward, then our results imply that prices converge to 0 even if competition is imperfect and sellers have tremendous bargaining power; therefore, each seller has little incentive to innovate. However, if imitation takes time, the first innovator can capitalize on his "first-mover" advantage, and in this case, awarding no monopoly rights may dominate over giving full monopoly rights. Our formal mechanism is therefore consistent with Boldrin and Levine (2004; 2013), who argue that when firms can enjoy strong first-mover advantages, patent protection may not be necessary to foster innovation.

Knowledge spillovers in rural economies: The framework of decentralized markets also speaks to issues of knowledge-sharing and spillovers in developing economies. A vast literature (e.g. Foster and Rosenzweig, 1995; Conley and Udry, 2010; Niehaus, 2011) articulates the importance of peer-to-peer knowledge transmission in technology adoption for households and farmers in rural settings, and a literature on social learning (e.g. Bala and Goyal, 1998; Golub and Jackson, 2010) explores the extent to which such knowledge diffuses through the community. But the skills and knowledge to apply a new technology is likely a source of rents or power within these village economies, and a knowledgeable farmer may attempt to extract surplus—an "implicit price"—when sharing her knowledge with others. Our results highlight how once a knowledgeable farmer teaches another farmer how to use a technology, she may be unable to extract further rents from the community on the basis of her knowledge. Therefore, endogenously, individuals may lack a motive to share their *know-how*, or do so to only those who can promise to not share it with others, which generates a bottleneck in information diffusion. Because individuals anticipate that the "implicit price" of buying knowledge from others collapses to 0, each may wish to free-ride on the efforts of others to learn new technologies, which then reduces the collective level of experimentation and innovation.

Related Literature: In the interests of space, we do not survey the vast literature on intellectual property and patents (see Scotchmer 2006 for a textbook treatment of these issues). We view the contribution of this paper as offering a tractable decentralized framework to study questions of information resale, imitation, and innovation. Accordingly, we describe the relationship of our contribution to the most closely related antecedents we have seen in the literature.

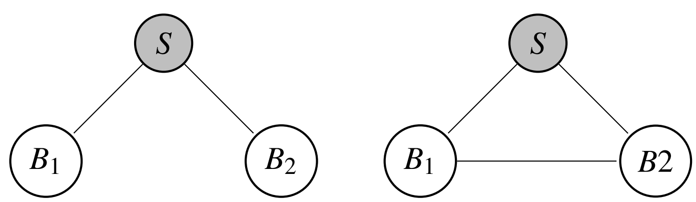
We build on the innovative study of Polanski (2007), who also studies information resale in decentralized markets. He focuses on arbitrary networks in a perfectly frictionless environment and uses a "trembling-hand" perturbation to select an immediate agreement equilibrium. In this equilibrium, prices converge to 0 along any cycle in the graph. We look at a special class of his framework—that in which the network graph is complete—but enrich this environment with frictions and derive bounds on prices across all equilibria. We characterize seller-optimal equilibria, which do not feature immediate agreement, and our motive is to compare this outcome with corresponding outcomes under different commitment regimes. We use this framework to investigate socially efficient investment, describe behavior with imitation, and consider the context of knowledge-spillovers in rural economies. Insofar as our focus is on the impact of prices on innovation under different commitment regimes, our analysis complements and builds on his work.

Other papers have studied the question of information sale and resale. Horner and Skrzypacz (forthcoming) (whose title motivates ours) study how a single seller may wish to sell information to a single buyer when neither party can commit to making payments or sharing knowledge within their bilateral relationship. We abstract from this issue, and assume that two parties can work out a way to sell information (perhaps using third-parties as disinterested mediators); our result highlights how once other buyers are involved, the problem of resale can limit the seller's ability to capture surplus from any buyer. The resale problem has been studied carefully in the context of financial markets, where the assumption is that the information is not re-sold (e.g. Admati and Pfleiderer, 1986; Admati and Pfleiderer, 1990). Muto (1986; 1990) studies conditions under which information can be sold but is "resale-proof" because selling information imposes negative externalities on its current owners, and so it is credible for it to not be re-sold. In our extensions, we consider a setting where the value of information depends on how many people hold information, and we show that if this value decreases sufficiently quickly in the number of information holders, then the monopolist can capture rents but otherwise, prices continue to vanish in the frictionless limit of the market.

3.2 Example

A single seller S ("she") has information that is valuable to two buyers, B_1 and B_2 (each of whom is a generic "he"). This information is of intrinsic value 1 to each buyer. All players have a discount rate of r, and each link meets with probability $\approx \lambda\, dt$ in a period of length dt. The ratio λ/r measures the *fluidity of trading*: a high ratio indicates that there are many trading opportunities per unit of effective time whereas a low ratio indicates that the expected effective time between trading opportunities is high.

When a pair meets, tranfers are determined through symmetric Nash Bargaining where players' outside options are their continuation values without trade occurring, but following the same equilibrium.



(a) No Resale **(b)** Resale

Figure 3.2.1. A Single Seller Trades Information with 2 Buyers.

Equilibrium without Resale: First, consider the setting depicted in Figure 3.2.1a: the buyers are isolated from each other and are connected to the seller. This corresponds to a setting in which the buyers cannot resell information. We can then think of bargaining separately within each pair, and the price p as that which divides the gains from trade equally between the buyer and seller. The gains from trade in this context are dynamic: the total gains from trade look at the difference between the joint surplus from trading today and waiting for the next opportunity to do so. Therefore, the price solves

$$p - \int_0^\infty e^{-rt} e^{-\lambda t} \lambda \, p \, dt = (1-p) - \int_0^\infty e^{-rt} e^{-\lambda t} \lambda \, (1-p) \, dt.$$

The LHS is the seller's gain from trading today versus waiting for the next time, and the RHS is that for the buyer. For all parameters, the solution is $p = \frac{1}{2}$, splitting the surplus within each trading relationship. The seller thus obtains half the social surplus.

An Immediate Agreement Equilibrium with Resale: We now consider the setting shown in Figure 3.2.1b where all three players are connected and can trade information. Throughout our discussion below, it is useful add one notational detail: let $\gamma \equiv \int_0^\infty e^{-rt} e^{-2\lambda t} \lambda \, dt$. Fixing a player, and one of his links, the term γ is the discounted weight that this is his next link that is recognized. In the frictionless limit, γ approaches $\frac{1}{2}$.

We first consider the "sub-game" after only one of the buyers is informed, and then consider the original game in which no buyer is informed.

Only one buyer is informed: Suppose that buyer B_1 is informed but buyer B_2 is not; the latter can then purchase information from one of two parties. Denote the equilibrium price in this sub-game by $p(2)$ (because there are two sellers). Splitting the gain in surplus from trade between the buyer and seller, $p(2)$ solves

$$\underbrace{p(1-\gamma)}_{\text{Seller's Gain from Trading Today}} = \underbrace{(1-p)(1-2\gamma)}_{\text{Buyer's Gain from Trading Today}} .$$

The current seller's gain from trading today is that she secures the sale; by contrast, if she waits, she can only sell to the uninformed buyer if that buyer does not meet the other seller. Therefore, for any strictly positive price p, the LHS is at least $p/2$. By contrast, the buyer's only gain from waiting is avoiding delay. As we approach the frictionless limit, the buyer's gain converges to 0, and so to maintain parity, the price $p(2)$ converges to 0 as we approach the frictionless limit.[2]

No buyer is informed: The low prices that emerge above influences negotiations at the earlier stage when only a single seller has information. The payoff of buying information at price p for the first buyer then is an immediate benefit of $(1-p)$, and the potential for reselling that information if he meets the other buyer first, which has a discounted value of $\gamma p(2)$. His "outside option" is his payoff from waiting and not trading today: in the future, either the seller meets him first in which case he is in the same position as today, or the seller meets the other buyer first, in which case he can buy information at a price of $p(2)$ from either of the other two players. The first contingency obtains a stochastic discount of γ (reflecting that the seller does not meet the other buyer first), and the second contingency obtains a stochastic discount of $2\gamma^2$ (reflecting that the other buyer buys information first, after which there are twice as many opportunities to buy information). Thus, his gain from buying information is

$$1-p+\gamma p(2)-\gamma(1-p+\gamma p(2))-2\gamma^2(1-p(2)) \to -\frac{p}{2},$$

which implies that for trade to occur, the price that the first buyer pays for information must converge to 0. The intuition is straightforward: because each buyer recognizes that he can wait to be the second buyer and obtain the information for virtually free, he has no gain from securing the information now at a strictly positive price.

Taking a step back from the analysis, the fundamental challenge is that the buyer cannot commit to resell information and the seller cannot commit to future prices being at

[2]The equilibrium price, $p(2)$, equals $p(2)=\frac{1-2\gamma}{2-3\gamma}$, which converges to 0 as $\frac{\lambda}{r}\to\infty$. We note that this outcome replicates Bertrand competition even though the buyer never meets both sellers simultaneously in a price competition game.

least some strictly positive $\underline{p}$. Accordingly, the second buyer finds himself in a privileged position where the competition between sellers ensures that he obtains information at vanishingly low prices in the frictionless limit. Because each buyer, in this equilibrium, can delay trade to guarantee himself this privileged position, the seller cannot extract surplus from either buyer. The seller-optimal equilibrium that we construct below offers a credible way for the seller to guarantee that at most one of the two buyers can find himself in that privileged position.

The Seller's Optimal Equilibrium: We construct an equilibrium in which the seller never trades with buyer B_2 *until* she has sold information to buyer B_1; after she sells information to B_1, then she and B_1 shall compete to sell information to B_2 at the price $p(2)$ characterized above. But the novelty is that buyer B_1 knows, in equilibrium, that he can never obtain information second, simply because the seller never sells it to B_2 first. Accordingly, the price that the seller and B_1 agree to solves

$$(p^* + \gamma p(2))\left(1 - \int_0^\infty e^{-rt} e^{-\lambda t} \lambda \, dt\right) = (1 - p + \gamma p(2))\left(1 - \int_0^\infty e^{-rt} e^{-\lambda t} \lambda \, dt\right).$$

The LHS is the seller's gain from trading today versus waiting for tomorrow. The RHS is buyer B_1's gain from doing so, where he knows that if he rejects this trade, the only way for him to obtain information is at the same price from the seller. Note that $\int_0^\infty e^{-rt} e^{-\lambda t} \lambda \, dt$ is equal to $\frac{\lambda}{r+\lambda}$, and so solving the above equation yields that $p^* \to \frac{1}{2}$ as $\lambda \to \infty$.

To verify that this is an equilibrium, we must also establish that the seller and B_2 do not trade until the seller has sold information to B_1. Note that a trade can occur only if their joint surplus after trade exceeds their joint surplus before trade because otherwise, there exists no transfer that can make both players better off. Thus trade occurs only if

$$\underbrace{\frac{\lambda}{r+\lambda}\left(p^{*}+\gamma p(2)\right)}_{\text{Seller's Surplus with No Trade}} + \underbrace{\frac{\lambda}{r+\lambda}\left(2\gamma(1-p(2))\right)}_{\text{Buyer's Surplus with No Trade}} \leq \underbrace{1+2\gamma p(2)}_{\text{Joint Surplus with Trade}} .$$

As $\frac{\lambda}{r} \to \infty$, the RHS converges to 1 whereas the LHS converges to $\frac{3}{2}$ (indeed, a sufficient condition is $\frac{\lambda}{r} > 5$). Therefore, in the best equilibrium, the most that the seller can gain is $\frac{1}{2}$ in the frictionless limit.

This example highlights how the resale problem directly limits the profits of a monopolistic seller. The analysis below elaborates on these intuitions with multiple buyers and sellers, and considers how the problem identified here influences the incentives to innovate.

3.3 Model

3.3.1 Environment

A set of buyers $\mathscr{B} \equiv \{b_1, \ldots, b_{N_B}\}$ interacts with a set of sellers $\mathscr{S} \equiv \{s_1, \ldots, s_{N_S}\}$, where N_B and N_S are the total number of buyers and sellers respectively. We denote by $\mathscr{A} \equiv \mathscr{B} \cup \mathscr{S}$ as the set of all agents. Each seller has identical information that is of value v to each buyer. Information is replicable so a seller can sell information separately to each buyer, and each buyer who gains information can resell it to others. Because the set of buyers and sellers changes over time, we refer to sellers as "informed agents" and buyers as "uninformed agents." Each pair of players has a "link", which reflects the potential to trade information for money if one party to that link is informed and the other is uninformed; we denote the link between players i and j as ij.

Each link meets in continuous time according to a "Poisson clock" that rings with probability $\lambda\, dt$ in a period of length dt. Each Poisson clock rings independently of other

Poisson clocks, and is memoryless. When link ij meets, that is when the pair have a trading opportunity (if one node is informed and the other is uninformed). All players have discount rate r. All behavior and trades are perfectly monitored.

The frequency of interaction per unit of *effective time*, $\frac{\lambda}{r}$, is a measure of the degree of friction in the market. The *frictionless limit* of many trading opportunities per unit of effective time then corresponds to $\frac{\lambda}{r} \to \infty$, and this captures both the case of no impatience and that of frequent trading opportunities with impatient players. To simplify notation, and since it is completely without loss of generality, we set $r = 1$ throughout the paper, and describe the frictionless limit as $\lambda \to \infty$.

3.3.2 Solution-Concept

We study this environment using a cooperative solution-concept that captures the essence of dynamic credibility. Our equilibrium concept emerges from combining *rational expectations* in how players perceive their continuation values from the different actions that they may choose, with the assumption that trading prices reflect *Nash Bargaining* with respect to those continuations values. We define each notion separately, and combine them to generate our equilibrium concept. This section formulates the solution concept for an n-clique with identical value of information to all agents, but the general formulation can be found in Appendix 3.A.

We use the set of informed players, M, as the payoff-relevant state space. The feasible set of states for an n-clique with an initial set of sellers, $\mathscr{S}$, is $|M| = m \in \{|\mathscr{S}|, \ldots, n\}$ where m is the number of informed agents. We can focus on the number of informed agents and not the set because we are considering a case were all agents have identical values. For each seller $i \in M$, and each buyer, $j \in \mathscr{A} \backslash M$, we define a value function $V_i : \{1, \ldots, n\} \to \Re$ or $V_j : \{1, \ldots, n\} \to \Re$ such that $V_x(m)$ represents player x's expected payoff with m informed players when they are a seller if $x \in M$ or buyer if

$x \in \mathscr{A} \backslash M$.

For a given state, m, Consider any player $s \in M$ and neighbor $b \in \mathscr{A} \backslash M$. We define *trading functions* $p_{sb} : \{1,\ldots,n\} \to \Re_{+\cup\{0\}}$ and $\alpha_{sb} : \{1,\ldots,n\} \to \{0,1\}$ such that $\alpha_{sb}(m) = 1$ if and only if player s sells information to player b at price $p_{sb}(m)$, and $\alpha_{sb}(m) = 0$ if the two players do not trade information.

Our conditions of rational expectations and Nash bargaining are defined separately for each of these operators, and then combined to define an equilibrium.

We define for any non-negative number d, $\Delta(d) \equiv \int_0^\infty e^{-(1+\lambda d)t}\lambda\, dt$. This is the stochastic discount factor associated with payoffs that emerge if among d links, one particular link is the next to be recognized. Note that as $\lambda \to \infty$, all clocks are ringing virtually immediately, and so $\Delta(d)$ converges to $1/d$.

Definition. *For a n-clique with identical consumption values, given trading functions* $(p_{ij}(\cdot), \alpha_{ij}(\cdot))_{ij\in M\times\mathscr{A}\backslash M}$, *the value functions* $(V_i(\cdot))_{i\in M}$ *satisfies* ***Rational Expectations*** *if for every i and for every* $m \in \{1,\ldots,n\}$, $V_i(m) =$

$$\Delta(\frac{n(n-1)}{2})\begin{pmatrix} V_i(m)\left(\frac{n(n-1)}{2} - m(n-m)\right) \\ \sum_{j\in\mathscr{A}\backslash M}[\alpha_{ij}(m)(p_{ij}(m) + V_i(m+1)) + (1-\alpha_{ij}(m))V_i(m)] \\ +(m-1)\sum_{j\in\mathscr{A}\backslash M}[\alpha_{ij}(m)V_i(m+1) + (1-\alpha_{ij}(m))V_i(m)] \end{pmatrix}$$

and $(V_j(\cdot))_{j\in\mathscr{A}\backslash M}$ *satisfies* ***Rational Expectations*** *if for every j and for every* $m \in \{1,\ldots,n\}$, $V_j(m) =$

$$\Delta(\frac{n(n-1)}{2})\begin{pmatrix} V_j(m)\left(\frac{n(n-1)}{2} - m(n-m)\right) \\ +\sum_{i\in M}[\alpha_{ij}(M)\left(v - p_{ij}(m) + V_i(m+1)\right) + (1-\alpha_{ij}(M))V_j(m)] \\ +(n-m-1)\sum_{i\in M}[\alpha_{ij}(m)V_j(m+1) + (1-\alpha_{ij}(m))V_j(m)] \end{pmatrix}$$

The term outside brackets is the stochastic discount factor waiting for a particular link to be the next to be recognized. The first line considers link recognitions between two informed players or two uninformed players, both of which result in no trade. The second line applies if player i considers all link recognitions with neighbors to whom he may sell (buy) information; if information is shared, which happens with if $\alpha_{ij}(m) = 1$, then the number of informed players expands from m to $m+1$, and otherwise, it remains the same. The third lines consider all link recognitions where information may be shared, but player i is not a party to the trade. Notice that after the sale to a buyer they switch to having the payoff of a seller in the next state. This is a slight abuse of notation because the agent has not changed, but their roll in the network has and all sellers will have the same payoff. A more rigorous formulation which treats these cases without the same abuse can be found in the general formulation of the solution concept and equilibrium objects in section 3.A.

Definition. *Given value functions $(V_i(\cdot))_{i\in M}$ and $(V_j(\cdot))_{j\in\mathscr{A}\setminus M}$, trading functions $(p_{ij}(\cdot), \alpha_{ij}(\cdot))_{ij\in M\times\mathscr{A}\setminus M}$ satisfies **Recursive Nash Bargaining** if for all $m \in \{1,\ldots,n\}$, $i \in M$, and $j \in \mathscr{A}\setminus M$,*

$$\alpha_{ij}(m) = 1 \Leftrightarrow \underbrace{V_i(m+1) + v + V_i(m+1)}_{\textit{Joint Surplus with Trade}} \geq \underbrace{V_i(m) + V_j(m)}_{\textit{Joint Surplus with No Trade}} \tag{3.3.1}$$

and $p_{ij}(m)$ is set to divide the change in surplus equally:

$$\underbrace{p_{ij}(m) + V_i(m+1) - V_i(m)}_{\textit{Change in Seller's Surplus}} = \underbrace{v - p_{ij}(m) + V_i(m+1) - V_j(m)}_{\textit{Change in Buyer's Surplus}}. \tag{3.3.2}$$

Equation 3.3.1 is a bilateral participation constraint: it specifies that information is traded in a linked pair if and only if the bilateral surplus from trade exceeds that from not trading. Equation 3.3.2 represents that if trade occurs, it does so at a price that ensures that both parties evenly share the gain in surplus from trade. Future work will consider the impact of arbitrary bargaining weights for the buyer and seller.

Definition. *An **equilibrium** is a sequence of value functions $(V_i(\cdot))_{i \in M}$ and $(V_j(\cdot))_{j \in \mathscr{A} \setminus M}$ and trading functions $(p_{ij}(\cdot), \alpha_{ij}(\cdot))_{ij \in M \times \mathscr{A} \setminus M}$ such that given the trading functions, the value functions satisfy Rational Expectations, and given the value functions, the trading functions satisfy Recursive Nash Bargaining.*

3.3.3 Discussion of Model

Before proceeding with our analysis, we describe several features of our environment that play an important role in simplifying our analysis.

Equilibrium concept: We are agnostic about the extensive-form that a pair faces when negotiating over prices, and adopt a cooperative solution-concept to facilitate a very tractable analysis of trade, intermediation, and resale across networks in markets with and without frictions, which is our central focus. Our solution-concept combines Nash Bargaining (Nash, 1953), Markov Perfection (Maskin and Tirole, 2001), and dynamic considerations, and coincides with that used in prior studies of intermediation (Rubinstein and Wolinsky, 1987), dynamic search decisions (Mortensen and Pissarides, 1994), organizational design (Grossman and Hart, 1986), and many others.

One may be concerned by the adoption of a cooperative solution-concept rather than specifying outcomes that emerge from a particular extensive-form game of negotiations. Although it is not our focus, we conjecture that extending 1986 to our setting yields appropriate non-cooperative foundations. Suppose that when a pair meets, they engage in a long Rubinstein-like sequence of alternating offers, which takes place very quickly—so that delay is not costly—and in which there is an exogenous risk of breakdown after the rejection of each offer. Breakdown is costly because the game then continues without the pair trading information. The resulting equilibrium from this process corresponds to that which we study.

Value for Information: The consumption value of information to a buyer, v, can represent a variety of settings. As highlighted in the introduction the information age is characterized by the prevalence of minimal or zero marginal cost goods. For example the information may be a song and the value would then be the utility to the buyer of the song. Alternatively, it may be some forms of intellectual property.

We do require that the information consumption value, v, does not vary with the state of the network which rules out "network effects" in the information value. Additionally, there is no assumption that the utility be realized instantaneously so it can represent the present value of the information.

3.4 Trading Equilibria with Exogenous Information

As outlined in the example in section 3.2 in equilibrium the value to selling the information comes from a combination of buyer consumption value and resale value. In this section we establish the existence of two types of equilibria in an n-clique: (1) an immediate agreement equilibrium and (2) a set of endogenous bottleneck equilibria.

3.4.1 Immediate Agreement

We first consider an equilibrium in which every interaction between an informed seller and an uninformed buyer results in agreement and trade. We prove that there exists a unique such equilibrium.

Proposition 3.4.1. *In an n-clique, for every λ, there exists a unique immediate agreement equilibrium where $\alpha_{ij}(m) = 1\ \forall i \in M\ \forall j \in \mathscr{A} \backslash M\ \forall m \in \{1, \dots, n\}$.*

Proof. **Existence** To show existence we must show that in any meeting the surplus from agreement is greater than the surplus from disagreement in any immediate agreement equilibrium. That is for any given pair sb

$$\underbrace{V_s(m+1)+v+V_s(m+1)}_{\text{Joint Surplus with Trade}} \geq \underbrace{V_s(m)+V_b(m)}_{\text{Joint Surplus with No Trade}}$$

when the continuation values are consistent with an immediate agreement equilibrium. This is done in 3.3.2 found in section 3.C.

Uniqueness To show uniqueness we use induction over the spread of information. First, establishing uniqueness in a network with one uninformed agent and then constructing an inductive argument to establish uniqueness generally. See 3.3.3 in section 3.C which proves uniqueness in the general formulation of section 3.A. □

Beyond existence and uniqueness, we are interested in understanding the welfare implications of this and other equilibria. To that end we care about the prices that are negotiated between the buyer and seller. We can establish that once two agents are informed the resulting negotiation will result in prices that converge to 0 in the frictionless limit. For any variable x, denote $\bar{x} = \lim_{\lambda\to\infty} x$.

Theorem 1. *In an n-clique, for all $M \in \mathscr{M}$, if there are at least two distinct informed agents ($m \geq 2$), then prices converge to* 0 *in the frictionless limit for all $s \in M$ $b \in \mathscr{A} \setminus M$ such that $\alpha_{sb}(m) = 1$*

$$\lim_{\lambda\to\infty} p_{sb}(m) = 0.$$

Proof. We show that regardless of the set of active links, $\alpha(m)$, if there are two informed agents in the network then limit prices must be zero. Let $d = \sum_{ij \in M\times\mathscr{A}\setminus M} \alpha_{ij}(m)$ and $d_b = \sum_{i\in M} \alpha_{ib}(m)$. The proof proceeds by induction on the number of uninformed agents.

-Base Case Consider the base case where $n-m=1$. Let $m \geq 2$ be the number of sellers b is linked to. Suppose that seller s and buyer b meet. Because, $V_i(n) = 0$ for every $i \in \mathscr{A}$, it follows that the joint agreement surplus is v. The highest possible joint disagreement surplus is one in which surplus v is realized when the next available meeting occurs yielding $\frac{m\lambda}{1+m\lambda}v$ because this is always less than v, the agreement surplus, all meetings end in agreement. The base case of 3.3.1 in section 3.C establishes that with one uninformed agent the unique prices when all links come to agreement solves

$$p_{sb}(n-1) = \frac{1}{2+(n-2)\lambda}v.$$

This implies that $\lim_{\lambda\to\infty} p_{sb}(n-1) = 0$, proving the base case.

-Inductive Case Now, suppose that when $n-m \leq k$, the price any b pays converges to 0, $\overline{p}_{sj}(m+1) = 0\ \forall s \in M,\ j \in \mathscr{A}\backslash M\backslash b$. Consider the case where $n-m = k+1$. Suppose some seller s and buyer b agree $\alpha_{sb}(m) = 1$ at a price $\overline{p}_{sb}(m) > 0$ in the limit in state m.

–Multiple active buyers Suppose there exist multiple active buyers, $\sum_{i\in M} \alpha_{ib}(m) \geq 1$, for at least two buyers b. For agreement at a positive limit price to occur on sb it must be the case that under Nash Bargaining both the seller and buyer are better off under agreement. After the sale, by the inductive hypothesis, $\overline{V}_s(m+1) = 0$. Where $V_s(m+1)$ denotes that the buyer would be a seller in the next state if the trade occurred. Additionally the continuation value under disagreement is, $\overline{V}_b(m) = \sum_{i\in M} \frac{\alpha_{ib}(m)}{d}(v - \overline{p}_{ib}(m)) + \frac{d-d_b}{d}v$ by Rational Expectations, where the first term is the value from b meeting any seller i again and the second term is from b not being involved in any transaction in this state and receiving v_b with certainty in the continuation value. Because all sellers are symmetric, in the limit they must all charge the same limit price to buyer b, $\overline{p}_{sb}(m)$. Note that with multiple active buyers $d_b < d$ making the disagreement value $\overline{V}_b(m) = v - \frac{d_b}{d}\overline{p}_{sb}(m)$ larger than the value to the buyer from the transaction $v - \overline{p}_{sb}(m)$ so agreement between s and b cannot occur at positive limit price with at least two active buyers.

–One active buyer and multiple active sellers In this case the inductive hypothesis implies that the problem is much like the base case with all agents having zero continuation value in the limit in the next state and there is one active buyer and multiple active sellers in this state. Therefore by a similar argument replacing the size of the network n with the number of active links will result in zero limit prices in this state.

–One active sellers, one active buyer Now, suppose that s and b are the only pair who trades in state m ($\alpha_{sb}(m) = 1$ and $\alpha_{s'b'}(m) = 0\ \forall s'b' \neq sb$). Then because there are at least two informed agents in state m, by the statement of the theorem, there exists an informed agent $s^* \neq s$ who is bargaining with b but who does not come to agreement in state m, $\alpha_{s^*b}(m) = 0$ therefore

$$V_{s^*}(m+1) + v + V_s(m+1) < V_{s^*}(m) + V_b(m).$$

Where $V_s(m+1)$ denotes that the buyer would be a seller in the next state if the trade occurred. By the inductive hypothesis $\overline{V}_{s^*}(m+1) = 0$ and $\overline{V}_s(m+1) = 0$. Additionally, $\overline{V}_{s^*}(m) = 0$ because along the equilibrium path s^* will not trade in this period and will get 0 continuation value in the limit. Finally, $\overline{V}_b(m) = v_b - \overline{p}_{sb}(m)$ because b will eventually trade with s along the candidate equilibrium, but this results in a contradiction because $v \not< v - \overline{p}_{sb}(m)$ given that $\overline{p}_{sb}(m) > 0$ in the candidate equilibrium.

This completes the proof for $k+1$ buyers and implies that regardless of active links limit prices converge to 0, $\overline{p}_{sb}(m) = 0$ if $m \geq 2$. □

The above property also holds when the initial seller is informed and meets with any buyer in the immediate agreement equilibrium that was shown to exist in 3.4.1

Proposition 3.4.2. *In an n-clique, in the immediate agreement equilibrium, if $s \in M$ and $b \in \mathscr{A} \backslash M$, then $p_{sb}(m) \to 0$ as $\lambda \to \infty$ for all m.*

Proof. As seen in Theorem 1 agreement occurs and prices converge to 0 for all buyers and sellers once two sellers are informed, $m \geq 2$. The additional step for this proposition is to note that the immediate agreement equilibrium yields prices converging to 0 for the initial seller as well. Consider a n-clique with only the initial agent informed $m = 1$.

In the immediate agreement equilibrium, where $\alpha_{sj}(1) = 1 \ \forall j \in \mathscr{A}\backslash M$, the number of active links is the number of uninformed agents, $d = n-1$. Fix any buyer b. Recursive Nash bargaining yields:

$$
\begin{aligned}
&p_{sb} + V_s(2) - \frac{\lambda}{1+(n-1)\lambda}[p_{sb} + V_s(2)] - \frac{\lambda}{1+(n-1)\lambda}\sum_{j\in\mathscr{A}\backslash M\backslash b}[p_{sj} + V_s(2)] \\
=&(v - p_{sb} + V_s(2)) - \frac{\lambda}{1+(n-1)\lambda}[v - p_{sb} + V_s(2)] - \frac{\lambda}{1+(n-1)\lambda}(d-1)V_b(2)
\end{aligned}
$$

Theorem 1 implies that $\overline{V}_s(2) = 0$. Importantly, $\overline{V}_b(2) = v$ by Theorem 1. This allows us to write the limiting first order conditions:

$$
\begin{aligned}
&\overline{p}_{sb} + 0 - \frac{1}{n-1}[\overline{p}_{sb} + 0] - \frac{1}{n-1}\sum_{j\in\mathscr{A}\backslash M\backslash b}[\overline{p}_{sj} + 0] \\
&\quad = v - \overline{p}_{sb} + 0 - \frac{1}{n-1}[v - \overline{p}_{sb} + 0] - \frac{1}{n-1}(d-1)v \\
&\Rightarrow \overline{p}_{sb} - \frac{1}{n-1}\sum_{j\in\mathscr{A}\backslash M}\overline{p}_{sj} = v_b - \overline{p}_{sb} - \frac{1}{n-1}v_b + \frac{1}{n-1}\overline{p}_{sb} - \frac{n-2}{n-1}v_b \\
&\Rightarrow (2 - \frac{1}{n-1})\overline{p}_{sb} - \frac{1}{n-1}\sum_{j\in\mathscr{A}\backslash M}\overline{p}_{sj} = 0
\end{aligned}
$$

Given this system of $n-1$ equations and $n-1$ prices a solution is $\overline{p}_{sj} = 0, \forall j \in \mathscr{A}\backslash M$ By 3.3.3 in Appendix 3.C we know that the solution is unique at every λ. By continuity of the price function we can conclude that $\overline{p}_{sb} = 0$ for all states in this equilibrium[3] □

[3] Note that zero limit prices for the initial seller relies on there being at least two uninformed agents that the initial seller trades with ($\sum_{j\in\mathscr{A}\backslash M}\alpha_{sj}(1) \geq 2$) which is the case in the immediate agreement equilibrium from Proposition 3.4.1, but could also hold in other equilibria.

While the immediate agreement equilibrium is of interest there is some sense in which it is not appealing because it has the seller competing with herself in a way that drives prices to 0 and eats away her payoff in the limit. This brings us to the second type of equilibrium.

3.4.2 Endogenous Bottleneck

We now focus attention on equilibrium in which immediate agreement is not achieved. This equilibrium will only differ from the previous one in the actions of the initially informed agent in the n-clique. The way in which she does so is that she designates a certain buyer as the buyer to whom she shall give the information first, and refuses to sell the information to any other buyer until that point.

Proposition 3.4.3. *In an n-clique, for sufficiently high λ, there exists an equilibrium where if no others are informed the initial seller, s, will only sell the information to buyer b ($\alpha_{sb}(1) = 1$ and $\alpha_{ij}(1) = 0\ \forall ij \neq sb$) at a positive limit price, $\overline{p}_{sb}(1) = \frac{v}{2} > 0$ and in all other states agreement occurs for all pairs at zero limit price, $\alpha_{ij}(m) = 1, \overline{p}_{ij}(m) = 0\ \forall m > 1$.*

Proof. As seen in Theorem 1 prices converge to 0 for all buyers and sellers once at least two sellers are informed and by 3.4.1 there exists an equilibrium with immediate agreement once two sellers are informed. Consider the candidate equilibrium described above which is different from the immediate agreement equilibrium in 3.4.1 when there is only one initially informed seller. We will first show that the limit price for sb is in fact positive, $\overline{p}_{sb}(1) = \frac{v}{2} > 0$, and then we will show that the candidate is indeed an equilibrium. The price for sb is found by Recursive Nash Bargaining

$$p_{sb}(1) + V_s(2) - V_s(1) = v - p_{sb}(1) + V_s(2) - V_b(1).$$

Because sb is the only link that bargains in the candidate equilibrium Rational Expectations yields $V_s(1) = \frac{\lambda}{1+\lambda}(p_{sb}(1) + V_s(2))$ and $V_b(1) = \frac{\lambda}{1+\lambda}(v - p_{sb}(1) + V_s(2))$ so the above equation can be rewritten and solved as

$$\begin{aligned}
p_{sb}(1) + V_s(2) - V_s(1) &= v - p_{sb}(1) + V_s(2) - V_b(1) \\
(1 - \frac{\lambda}{1+\lambda})[p_{sb}(1) + V_s(2)] &= (1 - \frac{\lambda}{1+\lambda})[v - p_{sb}(1) + V_s(2)] \\
p_{sb}(1) + V_s(2) &= v - p_{sb}(1) + V_s(2) \\
p_{sb}(1) &= \frac{v + V_s(2) - V_s(2)}{2}
\end{aligned}$$

Taking the frictionless limit we know by Theorem 1 that $\overline{V}_s(2) = 0$, alternatively the symmetry of s and b after b purchases the information, so in this candidate equilibrium $p_{sb}(1) = \frac{v}{2} > 0$. Now, consider a deviation in the bargaining between s and any $b' \in \mathscr{A} \setminus \{s, b\}$ and where they agree ($\alpha_{sb'}(1) = 1$) so

$$V_s(2) + v_{b'} + V_s(2) \geq V_s(1) + V_{b'}(1).$$

Taking the limit on both sides, by Theorem 1 $\overline{V}_s(2) = 0$. Additionally, $\overline{V}_s(1) = \overline{p}_{sb}(1)$ because b will eventually trade with s along the candidate equilibrium and s will get 0 continuation value in the limit. Finally, $\overline{V}_{b'}(1) = v$ because b' will eventually become informed at 0 cost after b is informed and have no continuation value, but this results in a contradiction because $v \ngeq \overline{p}_{sb}(1) + v$ in this equilibrium and so sb' will not deviate to agree. Consider a deviation where s and b disagree. In that case they would do strictly better by agreeing and realizing the joint agreement payoff v which would be larger than the joint disagreement payoff of s never selling the information. This completes the proof. $\square$

These equilibria are appealing because they allow the initial seller to leverage her monopolistic position to endogenously adjust the market structure with the benefit of extracting positive payoff in the frictionless limit.

Proposition 3.4.4. *Let π be the maximum expected continuation payoff for the initial seller across all equilibria. Then in the n-clique as $\lambda \to \infty$*

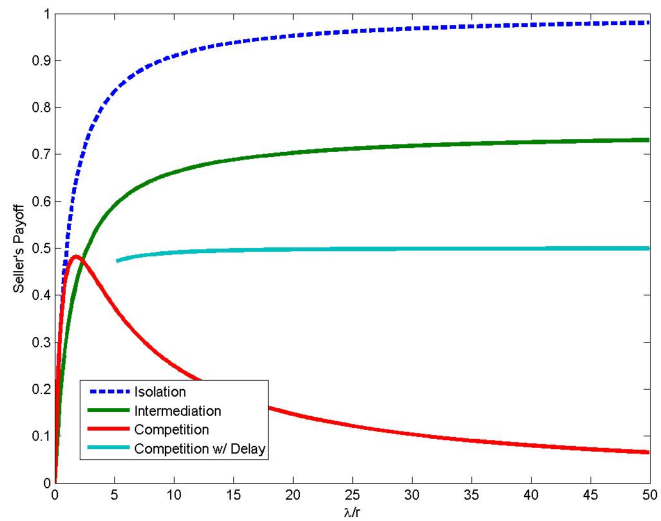
$$\pi \to \frac{v}{2}.$$

Proof. By Theorem 1 in any state with more than two informed agents the price will converge to 0 for any equilibria. The same holds for any state with one informed if the equilibrium involves the initially informed agent agreeing with at least two uninformed agents. The endogenous bottleneck equilibria are the only ones with positive limit prices and the initially informed seller, s, receives a price of $\frac{v}{2}$ as shown in 3.4.3. This means that in the limit the best equilibrium for the seller is the one in which she only trades with the buyer of the highest value and the continuation payoff π will converge to $\frac{v}{2}$. □

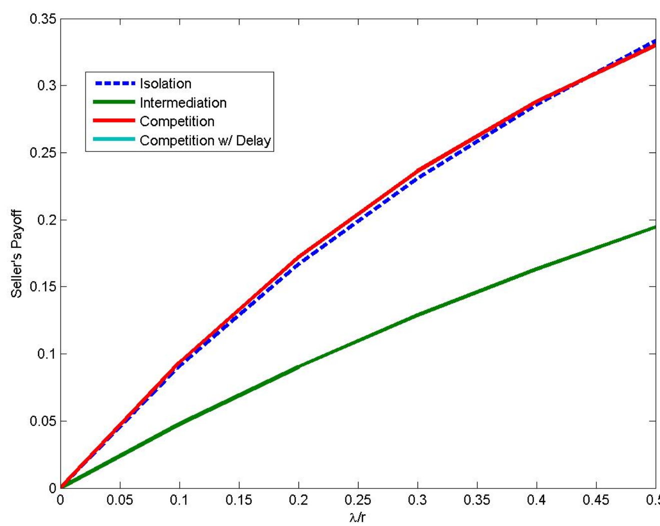
To this point we have shown that in the above model there are multiple equilibrium in the n-clique for low levels of friction (large λ). This helps us understand the features and incentives for a seller to want to be the first informed.

3.4.3 Monopoly Rights

Given the negative impacts of competition in the network there is potentially incentives for the initially informed agent to impose a no-resale contract on the buyers. This is equivalent to the n-clique being transformed into another network structure. We can use the mechanisms described in this paper to discuss if and how specific contracted network would be preferred by the initially informed seller. Some equilibrium concepts need to be generalized for non-clique networks and can be found in section 3.A. As seen in the example from section 3.2 the structure of the network can greatly impact the payoffs. One example is a *tree network* where only one path between any two players. Another is a *star network centered on* $i \in \mathscr{A}$ which is a tree network where everyone is linked to i and not to each other. If an n-clique represents a networked market for information the star represents a protected monopolistic market for information.



(a) Full Range



(b) Small λ

Figure 3.4.2. How Frictions Influence the Seller's Payoffs

The first comparison is between an n-clique and a star network of the same size.

Theorem 2. *The star centered on the initial seller is preferred to an n-clique of the same size for any consumption values for large λ.*

Proof. The maximum expected equilibrium continuation value for the initial seller converges to $\frac{v}{2}$ by 3.4.4 and in the star the equilibrium continuation payoff is $\sum_{i\in\mathscr{B}}\frac{v}{2}$, for all λ, following the reasoning in the no resale opportunities portion of section 3.2. Therefore for large λ the star will be preferred by the initial seller to the n-clique. □

One result of interest is that there are situation in which frictions result in higher payoffs for the initially informed

Theorem 3. *For small λ a* 3*-clique, Q_3, is preferred to a star with 2 buyers for the initial seller, $\bigstar_2(s_0)$, by the initial seller.*

This is seen numerically when Figure 3.4.2a is zoomed in for Figure 3.4.2b and the seller's initial payoff is indeed higher. For a more formal proof see section 3.C.

3.4.4 Single-Sale Commitment

We now consider a regime in which each seller is restricted to selling the information only once. Note that this is equivalent to removing the replicability from the good. Additionally, in this situation if there is only one initially informed seller, which is all we will consider, then there can only be one seller who has the ability to sell the good at any one point. This allows us to solve for the equilibrium recursively over the number of buyers with one seller.

Theorem 4. *The price of the first, and only, sale from the only active seller, s^*, in an n-clique with a single-sale constraint is*

$$p_{s^*b}(m)=\sum_{t=0}^{n-m-1}\frac{1}{2}\left(\frac{1}{2}\frac{\lambda}{1+\lambda}\right)^t v$$

Proof. The proof proceeds by induction over $n-m$ for an arbitrary m.

-Base Case Given that $n-m=1$ consider the only seller, s^*, who can currently sell the good, $s \in M$. This will be the last to purchase the good if $m>1$ or the initially informed seller if $m=1$. Consider the bargaining between $s^*=s$ and the last uninformed agent, $b \in \mathscr{A} \backslash M$ will result in agreement because the disagreement point is to introduce delay in s eventually obtaining the opportunity to sell to b. The price for this sale will solve:

$$\begin{aligned}
p_{sb}(m) - V_s(m) &= v - p_{sb}(m) + V_{s^*}(m+1) - V_b(m) \\
(1-\frac{\lambda}{1+\lambda})p_{sb}(m) &= (1-\frac{\lambda}{1+\lambda})[v - p_{sb}(m) + V_{s^*}(m+1)] \\
p_{sb}(m) &= v - p_{sb}(m) + V_{s^*}(m+1) \\
p_{sb}(m) &= \frac{v + V_{s^*}(m+1)}{2} = \frac{v}{2}
\end{aligned}$$

where the last equality is because the value of being the only active seller in a state with $m+1$ sellers, $V_{s^*}(m+1)$, when $n-m=1$ is zero. This proves the theorem in the base case because when $n-m$

$$p_{sb}(m) = \sum_{t=0}^{0} \frac{1}{2}(\frac{1}{2}\frac{\lambda}{1+\lambda})^t v = \frac{v}{2}$$

-Inductive Case Now consider the inductive case with $n-m=k>1$ and the theorem holding for all $n-m<k$. If the theorem holds for all $n-m<k$ then

$$V_{s^*}(m+1) = \sum_{t=1}^{n-(m+1)} (\frac{1}{2}\frac{\lambda}{1+\lambda})^t v$$

and adjusting the last step of the base case yields

$$p_{sb}(m) = \frac{v + V_{s^*}(m+1)}{2} = \frac{v}{2} + \frac{1}{2}\sum_{t=1}^{n-(m+1)} (\frac{1}{2}\frac{\lambda}{1+\lambda})^t v = \sum_{t=0}^{n-m-1} \frac{1}{2}(\frac{1}{2}\frac{\lambda}{1+\lambda})^t v$$

This completes the proof. □

We can then consider the frictionless limit of the single-sale regime.

Corollary 3.4.2. *In the frictionless limit, the price of the first, and only, sale to the initial seller, s^*, in an n-clique with a single-sale constraint is*

$$\overline{p}_{s^*b}(1) = (1 - (\frac{1}{2})^{n-1})v$$

Proof. By taking the frictionless limit of the price from Theorem 4 when only one individual is informed:

$$\overline{p}_{s^*b}(1) = \frac{v}{2}\frac{1-(\frac{1}{2})^{n-1}}{1-\frac{1}{2}} = (1 - (\frac{1}{2})^{n-1})v$$

□

This price is higher than that achieved in the seller-optimal competitive equilibrium, but still does not yield the monopoly payoff for the initially informed seller.

Single-sale is one particular example of a regime that restricts the sale of information. Additional forms of contracting that are beyond the scope of this paper include: (1) contracts that restrict specific links to be directed and thus prevent sale in one direction; (2) contracts that impose an arbitrary network structure; and (3) contracts that allow resale, but with a fixed price or price ceiling.

Given the range of payoffs available to an initially informed seller in a competitive, monopolistic, and single-sale market structure it is natural to turn to a discussion of how the market structure influences the incentives that agents have to become the initially informed.

3.5 Efforts To Acquire Information

We can now turn to the the first stage game where agents exert effort, σ, to generate the innovation and become an initially informed seller. Let $\vec{\sigma} \in [0,1]^k$ be the effort profile of all $k \leq n$ agents that are able to innovate.

Definition. *Let each agent i of the k participating agents have a convex cost to information acquisition effort,* $\sigma_i \in [0,1]$

$$c(\sigma_i) = \frac{\kappa\sigma_i^2}{2}$$

Then the expected payoff to an individual agent i is

$$\Pi_i(\vec{\sigma}) = \sum_{m=1}^{k} \mathbb{P}(m|\vec{\sigma})[\mathbb{1}\{i \in M\}v + V_i(m)] - \frac{\kappa\sigma_i^2}{2}$$

Where $\mathbb{P}(m|\vec{\sigma})$ is the probability of the m sellers learning the information given an effort profile, $\vec{\sigma}$. We will focus on symmetric equilibrium in the information acquisition game.

3.5.1 Socially Efficient, Equilibrium, Monopoly and Single Sale Information Acquisition

We can consider the social planners problem of effort choice in information acquisition. In the symmetric equilibrium the social welfare function is the value of at least one agent becoming informed minus the cumulative cost

$$\sum_{i \in k} \overline{\Pi}_i(\vec{\sigma}) = (1-(1-\sigma)^k)nv - k\frac{\kappa\sigma^2}{2} \tag{3.5.3}$$

Proposition 3.5.5. *In the frictionless limit, the social optimum effort acquisition is* σ^S *such that*

$$\frac{\sigma^S}{(1-\sigma^S)^{k-1}} = \frac{nv}{\kappa}$$

Proof. By the first order condition of the social welfare function (Equation 3.5.3)

$$\begin{aligned} k(1-\sigma^S)^{k-1}nv - k\kappa\sigma^S &= 0 \\ \frac{\sigma^S}{(1-\sigma^S)^{k-1}} &= \frac{nv}{\kappa} \end{aligned}$$

□

We can also determine the effort choice in the agreement and bottleneck equilibria. First consider the immediate agreement equilibrium. If this is the case then the limit payoff function can be split into the case where agent i obtains the information and the case where i does not, but another agent does:

$$\overline{\Pi}_i(\vec{\sigma}) = \sigma v + (1-\sigma)(1-(1-\sigma^A)^{k-1})v - \frac{\kappa\sigma^2}{2} \tag{3.5.4}$$

Proposition 3.5.6. *In the frictionless limit, the agreement equilibrium effort acquisition is* σ^A *such that*

$$\frac{\sigma^A}{(1-\sigma^A)^{k-1}} = \frac{v}{\kappa}$$

Proof. By the first order condition of the individual payoff function (Equation 3.5.4)

$$\begin{aligned} v - (1-(1-\sigma^A)^{k-1})v - \kappa\sigma^A &= 0 \\ (1-\sigma^A)^{k-1}v &= \kappa\sigma^A \\ \frac{\sigma^A}{(1-\sigma^A)^{k-1}} &= \frac{v}{\kappa} \end{aligned}$$

□

Next, consider the endogenous bottleneck equilibrium. In this case the limit payoff function can be split into the case where agent i is the only agent to obtain the information, the case where more than one agent receives the information and the case when another single agent receives the information with some chance that i is selected for the endogenous bottleneck:

$$\begin{aligned}\overline{\Pi}_i(\vec{\sigma}^B) = \sigma(1-\sigma^B)^{k-1}[v+\frac{v}{2}] + \sigma(1-(1-\sigma^B)^{k-1})v \\ +(1-\sigma)(k-1)\sigma^B(1-\sigma^B)^{k-2}(\frac{n-2}{n-1}v + \frac{1}{n-1}\frac{v}{2}) \\ +(1-\sigma)(1-(k-1)\sigma^B(1-\sigma^B)^{k-2} - (1-\sigma^B)^{k-1})v - \frac{\kappa\sigma^2}{2}\end{aligned} \quad (3.5.5)$$

Proposition 3.5.7. *In the frictionless limit, the best bottleneck equilibrium effort acquisition is σ^B such that*

$$\frac{\sigma^B}{(1-\sigma^B)^{k-1}} = \frac{3v}{2\kappa} + (k-1)\frac{\sigma^B}{(1-\sigma^B)}\frac{1}{n-1}\frac{v}{2\kappa}$$

Proof. By the first order condition of the individual payoff function (Equation 3.5.5)

$$\begin{aligned}(1-\sigma^B)^{k-1}[v+\frac{v}{2}] + (1-(1-\sigma^B)^{k-1})v \\ -(k-1)\sigma^B(1-\sigma^B)^{k-2}(\frac{n-2}{n-1}v + \frac{1}{n-1}\frac{v}{2}) \\ -(1-(k-1)\sigma^B(1-\sigma^B)^{k-2} - (1-\sigma^B)^{k-1})v - \kappa\sigma^B = 0 \\ (1-\sigma^B)^{k-1}\frac{v}{2} + v - (k-1)\sigma^B(1-\sigma^B)^{k-2}\frac{2n-3}{n-1}\frac{v}{2} \\ -v + (k-1)\sigma^B(1-\sigma^B)^{k-2}v + (1-\sigma^B)^{k-1}v = \kappa\sigma^B \\ \frac{3v}{2\kappa} + (k-1)\frac{\sigma^B}{(1-\sigma^B)}\frac{1}{n-1}\frac{v}{2\kappa} = \frac{\sigma^B}{(1-\sigma^B)^{k-1}}\end{aligned}$$

□

Note that the effort choice in this setting would be higher than the effort choice in the immediate agreement equilibrium. With these equilibrium effort levels characterized we can begin to understand comparative statics of the effort choice.

Returning to the first stage information acquisition game. We can consider the implications that the above contracting regimes have on incentives for innovation. For all the contracts assume that they are with respect to the initially informed agent (if there is only one).

Consider the case of full protection where the initially informed agent has complete property rights over the innovation and if multiple generate the innovation then only one agent, chosen uniformly at random, becomes initially informed. If this is the case then the limit payoff function is:

$$\overline{\Pi}_i(\vec{\sigma}) = \sigma(v + \sum_{j=1}^{k} \binom{k-1}{j-1} \sigma^{F(j-1)}(1-\sigma^F)^{k-j}\frac{1}{j}(n-j)\frac{v}{2}) \\ + (1-\sigma)(1-(1-\sigma^F)^{k-1})\frac{v}{2} - \frac{\kappa\sigma^2}{2} \tag{3.5.6}$$

Proposition 3.5.8. *In the frictionless limit, the full protection equilibrium effort acquisition is σ^F such that*

$$\frac{\sigma^F}{(1-\sigma^F)^{k-1}} = \frac{v}{2\kappa} + \frac{n}{k}\frac{(1-(1-\sigma^F)^k)}{\sigma^F(1-\sigma^F)^{k-1}}\frac{v}{2\kappa}$$

Proof. By the first order condition of the individual payoff function (Equation 3.5.6)

$$(v+\sum_{j=1}^{k}\binom{k-1}{j-1}\sigma^{F(j-1)}(1-\sigma^F)^{k-j}\frac{1}{j}(n-j)\frac{v}{2})-(1-(1-\sigma^F)^{k-1})\frac{v}{2}=\kappa\sigma^F$$

$$[1+n\sigma^{F(-1)}\sum_{j=1}^{k}\binom{k}{j}\sigma^{F(j)}(1-\sigma^F)^{k-j}\frac{1}{k}$$

$$-\sum_{j=1}^{k}\binom{k-1}{j-1}\sigma^{F(j-1)}(1-\sigma^F)^{k-1-(j-1)}+(1-\sigma^F)^{k-1}]\frac{v}{2\kappa}=\sigma^F$$

$$[1+\frac{n}{k}\sigma^{F(-1)}(\sum_{j=0}^{k}\binom{k}{j}\sigma^{F(j)}(1-\sigma^F)^{k-j}-\sigma^{F(0)}(1-\sigma^F)^{k-0})$$

$$-\sum_{j=0}^{k-1}\binom{k-1}{j}\sigma^{F(j)}(1-\sigma^F)^{k-1-j}+(1-\sigma^F)^{k-1}]\frac{v}{2\kappa}=\sigma^F$$

$$[1+\frac{n}{k}\sigma^{F(-1)}((\sigma^F+1-\sigma^F)^k-1(1-\sigma^F)^k)$$

$$-(\sigma^F+1-\sigma^F)^{k-1}+(1-\sigma^F)^{k-1}]\frac{v}{2\kappa}=\sigma^F$$

$$[1+\frac{n}{k}\sigma^{F(-1)}(1-(1-\sigma^F)^k)-1+(1-\sigma^F)^{k-1}]\frac{v}{2\kappa}=\sigma^F$$

$$[\frac{n}{k}\frac{(1-(1-\sigma^F)^k)}{\sigma^F(1-\sigma^F)^{k-1}}+1]\frac{v}{2\kappa}=\frac{\sigma^F}{(1-\sigma^F)^{k-1}}$$

Where the fourth step is by the binomial formula. □

3.5.2 Comparative Statics

Because all effort levels are a function of $\frac{v}{\kappa}$ it is without loss of generality to let $\kappa=1$ and interpret v as the cost normalized private payoff to innovation.

Proposition 3.5.9. *In the frictionless limit, equilibrium effort choice is independent of clique size, n, in the immediate agreement equilibrium.*

By inspection of 3.5.6.

Consider the special case of an innovation monopoly where there is only one innovator, $k=1$. In the frictionless limit with an innovation monopoly, the socially efficient information acquisition is:

$$\sigma^S = \min\{nv, 1\}$$

the agreement equilibrium effort acquisition is:

$$\sigma^A = \min\{v, 1\}$$

in the endogenous bottleneck equilibrium it is:

$$\sigma^B = \min\{\frac{3v}{2}, 1\}$$

Proposition 3.5.10. *In the frictionless limit with an innovation monopoly, $k = 1$, equilibrium effort choice is greater in the endogenous bottleneck equilibrium than in the agreement equilibrium by up to 50%, but both are less than the socially optimal effort acquisition which scales with the clique size.*

In the frictionless limit with an innovation monopoly, the full protection equilibrium effort acquisition is

$$\sigma^F = \min\{(n+1)\frac{v}{2}, 1\}$$

Proposition 3.5.11. *In the frictionless limit with an innovation monopoly, $k = 1$, equilibrium effort choice is increasing in clique size, n, under full protection and always less than the socially optimal effort investment in an innovation monopoly.*

Consider the next case of an innovation duopoly where there are two innovators, $k = 2$. In the frictionless limit with an innovation duopoly, the socially efficient information acquisition is:

$$\frac{\sigma^S}{(1-\sigma^S)} = nv \Rightarrow \sigma^S = \frac{nv}{nv+1} \tag{3.5.7}$$

the agreement equilibrium effort acquisition is

$$\frac{\sigma^A}{(1-\sigma^A)} = v \Rightarrow \sigma^A = \frac{v}{v+1} \tag{3.5.8}$$

in the endogenous bottleneck equilibrium it is

$$\frac{\sigma^B}{(1-\sigma^B)} = \frac{3v}{2} + \frac{\sigma^B}{(1-\sigma^B)} \frac{1}{n-1} \frac{v}{2}$$

which simplifies to

$$\frac{\sigma^B}{(1-\sigma^B)} = \frac{3v(n-1)}{2(n-1)-v} \Rightarrow \sigma^B = \frac{3v(n-1)}{[3v+2](n-1)-v} \tag{3.5.9}$$

Proposition 3.5.12. *In the frictionless limit with an innovation duopoly, $k = 2$, equilibrium effort choice is decreasing in clique size, n, in the best bottleneck equilibrium and increasing in clique size when socially optimal.*

By inspection of Equation 3.5.7 and Equation 3.5.9.

Proposition 3.5.13. *In the frictionless limit with an innovation duopoly, $k = 2$, equilibrium effort choice is greater in the endogenous bottleneck equilibrium than in the agreement equilibrium for all n and is smaller than the socially optimal effort level for n such that $v < 2n - 5 + \frac{3}{n}$.*

Proof. Endogenous bottleneck effort will be more than agreement effort if

$$\sigma^B = \frac{3v(n-1)}{[3v+2](n-1)-v} > \frac{v}{v+1} = \sigma^A$$
$$\frac{3(n-1)(v+1)}{[3v+2](n-1)-v} > 1$$

and this is true given that $\frac{[3v+3](n-1)}{[3v+2](n-1)-v} > \frac{[3v+2](n-1)}{[3v+2](n-1)-v} > \frac{[3v+2](n-1)}{[3v+2](n-1)} = 1$ And the endogenous bottleneck effort will me less than socially optimal effort if

$$\sigma^B = \frac{3v(n-1)}{[3v+2](n-1)-v} < \frac{nv}{nv+1} = \sigma^S$$
$$3(n-1)(nv+1) < n[3v+2](n-1)-nv$$
$$3nv(n-1)+3(n-1) < 3nv(n-1)+2n(n-1)-nv$$
$$3(n-1) < 2n(n-1)-nv$$
$$v < \frac{(2n-3)(n-1)}{n} = 2n-5+\frac{3}{n}$$

given that the right hand side is increasing in n this is true for all $n \geq 2$ only if $v < 2 \times 2 - 5 + \frac{3}{2} = \frac{1}{2}$ otherwise it will hold for n large enough such that $v < 2n-5+\frac{3}{n}$. $\square$

Finally, in the frictionless limit the full protection equilibrium effort acquisition in an innovation duopoly is

$$\frac{\sigma^F}{(1-\sigma^F)} = \frac{v}{2} + \frac{n}{2}\frac{(1-(1-\sigma^F)^2)}{\sigma^F(1-\sigma^F)}\frac{v}{2}$$
$$\frac{\sigma^F}{(1-\sigma^F)} = \frac{2\sigma^F(1-\sigma^F)v + n(1-(1-2\sigma^F+\sigma^{F2}))v}{2\sigma^F(1-\sigma^F)2}$$
$$\sigma^F = \frac{2\sigma^F(1-\sigma^F)v + n(2\sigma^F-\sigma^{F2})v}{2\sigma^F 2}$$
$$\sigma^F = \frac{(n+1)v}{2} - \frac{(n+2)v}{4}\sigma^F$$
$$\sigma^F = \min\{\frac{2(n+1)v}{4+(n+2)v}, 1\}$$

Proposition 3.5.14. *In the frictionless limit, information acquisition effort in the full protection equilibrium is greater than the socially optimal effort level in an innovation duopoly when the private value of exerting full effort is preferred to the private value of exerting no effort, $v > \frac{1}{2}$.*

Proof. Given that it is trivial to show that if $\sigma^F = 1 > \sigma^S$ it is left to prove the proposition for $\sigma^F < 1$

$$\sigma^F = \frac{2(n+1)v}{4+(n+2)v} > \frac{nv}{nv+1} = \sigma^S$$
$$2(n+1)(nv+1) > n(4+(n+2)v)$$
$$2n^2v + 2nv + 2n + 2 > 4n + n^2v + 2nv$$
$$vn^2 - 2n + 2 > 0$$

This will be true for every n if the cost normalized private payoff to innovation $v > \frac{1}{2}$. This can be interpreted economically as the private payoff (without any sales) of investing full effort ($\sigma = 1$), $v - 1^2/2$, exceeds the payoff from investing no effort ($\sigma = 0$), 0. Note that if $v < 1$, then a person only puts in partial effort. □

If we restrict attention to pairs of market sizes and cost normalized private information value, n, v such that $2n - 5 + \frac{3}{n} > v > \frac{1}{2}$ we know by Propositions 3.5.13 and 3.5.14 that the equilibrium effort levels can be ordered:

$$\sigma^F > \sigma^S > \sigma^B > \sigma^A$$

With competition leading to underinvestment in effort and full protection leading to overinvestment. To obtain the socially efficient level of effort one can imagine a hybrid model that randomizes between a protection and competition.

3.5.3 Probabilistic Protection

This probabilistic protection would be parametrized by π, the probability of protection. We return to the general case to derive the equilibrium effort level under this specification and we restrict attention to the case where no protection results in the endogenous bottleneck equilibrium. If this is the case then the limit payoff function is:

$$\begin{aligned}\overline{\Pi}_i(\vec{\sigma}) = \pi\{\sigma(v + \sum_{j=1}^{k}\binom{k-1}{j-1}\sigma^{P(j-1)}(1-\sigma^P)^{k-j}\frac{1}{j}(n-j)\frac{v}{2}) \\ + (1-\sigma)(1-(1-\sigma^P)^{k-1})\frac{v}{2}]\} \\ +(1-\pi)\{\sigma(1-\sigma^P)^{k-1}[v+\frac{v}{2}] + \sigma(1-(1-\sigma^P)^{k-1})v \\ + (1-\sigma)(k-1)\sigma^P(1-\sigma^P)^{k-2}(\frac{n-2}{n-1}v + \frac{1}{n-1}\frac{v}{2}) \\ + (1-\sigma)(1-(k-1)\sigma^P(1-\sigma^P)^{k-2} - (1-\sigma^P)^{k-1})v\} - \frac{\kappa\sigma^2}{2}\end{aligned} \tag{3.5.10}$$

Proposition 3.5.15. *In the frictionless limit, the probabilistic protection equilibrium* *effort acquisition is σ^P such that*

$$\frac{\sigma^P}{(1-\sigma^P)^{k-1}} = \frac{3v-2v\pi}{2\kappa} + [\frac{\pi n}{k}\frac{(1-(1-\sigma^P)^k)}{\sigma^P(1-\sigma^P)^{k-1}} + \frac{(1-\pi)(k-1)}{n-1}\frac{\sigma^P}{(1-\sigma^P)}]\frac{v}{2\kappa}$$

Proof. The first order condition of the individual payoff function (Equation 3.5.10) and algebra from previous propositions yields:

$$\begin{aligned}
&\pi[\frac{v}{2\kappa} + \frac{n}{k}\frac{(1-(1-\sigma^P)^k)}{\sigma^F(1-\sigma^P)^{k-1}}\frac{v}{2\kappa}] \\
&+(1-\pi)[\frac{3v}{2\kappa} + (k-1)\frac{\sigma^P}{(1-\sigma^P)}\frac{1}{n-1}\frac{v}{2\kappa}] = \frac{\sigma^P}{(1-\sigma^P)^{k-1}} \\
&\frac{\pi v + (1-\pi)3v}{2\kappa} + [\pi\frac{n}{k}\frac{(1-(1-\sigma^P)^k)}{\sigma^P(1-\sigma^P)^{k-1}} \\
&+(1-\pi)(k-1)\frac{\sigma^P}{(1-\sigma^P)}\frac{1}{n-1}]\frac{v}{2\kappa} = \frac{\sigma^P}{(1-\sigma^P)^{k-1}} \\
&\frac{3v-2v\pi}{2\kappa} + [\frac{\pi n}{k}\frac{(1-(1-\sigma^P)^k)}{\sigma^P(1-\sigma^P)^{k-1}} \\
&+\frac{(1-\pi)(k-1)}{n-1}\frac{\sigma^P}{(1-\sigma^P)}]\frac{v}{2\kappa} = \frac{\sigma^P}{(1-\sigma^P)^{k-1}}
\end{aligned}$$

$\square$

It is then possible to return to the innovation duopoly with normalized costs where the partial protection regime implies effort defined by

$$\frac{\sigma^P}{(1-\sigma^P)} = \frac{3v-2v\pi}{2} + [\frac{\pi n}{2}\frac{(1-(1-\sigma^P)^2)}{\sigma^P(1-\sigma^P)} + \frac{(1-\pi)}{n-1}\frac{\sigma^P}{(1-\sigma^P)}]\frac{v}{2}$$

simplifying

$$\frac{\sigma^P}{(1-\sigma^P)} = \frac{3v-2v\pi}{2}+[\frac{\pi n(2\sigma^P-\sigma^{P2})}{2\sigma^P(1-\sigma^P)}+\frac{(1-\pi)\sigma^P}{(n-1)(1-\sigma^P)}]\frac{v}{2}$$

$$\frac{\sigma^P}{(1-\sigma^P)} = \frac{3v-2v\pi}{2}+[\frac{\pi n}{2(1-\sigma^P)}+\frac{\pi n}{2}+\frac{(1-\pi)\sigma^P}{(n-1)(1-\sigma^P)}]\frac{v}{2}$$

$$[1-\frac{(1-\pi)}{(n-1)}\frac{v}{2}]\frac{\sigma^P}{(1-\sigma^P)} = \frac{3v-2v\pi}{2}+\frac{\pi n}{2}\frac{v}{2}+\frac{\pi n}{2(1-\sigma^P)}\frac{v}{2}$$

$$\frac{(n-1)2-(1-\pi)v}{(n-1)}\frac{\sigma^P}{(1-\sigma^P)} = \frac{(3v-2v\pi)(2)(1-\sigma^P)+\pi nv(1-\sigma^P)+\pi nv}{2(1-\sigma^P)}$$

$$[(n-1)(4+6v+(n-4)v\pi)-2(1-\pi)v]\sigma^P = (n-1)(6v+(2n-4)v\pi)$$

$$\sigma^P = \min\{\frac{(n-1)(6v+(2n-4)v\pi)}{(n-1)(4+6v+(n-4)v\pi)-2(1-\pi)v},1\}$$

Note that if $\pi = 0$ then $\sigma^P = \sigma^B$ and if $\pi = 1$ then $\sigma^P = \sigma^F$.

Proposition 3.5.16. *In the frictionless limit if* $2n-5+\frac{3}{n} > v > \frac{1}{2}$*, information acquisition effort in the probabilistic protection equilibrium is equal to the socially optimal effort level in an innovation duopoly for some* $\pi^* \in [0,1]$.

Proof. We can then determine the probability or protection need to induce the socially optimal effort by finding π such that $\sigma^P = \sigma^S$. This will only occur if $\sigma^F > \sigma^S > \sigma^B$ so we restrict attention to the appropriate range of v. The only discontinuity in σ^P will occur when the denominator is 0 which will only occur at a negative π because it is increasing in π and positive for $\pi = 0$. Therefore there will exist a $\pi^* \in [0,1]$ such that probabilistic protection induces socially optimal effort. □

In future work we will also consider the result of imposing a patent duration, or limited protection, which will similarly result in minimizing the overinvestment in innovation effort.

3.6 Discussion

In this paper, we studied a decentralized market where sellers and prospective buyers of information can negotiate over its price, and the buyers of information cannot commit to not resell it. We studied how the potential for resale influences the pricing of information, and the incentives to acquire information when trading frictions are small. We proved that in a no-delay equilibrium, all prices converge to 0, even if the initial seller is an informational monopolist. The seller-optimal equilibrium features delay: the seller is able to sell information at a strictly positive price to a single buyer, but once two players possess information, prices converge to 0.

This work is complementary to the existing work on the decentralized sale of information (Polanski, 2007) and intellectual property policy (Boldrin and Levine, 2004; Boldrin and Levine, 2013; Cohen, Gurun, and Kominers, 2014). As opposed to much of the literature, the insights we discuss are found outside of the large market setting. We find that the inability to capture much of the social surplus from selling information results in sellers underinvesting in their technology to acquire information. By contrast, a "patent policy" that permits an informed seller to be the sole seller of information leads to overinvestment in information acquisition. Socially efficient information acquisition emerges under a random patent policy. Future work will explore the impact of bargaining weights on the resale of information and explore patent duration as an alternative to the random patent framework.

3.6.1 Acknowledgements

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Appendix - Chapter 3

3.A General Solution Concept

The following is the generalization of subsection 3.3.2 to arbitrary network structures. Let the set on agents linked to i be denoted N_i. We use the set of informed players as the payoff-relevant state space. The feasible set of states is

$$\mathscr{M} \equiv \{M \subseteq \mathscr{A} : M \supseteq \mathscr{S} \text{ and for all } i \in M \backslash \mathscr{S}, \exists \text{ a path from } i \text{ to } \mathscr{S} \text{ through } M.\}$$

A set M in $\mathscr{M}$ includes the set of initial sellers and buyers who have acquired information, with the restriction that a buyer could have acquired information only from someone who possesses it. For each agent i in $\mathscr{A}$, we define a value function $V_i : \mathscr{M} \to \Re$ such that $V_i(M)$ represents player i's expected payoff when the set of informed players is M.

Consider any player i and neighbor j such that there exists M in $\mathscr{M}$ where $i \in M$ and $j \notin M$. The set of all such pairs is $\mathscr{T}$, the set of feasible trading partners. Let $\mathscr{M}_{ij} = \{M \in \mathscr{M} : i \in M, j \notin M\}$. These are the feasible states where player i may sell information to player j. We define *trading functions* $p_{ij} : \mathscr{M}_{ij} \to \Re_{+\cup\{0\}}$ and $\alpha_{ij} : \mathscr{M}_{ij} \to \{0,1\}$ such that $\alpha_{ij}(M) = 1$ if and only if player i sells information to player j at price $p_{ij}(M)$, and $\alpha_{ij}(M) = 0$ if the two players do not trade information.

Our conditions of rational expectations and Nash bargaining are defined separately for each of these operators, and then combined to define an equilibrium.

We define for any non-negative number d, $\Delta(d) \equiv \int_0^\infty e^{-(1+\lambda d)t}\lambda\, dt$. This is the stochastic discount factor associated with payoffs that emerge if among m links, one particular link is the next to be recognized. Note that as $\lambda \to \infty$, all clocks are ringing virtually immediately, and so $\Delta(d)$ converges to $1/d$.

Definition. *Given trading functions $(p_{ij}(\cdot), \alpha_{ij}(\cdot))_{ij\in\mathscr{T}}$, the value functions $(V_i(\cdot))_{i\in\mathscr{A}}$ satisfies **Rational Expectations** if for every i and for every $M \in \mathscr{M}$, $V_i(M) =$*

$$\Delta(|G|)\left(\begin{array}{c} V_i(M)\left(\sum_{k\in M}(|N(k)\cap M|)+\sum_{k\in\mathscr{A}\setminus M}(|N(k)\setminus M|)\right) \\ +\sum_{k\in M\setminus\{i\}}\sum_{l\in N(k)\setminus(M\cup\{i\})}[\alpha_{kl}(M)V_i(M\cup\{l\})+(1-\alpha_{kl}(M))V_i(M)] \\ +\mathbb{1}_{i\in M}\sum_{l\in N(i)\setminus M}[\alpha_{il}(M)(p_{il}(M)+V_i(M\cup\{l\}))+(1-\alpha_{il}(M))V_i(M)] \\ +\mathbb{1}_{i\notin M}\sum_{k\in N(i)\cap M}[\alpha_{ki}(M)\left(v_i-p_{ki}(M)+V_i(M\cup\{i\})\right) \\ +(1-\alpha_{ki}(M))V_i(M)] \end{array}\right).$$

The term outside brackets is the stochastic discount factor waiting for a particular link to be the next to be recognized that is the effective. The first line considers link recognitions between two informed players or two uninformed players, both of which result in no trade. The second line considers all link recognitions where information may be shared, but player i is not party to it; if information is shared, which happens with probability $\alpha_{kl}(M)$, then the set of informed players expands from M to $M\cup\{l\}$, and otherwise, it remains the same. The third line applies if player i is informed, and considers all link recognitions with uninformed neighbors to whom he may sell information. The fourth line applies if player i is uninformed, and considers all link recognitions with informed neighbors from whom he may buy information.

Definition. *Given value functions $(V_i(\cdot))_{i\in\mathscr{A}}$, trading functions $(p_{ij}(\cdot), \alpha_{ij}(\cdot))_{ij\in\mathscr{T}}$ satisfies **Recursive Nash Bargaining** if for all $M \in \mathscr{M}$, $i \in M$, and $j \in N(i)\setminus M$,*

$$\alpha_{ij}(M) = 1 \Leftrightarrow \underbrace{V_i(M\cup\{j\})+v_j+V_j(M\cup\{j\})}_{\textit{Joint Surplus with Trade}} \geq \underbrace{V_i(M)+V_j(M)}_{\textit{Joint Surplus with No Trade}} \tag{3.A.1}$$

and $p_{ij}(M)$ is set to divide the change in surplus equally:

$$\underbrace{p_{ij}(M)+V_i(M\cup\{j\})-V_i(M)}_{\textit{Change in Seller's Surplus}} = \underbrace{v_j - p_{ij}(M)+V_j(M\cup\{j\})-V_j(M)}_{\textit{Change in Buyer's Surplus}}. \tag{3.A.2}$$

Equation 3.3.1 is a bilateral participation constraint: it specifies that information is traded in a linked pair if and only if the bilateral surplus from trade exceeds that from not trading. Equation 3.3.2 represents that if trade occurs, it does so at a price that ensures that both parties evenly share the gain in surplus from trade.

Definition. *An* ***equilibrium*** *is a sequence of value functions $(V_i(\cdot))_{i\in\mathscr{A}}$ and trading functions $(p_{ij}(\cdot),\alpha_{ij}(\cdot))_{ij\in\mathscr{T}}$ such that given the trading functions, the value functions satisfy Rational Expectations, and given the value functions, the trading functions satisfy Recursive Nash Bargaining.*

3.B Triangle/3-clique, Q_3, Solution

The following is the solution for prices in a Triangle/3-clique, Q_3, with A initially informed and uninformed agents B and C.

2-informed

$$
\begin{aligned}
p_{AB}(\{A,C\}) = \arg\max_{p} & \Big(p + 0 - \frac{\lambda}{1+2\lambda} p_{AB}(\{A,C\})\Big) \times \\
& \Big((v-p) + 0 - \frac{\lambda}{1+2\lambda}(v - p_{AB}(\{A,C\})) \\
& - \frac{\lambda}{1+2\lambda}(v - p_{CB}(\{A,C\}))\Big) \\
p_{CB}(\{A,C\}) = \arg\max_{p} & \Big(p + 0 - \frac{\lambda}{1+2\lambda} p_{CB}(\{A,C\})\Big) \times \\
& \Big((v-p) + 0 - \frac{\lambda}{1+2\lambda}(v - p_{CB}(\{A,C\})) \\
& - \frac{\lambda}{1+2\lambda}(v - p_{AB}(\{A,C\}))\Big)
\end{aligned}
$$

The FOC is then

$$
\begin{aligned}
\Big(p - \frac{\lambda}{1+2\lambda} p_{AB}(\{A,C\})\Big) &= \Big((v-p) - \frac{\lambda}{1+2\lambda}(v - p_{AB}(\{A,C\})) \\
& - \frac{\lambda}{1+2\lambda}(v - p_{CB}(\{A,C\}))\Big) \\
\Big(p - \frac{\lambda}{1+2\lambda} p_{CB}(\{A,C\})\Big) &= \Big((v-p) - \frac{\lambda}{1+2\lambda}(v - p_{CB}(\{A,C\})) \\
& - \frac{\lambda}{1+2\lambda}(v - p_{AB}(\{A,C\}))\Big)
\end{aligned}
$$

This simplifies and substituting leads to:

$$
\begin{aligned}
2(1 - \frac{\lambda}{1+2\lambda}) p_{AB}(\{A,C\}) - \frac{\lambda}{1+2\lambda} p_{CB}(\{A,C\}) &= (1 - \frac{2\lambda}{r+2\lambda})v \\
-\frac{\lambda}{1+2\lambda} p_{AB}(\{A,C\}) + 2(1 - \frac{\lambda}{1+2\lambda}) p_{CB}(\{A,C\}) &= (1 - \frac{2\lambda}{r+2\lambda})v
\end{aligned}
$$

Simplifying and solving yields:

$$p_{AB}(\{A,C\}) = \frac{1}{2+\lambda}v = p_{CB}(\{A,C\}) = p_{AC}(\{A,B\}) = p_{BC}(\{A,B\})$$

With idiosyncratic valuations:

$$p_{AB}(\{A,C\}) = \frac{1}{2+\lambda}v_B = p_{CB}(\{A,C\})$$
$$p_{AC}(\{A,B\}) = \frac{1}{2+\lambda}v_C = p_{BC}(\{A,B\})$$

1-informed

$$p_{AB}(\{A\}) =$$

$$\begin{aligned}
\arg\max_p \Big(p + \frac{\lambda}{1+2\lambda}p_{AC}(\{A,B\}) - [\frac{\lambda}{1+2\lambda}\{p_{AB}(\{A\}) + \frac{\lambda}{1+2\lambda}p_{AC}(\{A,B\})\} \\
+ \frac{\lambda}{1+2\lambda}\{p_{AC}(\{A\}) + \frac{\lambda}{1+2\lambda}p_{AB}(\{A,C\})\}]\Big) \\
\times\Big((v-p) + \frac{\lambda}{1+2\lambda}p_{BC}(\{A,B\}) - [\frac{\lambda}{1+2\lambda}\{v - p_{AB}(\{A\}) + \frac{\lambda}{1+2\lambda}p_{BC}(\{A,B\})\} \\
+ \frac{\lambda}{1+2\lambda}[\frac{\lambda}{1+2\lambda}(v - p_{CB}(\{A,C\})) + \frac{\lambda}{1+2\lambda}(v - p_{AB}(\{A,C\}))]]\Big)
\end{aligned}$$

Taking FOC, using prices solved for previously and recognizing symmetry to substitute yields:

$$p_{AC}(\{A\}) = p_{AB}(\{A\}) = \frac{(2+3\lambda)}{(2+\lambda)^2}v$$

With idiosyncratic valuations:

$$p_{AB}(\{A\}) = \frac{(2(1+\lambda)v_B + \lambda v_C)}{(2+\lambda)^2} \qquad p_{AC}(\{A\}) = \frac{(2(1+\lambda)v_B + \lambda v_C)}{(2+\lambda)^2}$$

3.C Omitted Proofs

Lemma 3.3.1. *In an n-clique, for every λ, if all agents have the same consumption value the prices defined by Recursive Nash Bargaining and Rational Expectations where pairs have immediate agreement are positive.*

Proof. First note that with identical consumption values the state of a network can be simplified to the number of informed agents $m = |M|$ the symmetry also means that the price of sale $p_{sb}(m)$ will be the same on all active links, the continuation value of being a seller will be the same for all seller, $V_s(m)$, as will the value of any buyer, $V_b(m)$. Consider all cliques of at least 2 agents ($n \geq 2$) because the case with one agent is trivial. The proof proceeds by induction over the number of uninformed agents

Base Step: If $m = n-1$ then

$$\begin{aligned}
p_{sb}(n-1) &= \frac{1}{2}[v + V_s(n-1) - V_b(n-1)] \\
&= \frac{1}{2}[v + \Big[\frac{\lambda}{1+(n-1)\lambda} p_{sb}(n-1) + \frac{(n-1)\lambda}{1+(n-1)\lambda} V_s(n)\Big] \\
&\quad - \Big[\frac{(n-1)\lambda}{1+(n-1)\lambda}(v - p_{sb}(n-1) + V_s(n)) + \frac{(n-1)\lambda}{1+(n-1)\lambda} V_b(n)\Big]] \\
&= \frac{1}{1+(n-1)\lambda}\frac{1}{2}v + \frac{n\lambda}{1+(n-1)\lambda}\frac{1}{2}p_{sb}(n-1)
\end{aligned}$$

$$\begin{aligned}
\frac{2(1+(n-1)\lambda) - n\lambda}{2(1+(n-1)\lambda)} p_{sb}(n-1) &= \frac{1}{1+(n-1)\lambda}\frac{v}{2} \\
p_{sb}(n-1) &= \frac{1}{2+2(n-1)\lambda - n\lambda} v = \frac{1}{2+(n-2)\lambda} v \geq 0
\end{aligned}$$

because $n \geq 2$.

Inductive Step: Given that $p_{sb}(m) \geq 0$ if $m \geq x$. Now consider the case of $m = x-1 <$

$n-1$

$$
\begin{aligned}
p_{sb}(m) &= \frac{1}{2}[v+V_s(m)-V_b(m)] \\
&= \frac{1}{2}[v+\Big[\frac{(n-m)\lambda}{1+m(n-m)\lambda}p_{sb}(m)+\frac{m(n-m)\lambda}{1+m(n-m)\lambda}V_s(m+1)\Big] \\
&-\Big[\frac{m\lambda}{1+m(n-m)\lambda}(v-p_{sb}(m)+V_s(m+1))+\frac{m(n-m-1)\lambda}{1+m(n-m)\lambda}V_b(m+1)\Big]] \\
&= \frac{1}{2}[\frac{1+m(n-m-1)\lambda}{1+m(n-m)\lambda}v+\frac{n\lambda}{1+m(n-m)\lambda}p_{sb}(m) \\
&+\frac{m(n-m-1)\lambda}{1+m(n-m)\lambda}V_s(m+1)-\frac{m(n-m-1)\lambda}{1+m(n-m)\lambda}V_b(m+1)] \\
&= \frac{1}{1+m(n-m)\lambda}\frac{v}{2}+\frac{n\lambda}{1+m(n-m)\lambda}\frac{1}{2}p_{sb}(m)+\frac{m(n-m-1)\lambda}{1+m(n-m)\lambda}p_{sb}(m+1)
\end{aligned}
$$

$$
\begin{aligned}
\frac{2+2m(n-m)\lambda-n\lambda}{2(1+m(n-m)\lambda)}p_{sb}(m) &= \frac{1}{1+m(n-m)\lambda}\frac{v}{2}+\frac{m(n-m-1)\lambda}{1+m(n-m)\lambda}p_{sb}(m+1) \\
p_{sb}(m) &= \frac{2}{2+[2m(n-m)-n]\lambda}[\frac{v}{2}+m(n-1-m)\lambda p_{sb}(m+1)]
\end{aligned}
$$

By the inductive hypothesis $p_{sb}(m+1)$ is positive as is the coefficient because $m<n-1$. Note that $2m(n-m)$ is a downward facing parabola in m with intercepts at 0 and n and so if it is weakly greater than n for $m=1$ and $m=n-1$ it will be greater for all $m\in\{2,3,\ldots,n-3,n-2\}$. If $m=1$ then $2(1)(n-1)\geq n$ if $n\geq 2$ which is true. If $m=n-1$ then $2(n-1)(1)\geq n$ in the same cases. Therefore the denominator is positive so $p_{sb}(m)\geq 0$ for all m for all pairs. This completes the inductive step and the proof $\square$

Lemma 3.3.2. *In an n-clique, for every λ, an immediate agreement equilibrium exists if all players have the same consumption value.*

Proof. First note that with identical consumption values the state of a network can be simplified to the number of informed agents $m=|M|$ the symmetry also means that the price of sale $p_{sb}(m)$ will be the same on all active links, the continuation value of being a seller will be the same for all seller, $V_s(m)$, as will the value of any buyer, $V_b(m)$. To show that an immediate agreement equilibrium exists it suffices to show that the Recursive Nash Bargaining condition holds

$$v + 2V_s(m+1) \geq V_s(m) + V_b(m)$$

which is the same condition for all active pairs in state M. This must hold for all M which are characterized by m. First, use the Rational Expectations solution for $V_s(m)$ to solve for $V_s(m+1)$ in terms of $V_s(m)$ and $p_{sb}(m)$

$$V_s(m) = \frac{(n-m)\lambda}{1+m(n-m)\lambda} p(m) + \frac{m(n-m)\lambda}{1+m(n-m)\lambda} V_s(m+1)$$

$$\frac{1+m(n-m)\lambda}{m(n-m)\lambda} V_s(m) - \frac{1}{m} p(m) = V_s(m+1)$$

This can then be substituted into the left hand side of the agreement condition

$$\begin{aligned}
v + 2V_s(m+1) &= v + 2[\frac{1+m(n-m)\lambda}{m(n-m)\lambda} V_s(m) - \frac{1}{m} p(m)] \\
&= v + 2\frac{1}{m(n-m)\lambda} V_s(m) + 2V_s(m) - \frac{1}{m} 2p(m) \\
&\geq v + 2V_s(m) - \frac{1}{m} 2p(m) \\
&= [v + V_s(m) - V_b(m)] - \frac{1}{m} 2p(m) + [V_s(m) + V_b(m)] \\
&= (1 - \frac{1}{m}) 2p(m) + [V_s(m) + V_b(m)] \\
&\geq V_s(m) + V_b(m)
\end{aligned}$$

Where the last equality is by the definition of price. The first inequality is because it must hold for all levels of friction λ and the second inequality is because prices are weakly positive in this setting, by 3.3.1. This completes the inductive step and the proof. $\square$

Lemma 3.3.3. *In an n-clique, for every λ, if an immediate agreement equilibrium exists it is unique.*

Proof. For every M in $\mathscr{M}$, let $\mathscr{T}(M)$ be the set of pairs ij such that $i \in M$ and $j \notin M$. These are the "active" trading pairs when the set of informed players is M, recall $d = |\mathscr{T}(M)|$. We prove uniqueness by induction.

Base Step: Suppose that $|\mathscr{A} \backslash M| = 1$, with only one remaining uninformed buyer, j. Then $\mathscr{T}(M)$ involves the links between players in M and j. Then for any $i \in M$, Recursive Nash Bargaining implies that

$$\underbrace{p_{ij}(M)(1-\Delta(d))}_{\text{Seller } i's \text{ gain from trade}} = \underbrace{v_j - p_{ij}(M) - \Delta(d) \sum_{\phi \in \mathscr{T}(M)} (v_j - p_\phi(M))}_{\text{Buyer's gain from trade}}.$$

which can be re-written as

$$p_{ij}(M) - \frac{\Delta(d)}{2-\Delta(d)} \sum_{\phi \in \mathscr{T}(M)} p_\phi(M) = (1 - d\Delta(d))v_j.$$

An analogous equation holds for any other pair $kj \in \mathscr{T}(M)$, and subtracting that equation from the one above implies that $p_{ji}(M) = p_{kj}(M)$, and therefore, $p_\phi(M)$ is constant for every ϕ in $\mathscr{T}(M)$. Therefore, for every $\phi \in \mathscr{T}(M)$,

$$p_\phi(M) = \frac{(1-d\Delta(d))(2-\Delta(d))}{2-(d+1)\Delta(d)} v_i.$$

Inductive Step: Suppose that for every M' with $|\mathscr{A} \backslash M'| \leq k$, prices $p_\phi(M')$ are uniquely determined for every ϕ in $\mathscr{T}(M')$. Prices being uniquely determined imply that for each player i, $V_i(M')$ is also unique. We argue that prices in M with $|\mathscr{A} \backslash M| = k+1$ must also be unique.

For any pair ij in $\mathscr{T}(M)$, Recursive Nash Bargaining implies that

$$p_{ij}(M)+V_i(M\cup\{j\})-V_i(M)=v_j-p_{ij}(M)+V_j(M\cup\{j\})-V_j(M). \tag{3.C.3}$$

By Rational Expectations, we can write

$$\begin{aligned}V_i(M)&=\Delta(d)\sum_{l\in\mathscr{A}\setminus M}p_{il}(M)+\Delta(d)\sum_{kl\in\mathscr{T}(M)}V_i(M\cup\{l\}),\\ V_j(M)&=\Delta(d)\sum_{l\in M}(v_j-p_{lj}(M))+\Delta(d)\sum_{kl\in\mathscr{T}(M)}V_j(M\cup\{l\}).\end{aligned} \tag{3.C.4}$$

We insert (3.C.4) into (3.C.3) to obtain

$$\begin{aligned}&p_{ij}(M)+V_i(M\cup\{j\})-\left[\Delta(d)\sum_{l\in\mathscr{A}\setminus M}p_{il}(M)+\Delta(d)\sum_{kl\in\mathscr{T}(M)}V_i(M\cup\{l\})\right]\\ =&v_j-p_{ij}(M)+V_i(M\cup\{j\})-\left[\Delta(d)\sum_{l\in M}(v_j-p_{lj}(M))+\Delta(d)\sum_{kl\in\mathscr{T}(M)}V_j(M\cup\{l\})\right].\end{aligned}$$

We collect all terms that involve prices in state M on the LHS and others on the the RHS to obtain

$$p_{ij}(M)(2-2\Delta(d))-\Delta(d)\sum_{l\in(\mathscr{A}\setminus M)\setminus j}p_{il}(M)-\Delta(d)\sum_{l\in M\setminus i}p_{lj}(M)=\kappa_{ij}(\lambda,M).$$

Note that $\kappa_{ij}(\lambda,M)$ is uniquely determined in equilibrium since it depends only on constants (v_i) and future continuation values. Similar equations hold for every link in $\mathscr{T}(M)$.

We enumerate these links using the index $1,\ldots,d$ (the choice of this mapping is irrelevant) and define a $d\times d$ matrix Φ where $\Phi_{uv}=1$ if link u and link v share a common vertex and 0 otherwise. Combining the d equations yields the following matrix equation:

$$\Rightarrow [I_d - \frac{1}{2}\frac{\Delta(d)}{1-\Delta(d)}\Phi(M)]p = \frac{1}{2}\frac{1}{1-\Delta(d)}\kappa(\lambda, M)$$

Where $\kappa_{ij}(\lambda, M)$ is some unique function (by the inductive hypothesis), and $\kappa(\lambda, M)$ is the corresponding $d \times 1$ vector of these for all active links. Since the right hand side of this last equation is unique, the current state price vector p is unique if and only if $\Psi(M) = [I_d - \frac{1}{2}\frac{\Delta(d)}{1-\Delta(d)}\Phi(M)]$ is invertible.[4]

The only remaining task is to show that $\Psi(M)$ is invertible for any network and informed set (which will also cover the base case, in particular). Note that $\Psi(M)$ is a Z-matrix because the off-diagonal elements are all negative. Additionally, we can show that $\Psi(M)$ exhibits semipositivity, that is there exists a vector $x > 0$ such that $\Psi(M)x > 0$. This is done by using a vector of all ones and noting that for all a $(\Psi(M)x)_a > 1 - (d-1)\frac{1}{2}\frac{\Delta(d)}{1-\Delta(d)} = 1 - \frac{1}{2}\frac{(d-1)\lambda}{1+(d-1)\lambda} > 0$. $\Psi(M)$ being a Z-matrix that exhibits semipositivity is equivilant to it being a non-singular M-matrix and thus invertible (Plemmons, 1977). This completes the proof. $\square$

Proof of Theorem 3 on p. 148 In section 3.2 we showed algebraically that an immediate agreement equilibrium exists for low λ and is unique. The expected initial value to the initial seller in a star with two buyers is

$$\sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+\lambda} p_{s_0 i}(\{s_0\}, \bigstar_2(s_0))$$

[4]Notice that if $d = 1$, then $\Delta(d) \to 1$ as $\lambda \to \infty$. This means that the left hand side diverges, while the right hand side is constant. This is why we get uniqueness for any fixed λ but not in the limit.

and in a 3-clique is

$$\sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+2\lambda}[p_{s_0 i}(\{s_0\}, Q_3) + \frac{\lambda}{1+2\lambda} p_{s_0 i}(\{s_0, i\}, Q_3)]$$

It will always be the case that the price on a star is $\frac{v_i}{2}$. As shown in section 3.B, the price between s_0 and i if two agents are informed is $\frac{1}{2+\lambda} v_i$ and if only the seller is informed is is $\frac{(2(1+\lambda)v_i + \lambda v_{-i})}{(2+\lambda)^2}$. Therefore it is the case that the 3-clique will be preferred to the star if

$$\sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+\lambda} \frac{v_i}{2} < \sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+2\lambda}[\frac{(2(1+\lambda)v_i + \lambda v_{-i})}{(2+\lambda)^2} + \frac{\lambda}{1+2\lambda} \frac{1}{2+\lambda} v_{-i}]$$

$$\sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+\lambda} \frac{v_i}{2} < \sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+2\lambda}[\frac{(2(1+\lambda)v_i + \lambda v_{-i})}{(2+\lambda)^2} + \frac{\lambda}{1+2\lambda} \frac{1}{2+\lambda} v_{-i}]$$

$$\sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+\lambda} \frac{v_i}{2} < \frac{\lambda}{1+2\lambda}\{\sum_{i \in \mathscr{A} \setminus M} \frac{2(1+\lambda)}{(2+\lambda)^2} v_i + \sum_{i \in \mathscr{A} \setminus M} [\frac{\lambda}{(2+\lambda)^2} v_i + \frac{\lambda}{1+2\lambda} \frac{1}{2+\lambda} v_i]\}$$

$$\sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+\lambda} \frac{v_i}{2} < \sum_{i \in \mathscr{A} \setminus M} \frac{\lambda}{1+2\lambda} \frac{(2+3\lambda)(1+2\lambda) + \lambda(2+\lambda)}{(2+\lambda)^2(1+2\lambda)} v_i$$

This will be the case if $\frac{\lambda}{1+\lambda}\frac{1}{2} < \frac{\lambda}{1+2\lambda}\frac{(2+3\lambda)(1+2\lambda)+\lambda(2+\lambda)}{(2+\lambda)^2(1+2\lambda)}$ which can be solved and will be the case for λ between 0 and ≈ 0.4466. This is seen numerically when the Example Figure 3.4.2a is zoomed in for Figure 3.4.2b and the seller's initial payoff is indeed higher.

□

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