THE POWER OF GOOD NEIGHBORS

AN ANALYSIS OF INTERGENERATIONAL MOBILITY

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A DISSERTATION

in

ECONOMICS

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2024

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ACKNOWLEDGEMENT

I am deeply indebted to my advisors, Jesús Fernández-Villaverde, Margaux Luflade and Wayne Gao for their useful feedback and constant support. I also thank Enrique Mendoza for all the support and advice throuhgout the years. I am also thankful to my mentors, colleagues and friends at the University of Pennsylvania, Banco de México, Federal Reserve and elsewhere, Francesco Agostinelli, José Ambrozic, Paweł Bednarek, José Antonio Borbolla Schega, Harold Cole, Pablo D'Erasmo, Alessandro Dovis, Jeremy Greenwood, Kevin He, Ashwin Kambhampati, Dirk Krueger, Stephen Pitts, Andrew Postlewaite, Guillermo Ordóñez, Víctor Ríos-Rull, Diana Sieh, Pedro Brandao Solti, Nicolás Stevens, Rakesh Vohra, and all the seminar attendees, for their time, useful insights and comments.

The collection of data used in this study was partly supported by the National Institutes of Health under grant number R01 HD069609 and R01 AG040213, and the National Science Foundation under award numbers SES 1157698 and 1623684.

ABSTRACT

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This paper provides a theoretical and quantitative analysis of how the interaction with neighbors (that have better information signals) affects saving and human capital formation outcomes. Theoretically, it introduces a novel network-based model of information cluster formation, incorporating endogenous neighborhood selection. Living in neighborhoods with high connectivity (i.e., a higher fraction of high- to low-informed neighbors) produces stronger information spillovers, so that better financial choices result from those connections and are ultimately reflected in savings decisions and wealth accumulation. Similarly, the spillovers affect the parents' choice about the education of their children, further enhancing wealth accumulation. A network is more homogeneous (heterogeneous) when the agents are more (less) connected at the same information level. The study characterizes the unobservable parameter values, returns on investment and precision signal of the agents for which there is a stable homogeneous outcome. Notably, this outcome does not maximize the sum expected returns across agents. The unobserved parameters are then estimated with data from the Opportunity Atlas. Quantitatively, the compensating value in welfare for a low-information household (an agent with a less precise signal) of living in a neighborhood with 25% of high-information neighbors, instead of none, is estimated to be roughly 16% of the median saving. Furthermore, the simulation based on the estimated parameters in the network structure predicts a ten-percent decrease in connectivity for the next generation.

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CHAPTER 1

Introduction

Recent literature has focused on the decreasing income mobility and the increasing segregation in the US over the last decades. Despite its importance, both its mechanical causes and its welfare effects remain unclear. At the same time, the role of information flows on these topics and its relevance are surprisingly strongly understudied, partly due to its complexity and the lack of data availability. Understanding the mechanisms that drive them is fundamental to establish whether it is worth attending to, and to know how to do deal with it in the optimal manner, should any adverse outcome ensue otherwise.

Information sharing is not uniformly distributed. What is its relationship to inequality and mobility? While it is typically understood that low mobility is bad, under what circumstances can information clusters be harmful or beneficial for society? Furthermore, what is the private value of Social Capital? That is, what is the dollar effect of having a powerful network connectivity? And how do these clusters generate and affect what determines a good or a bad neighborhood, through the economic decisions of the agents in them?

Families with more knowledge and access to data sources can provide better opportunities for their community. The effect of this on inequality and growth is critical for tackling issues like the sharp decline in intergenerational mobility of the past four decades. Examples of information flows include reading the news and providing financial advice. Understanding how these flows impact intergenerational transfers is essential for regulatory bodies and to address the disparities that may arise.

This paper studies the relationship between spillover effects of neighborhood selection, inequality and networks, by quantifying the importance of having good neighbors for better saving outcomes and human capital choices.

I lay out an iterated game network model based on the herding literature, where agents choose their

neighbors based on the information they can extract from them, and I derive from it conditions for externalities that arise due to neighborhoods better informed than others. Then, I bring the model to the data and estimate the compensating value for an agent of living with a marginal increase of 25% of high-information neighbors. The first quarter of high-information neighbors (versus none) for a low information agent is estimated to be approximately 16% of the median wealth. Furthermore, the estimation is used for a simulation of the wealth mobility in the network, for a predicted decrease in Economic Connectedness – the fraction of high-informed friends among low-informed individuals – of 10%, compared to a random network. A network is more homogeneous (heterogeneous) when the agents are more (less) connected at the same information level.

The key mechanism of the model is this: better-connected agents (i.e., have access to better-informed neighbors) get better returns on their real assets, because they obtain more informative signals about the true state of the economy and this allows them to make better investments, as well as education choices for their children. There are two investment sub-periods. In the first, agents make choices with only their private information. In the second, they learn from their neighbors' actions as to what their signals are. In general, agents with high-information neighbors (i.e., a neighbor who is better informed about the fundamentals) choose to delay their investment choices one period to gain certainty about the economy, which is at odds with the premium of early investment. The stable outcome of the network is aligned with the standard definition in the literature: no agent can make an offer to another agent that would make them both better off, thus stealing the node. There is also a time constraint (a maximum number of switches) to guarantee that there is an endpoint. Given the finite structure of the model, complete learning will only be achieved under rare circumstances[1]. In the same vein, the quantitative results are aligned with recent findings in the literature regarding the effects of Social Capital.

The main contribution is twofold. First and foremost, it provides a method of estimating network economies, using a Ecological Inference algorithm adaptation. Secondly, it adds an endogenous decision of the players on their neighbors to a theoretical framework based on the herding liter-

[1]It is a well established fact in the literature that in finite agent societies learning is typically incomplete.

ature with saving technology for intergenerational mobility. This results in both theoretical and quantitative contributions to the growing literature on intergenerational mobility.

The key theoretical findings of the model are as follows. Regarding the stability of the network, when the initial monetary endowment of the agents is the same across the network, a more heterogeneous outcome comes about (compared to a random network). However, in such scenario, the sum of the expected returns of the agents is lower when the accuracy of the highly informed agents is sufficiently low[2]. Low accuracy implies that a more homogeneous network would otherwise raise the returns of the cliques of high-information agents by allowing them to gain from the sharing of their signals to confirm the state of nature. In contrast, when the initial endowment is rather correlated with the information level and the disparity is large enough, more homogeneous networks arise naturally, compared to random networks, because the gains to the low-information agents of having a highly informed neighbor are sufficiently low (simply because their endowment is low). The sum of the expected returns for a given network structure in such case could be both ways. When the proportion of low-information agents is low enough, the returns are maximised in a rather homogeneous network allocation. However, when the network is such that the proportion of low-information agents is sufficiently large, a strategic replacement of a high-information agent can have important spillover effects, suggesting that in such instances policies like affordable housing could potentially fix the externality, thus increasing the sum of the expected returns of the network. The model also shows a diminishing return of having good neighbors, and that networks with little structure in general lead to bigger dispersion on the outcome.

The investment is intentionally broadly defined, so that it could be a financial asset, a medical decision, or in general any choice that requires active or voluntary determination whether two main alternatives: the main or standard option, and the actual investment on a specific asset that is riskier in some way. Hence, when considering the potential data that could show the power of the model, the options were vast. However, what is really complex is to find a dataset that reveals connections between the agents.

[2]The accuracy of the signal is a measure of the dispersion of the signal with respect to the true state of the economy.

The paper explains the mechanism through which to quantify how much of the saving behavior of the agents is due to their network. It uses data from the Opportunity Atlas to estimate the value of each marginal quarter of high-information neighbors for low and high-information agents, where the information level is proxied by college degree. To get the compensating value in welfare for a low-information household (an agent with a less precise signal) of living in a neighborhood with each 25% of high-information neighbors, first the non-observed parameters of the model are estimated with a generalized method of moments, using the predicted equations of the models, and the transformations of the variables to match it, minimizing the square error of the corresponding objective functions. The network structure is fundamental for the estimation. An algorithm was disciplined to perform ecological inference over the agents, whose connectedness is only known at the county level.

The seminal papers on herding behavior, like that of Banerjee (1992) focus on how a game of signals left by previous players can explain imitation behavior, and potentially lead to loss of information once a particular behavior is sufficiently repeated. In general, the framework required is a discrete set of actions, as well as a finite or countable set of possible states, both of which generate beliefs from the agents, who use Bayes updates for their learning process.

The classical papers by Becker and Tomes (1979) or Solon (2004) introduce the notion that families' decisions have an effect on capital investment in children, and establish for the first time the complicated issue that mobility is decreasing both in the UK and the US. However, by their nature, they do not consider neighborhood or peer effects. Regarding the theoretical framework, this paper is a contribution to social learning, as well as to the theory of Bayesian learning. Specifically, Bala and Goyal (1998) study properties of connected societies, and find that all agents obtain the same payoffs in the long run. They conclude with a question on "*what types of information structures are likely to occur/emerge in societies?*"[3]. My paper addresses precisely such issue. One characteristic of that environment is that there are many periods in time, there is a notion of 'royal family' (those who spread information to all the network eventually), as well as of connectedness.

[3]Bala and Goyal (1998)

Given that only connected networks are considered, local learning ensures that all agents obtain the same utility. This type of models rely heavily on the network structure, as Jackson (2014a) and Jackson et al. (2016) has pointed out. My model, however, does not necessarily consider connected networks, and there are only two investment periods. Also, there is no notion of '*royal family*' involved, although the introduction of such structures could constitute an interesting extension. The empirical analysis of the paper constitutes a further contribution to this literature, together with the endogenous formation of neighborhoods.

It is well documented in the literature (Chamley (2004)) that there are multiple examples in culture and society where public behavior emerges from signal sharing. The phenomenon where there is loss of information from the previous interactions of the agents, like when many agents go to one restaurant and therefore a new comer decides to go and eat there despite his own signal, is called cascading, and it typically brings negative externalities. As Bikhchandani et al. (1992) mention, it is not trivial how people decide to engage in such behaviors in the first place or the mechanisms that compose it. My main focus is not so much on cascading effects themselves, but rather on finding the conditions that make the society more or less prone to them.

Bala and Goyal (2008) were the first studying the network effects of information, and developed a model in which they account for neighborhood information flows. They find mainly that under certain basic conditions of the network, such as connectedness, cascading is still possible. Hirshleifer and Hong Teoh (2003) - review theory and evidence relating to herd behavior, payoff and reputational interactions, social learning, and informational cascades in capital markets. This paper builds on that tradition, and accounts for the endogenous decision of the agents on their neighbors, providing a rich analysis on how different trade-offs and externalities arise thereof.

Interestingly, Grossman and Stiglitz (1980) wrote about the impossibility of informationally efficient markets. Their model has informed and uninformed agents, and the inefficiency comes from the fact that price, the way they set it up, reveals at least a noisy version of the signal from the market, eliminating the compensation to those who spent resources to obtain the information. Therefore, there is a conflict between the efficiency with which markets spread information and the incentives

to acquire information. They do not examine welfare properties or social benefits, which this papers contributes to.

There is also literature, e.g. Chade and Eeckhout (2018), that relates to this work in matching and team formation. For example, Kambhampati (2020) builds a moral hazard model to study conditions where team incentives, such as team bonuses and employee stock options, are justified. Similarly, Kambhampati et al. (2020) finds two inefficiencies of non-hierarchical team formations: excluded workers must form relatively unproductive teams, and some productive teams might not form. Although these models don't perhaps at first sight relate directly to my model, they are relevant because they provided insights of potential coalitions and equilibrium conditions.

The paper can also be regarded as a study of the spillovers of education. Among others, it adds to the literature by Chetty and Hendren (2018), Heckman (2006), Agostinelli and Sorrenti (2018), Björklund and Jäntti, (2009) by providing a theoretical framework on which to think about the channel through which agents learn from their neighbors. Similarly, it contributes to papers like that of Fogli, A., & Guerrieri, V. (2019) or Fogli and Veldkamp (2015), by introducing the endogenous decision of the agents of their neighborhoods.

Finally, as part of the motivation regarding mobility an inequality, the famous paper by Chetty and Hendren (2018a) shows the effect on college attendance, earnings, fertility and marriage patterns from the neighborhood in which children are raised. "The findings show that neighborhoods affect intergenerational mobility primarily through childhood exposure, helping reconcile conflicting results in the prior literature." In a similar vein, affordable housing has been proposed as one measure to help alleviate this phenomenon, for example, Del Pero et al. (2016). My study provides insights on some potential effects of such policies, analyzing one channel of externalities in endogenous network formation.

CHAPTER 2

Model

I now propose a model that imputes all the choice of neighborhood to the value of information sharing within a neighborhood, where families choose the investment level and education for their children.

2.1. Set up

The economy is populated by a network, G_D, of N individuals, each with a random initial monetary endowment, denoted $M_i \sim \mathcal{F}_{\mathcal{M}}(\eta)$ (wealth), and a random information level, $e_i \sim \mathcal{F}(\theta)$, high or low. The set of agents is a non-empty countable set, NN. For each $i \in NN$, let $N(i)$ denote the set of neighbors of agent i. Let $N^{-1}(i) = \{j \in N | i \in N(j)\}$ be the set of all agents who observe agent i. Furthermore, denote by $GN(i)$ the set of neighbors of agent i with high information, and call this the set of "good neighbors".

Denote N_D the set of all nodes in the network, each node representing each neighborhood, and let A be the arcs, representing the associated connectivity between neighborhoods.[4] The arcs are binary and undirected. The network is connected by county, so that the nodes in each county are connected, but are not connected to other counties, so that the network G_D has different connected components (sub-graphs).Thus, a connected sub-graph (or component) representing a county can be denoted by $G_i = (N_{Di}, A_i)$. Figure 5.3 depicts a simple example of a county sub-network.

The agents are initially randomly allocated in nodes of the network. One agent in each node. While the number of connections is fixed, as the network structure is given, the quantity of (good) neighbors[5] for each node is endogenous, as it depends on the information level of the agents living in each node. The information level of the neighbors is publicly known.

Following, Chetty et al. (2022b), I use the following concept,

[4] We shall say that i, j is connected if there exists a sequence of agents $\{i_1, i_2, ..., i_m\}$ such that $i_1 \in N(i)$, $i_2 \in N(i_1)$, and so on, until $j \in N(i_m)$.

[5] A good neighbor is one with high-information.

Definition 1. *Economic Connectedness is the is the average share of high information neighbors among low-information agents, multiplied by* 2.

Economic Connectedness, which I refer to simply as EC, is divided by 50% to quantify the average degree of under-representation of high-information neighbors among low-information agents. A value of 0 for EC implies that a network has no connections between low- and high-information agents, whereas a value of 1 implies that low-information agents have an equal number of low-information and high-information friends.

Definition 2. *Homophily is the probability that a node in a connected network is the average number of the proportion of individuals similar to a node, across all nodes.*

Homophily is a measure of the tendency of individuals to associate a bond with similar others. Typically, the literature uses different measures of homophily, such as the homophily index. Furthermore, homophily gives the framework to have a rule of when a network is homogeneous or heterogeneous. The definition provided of Economic Connectedness allows to have a such a measure. That is, higher (lower) connectivity implies an increase in heterogeneity (homogeneity).

Definition 3. *A network is homogeneous (heterogeneous) when the EC is above (below)* 1.

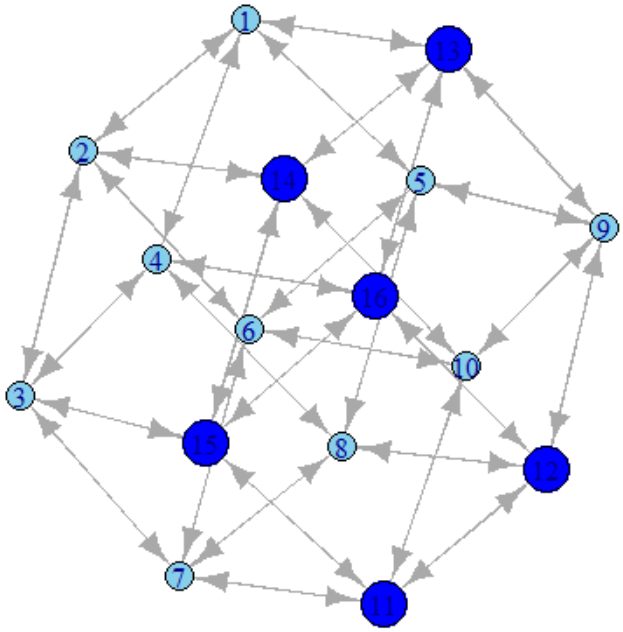


Figure 2.1: The figure shows an example of a random sub-network representing a county. Nodes in dark blue represent agents living in the neighborhood that have high information level, while light blue ones are low-information ones. The size of the bubble is proportional to the monetary endowment.

There are three periods for a given household. In general one can think of household and parent alike for the first two periods. In the first period, agents choose their neighborhood based on their expected payoffs. In the second period, they make their investment and education decisions for their children. Finally, in the third period, the children collect the returns and choose a neighborhood again.

Period 1. Neighborhood selection

Payoffs for the household are the expected returns of information gained by neighbors, so that in terms of their strategies, the transfer value (willingness to pay and to accept) depends fundamentally on the number of high-information neighbors each house has.

There is a sequential game, Γ, where agents select their location by proposing a transfer to the agents in other neighborhoods, as follows:

1. Randomly choose a node, i.

2. The agent living in that node is allowed to offer a transfer to an agent j to switch nodes, with no restriction, except to a current neighbor[6]. The agent will choose the node that gives him the greatest increase in expected returns, and offer that amount.[7]

3. If the offer is rejected, allow the same agent to offer another transfer to another node. In general, as in (2) the node that gives the greatest return is always chosen.

4. Iterate (2-3) until all offers from agent i are exhausted or one of them is accepted.

5. Iterate (1-4) until no node wants to make a new offer or a maximum number of iterations has been achieved.[8]

For a chosen node i in step 1, denote $B(i) \subset NN \setminus N(i)$ the set of nodes i is allowed to propose a transfer to. Each agent has a proposed transfer value for any given node, $tr_i : B(i) \to \mathbb{R} \quad \forall i$, where $tr_i(b|\#GN(i), \#GN(b))$ is a function that depends on how many good neighbors $\#GN(b)$ has as opposed to $\#GN(i)$. Similarly, each household also has an acceptance threshold above which it is willing to exchange node (or neighborhood). Denote this by the function $acc(\#GN(j)|\#GN(i))$. This function also depends on the number of good neighbors in each node. Notice that after each transfer, the monetary endowment of the agents involved updates, $\bar{M}_i = M_i \pm transfer$.

<u>Period 2. Investment and education decisions.</u>

There is a unique investment project, which can be successful or not with a given probability, thus

[6]The restriction of no switching between neighbors is introduced mechanically, because switching between neighbors forces the agent to estimate what the new number of neighbors will be after the switch (as the network is not directed). This assumption could be relaxed without significant consequences for the stability of the algorithm. If anything, it enhances it, as it prevents certain switches to be made.

[7]Since the agents are numbered, and merely to introduce structure to the switching, the node chosen is always the first that gives the greatest increase in expected return.

[8]This is an endpoint condition which will be further explained in the section Network Selection

potentially giving risky real returns in the future. Nature chooses the state of the project (called indistinctly high or low, H or L, good or bad, successful or not successful, 1 or 0), with a probability t. There are two basic investment subperiods, one with private information and one with public information.

Given the information level (publicly known by everyone), each agent gets a private signal R_i, high or low, that indicates whether the project is successful, which is correct with probability $q_i = q(e_i)$, so there is a probability $1 - q_i$ that the signal is wrong. The information level e_i affects the variance of the signal: more information means less noise (q_i is closer to 1 and further from $\frac{1}{2}$), so the signal is more reliable.

$$R_i = \begin{cases} 0 & low \\ 1 & high \end{cases} \qquad R_i \sim Be(q_i * state + (1 - q_i) * (1 - state)), \qquad state \in \{0, 1\}, \tag{2.1}$$

so that $P(R_i = 1 | state = 1) = q_i$.

In order to make the prices not reveal the state of nature, the investment project is simply reflecting a real return payable on the principal, so that there is a unitary price of the asset.

A child for each agent is born with talent t_i, independent of e_i. The talent is not observable to parents, but they make a guess about it, reflected by a belief variable, $\hat{t}_i$, which is correlated to e_i. Each household chooses $f_i \in \{high, low\}$, the choice of education for the child. High education bears cost D payable through debt. The choice of investment and education is simultaneous.

Parents care both about their own consumption and about their children's future wage. In particular, they face the problem:

$$
\begin{aligned}
V(\bar{M}_i, e_i, \{e_j\}_{j\in N(i)}, x) :=& \\
\max_{s_0^i, b_0^i, s_1^i, b_1^i, f_i} \quad & \mathbb{E}[u_{parent}((1-\phi)return) + \psi u_{child}(\phi return + w_i(\hat{t}_i, f_i) - f_i * D_i)] \\
\text{s.t.} \quad & return = s_0^i S_0(state) + s_1^i S_1(state) + R b_1^i + x, \\
& b_0^i + s_0^i \leq \bar{M}_i, \\
& b_1^i + s_1^i \leq R b_0^i, \\
& f_i \cdot D_i \leq \bar{M}_i, \\
& s_t^i \geq 0, \\
& b_t^i \geq 0,
\end{aligned}
\tag{2.2}
$$

where s_t^i is the investment choice, early or late, b_t^i is the money market choice, f_i is the choice of education for the child, $w(.)$ is the mincerian wage function of the child, that depends on talent and education choice, D is the cost of education, ψ is a discount factor, ϕ is the proportion of bequest, $\hat{t}_i$ is the belief of the talent of the child, $S_t(state)$ is the contingent return of the asset, R is the risk free factor of accumulation, $\bar{M}_i$ is the initial endowment of the household, and x is just a transfer variable which will be used for the compensating variation. Low income families face a liquidity constraint, because of which they cannot borrow.[9] The constraints will be explained in each sub-period in what follows.

Period 2.0: given the private signal, R_i, exclusively, agent i can choose to invest s_0^i in the project or in the money market (earning the risk free rate), b_0^i:

$$
b_0^i + s_0^i \leq \bar{M}_i. \tag{2.3}
$$

Notice that, for example, if e_i is low, the agent might prefer to wait and see what the neighbors do,

[9]This assumption is common in this class of models. The assumption that agents cannot borrow is for realism, given that typically people cannot borrow against children's future income.

in particular if he happens to have neighbors with high information level. If he himself has a high e_i, he might prefer to choose straight away, depending on the payoffs.

Period 2.1: With R_i and the **neighbors'** information $\{e_j, s_0^j, b_0^j\}_{j \in N(i)}$, agent i chooses whether to invest in the project s_1^i or in the money market, b_1^i:

$$b_1^i + s_1^i \leq R b_0^i, \tag{2.4}$$

where R is the risk free factor of accumulation.

Notice that it is possible that if the information level is too low and the neighbors provide little information or don't reveal their signal (by not investing on the project), the agent will prefer to stick with the safe investment, the money market, and get R.

Period 2.2: agents collect the gains according to returns on equation 2.1 and consume:

$$s_0^i S_0(state) + s_1^i S_1(state) + R b_1^i, \qquad state \in \{L, H\}, \tag{2.5}$$

which is maximized under logarithmic preferences.

In what follows, let $R = 1 + r$, where r is the risk free rate. The return of the project is given by the function:

$$S_t(state) = \begin{cases} u_t & \textit{if state} = H \\ d_t & \textit{if state} = L \end{cases} \quad t \in \{0, 1\}. \tag{2.6}$$

where $d_t < (1 + r) < u_1 < u_0$, so that if the project is successful there are gains for investing early. Let $d_0 = d_1 = 0$ as a normalization.

Furthermore, define $u_0/u_1 = \mu$, and let $S_1(H) = \rho$ so that $S_0(H) = \mu\rho$.

The agents need to solve two problems, in a backward order, one for each sub-period.

Definition 4. *Let the probability of a high state, given neighbors' signals be defined as* $\hat{p} = P_{rob}\left(state = H | R_i, q_i, \{e_j, s_0^j, b_0^j\}_{j \in N(i)}\right)$.

Definition 5. *Let the probability of high state given private signal be defined as* $p = P_{rob}\left(state = H | R_i, q_i\right)$.

The probabilities are updated with a Bayesian rule, and they are based on rational expectations. Let t be the probability of the state of nature be good. Then, for example, for an agent i with e_i with a positive signal $Ri = 1$, the probability of the project being successful is given by:

$$\begin{aligned} P_{rob}\left(state = H | R_i = 1, q_i\right) &= \frac{P_{rob}\left(R_i = 1 | state = H, q_i\right) P_{rob}\left(state = H\right)}{P_{rob}\left(R_i = 1\right)} \\ &= \frac{q_i \cdot t}{q_i \cdot t + (1 - q_i) \cdot (1 - t)}. \end{aligned} \tag{2.7}$$

The probability $\hat{p}$ is updated in a similar fashion, including the signals of the neighbors $\{R_j\}_{j \in N(i)}$ along with their corresponding signal precisions $\{q_j\}_{j \in N(i)}$.

First, agents solve for the late investment, s_1, taking $s_0, \bar{s}_0^i, \bar{b}_0^i$ as given:

$$\max_{s_1^i, b_1^i} E_{state}[\log\left(\bar{s}_0^i S_{0,2}(state) + s_1^i S_{1,2}(state) + (1+r) b_1^i\right) | R_i, q_i, \{e_j, s_0^j, b_0^j\}]$$
$$s.t. \qquad b_1^i + s_1^i = (1+r)\bar{b}_0^i.$$

Then, knowing R_i, q_i only, agent i solves:

$$\begin{aligned} \max_{s_0^i, b_0^i} E_{state}[E_{R_j}[\log\big(s_0^i S_{0,2}(state) + s_1^i(s_0^i, R_i, e_i, e_j, R_j) S_{1,2}(state) + \\ R b_1^i(s_0^i, R_i, e_i, e_j, R_j)\big) | state; R_i, q_i]] \\ s.t. \qquad b_1^i(s_0^i, R_i, e_i, e_j, R_j) + s_1^i(s_0^i, R_i, e_i, e_j, R_j) = (1+r) b_0^i, \\ \& \qquad b_0^i + s_0^i = \bar{M}_i. \end{aligned}$$

Information externalities at this stage arise due to the fact that information generates spillover to the agents that surround them. This increases their ability to make better choices, as they receive the signals of their neighbors, especially of the good ones. Then, when agents choose to relocate, they don't internalise the (positive or negative) effect they bring into the new neighborhood by switching. However, there is also an aggregate externality that I will expand on when discussing the stability conditions. Suffice it to say for now that the aggregate externality arises when the stable outcome produces an expected return that could have otherwise have been greater. Although the aggregate and the simple information externalities are related, they are not the same.

Period 3: Children choose neighborhood.

The children get $w_i = g(t_i, f_i)$, a fraction δ of the return of the parents' investment, and pay for their education (D_i).

Then they choose a new neighborhood, playing Γ (as defined in period 1) again.

2.2. Investment choices equilibrium

Definition 6. *Period 2 equilibrium is a set of functions $(s_0^i, s_1^i, b_0^i, b_1^i, f_i)$ such that given their initial endowment $\bar{M}_i$, their information level e_i, neighbors $N(i)$, prime of returns (μ, ρ) and their signals $R_i, \{R_j\}_{j \in N(i)}$ agent i maximizes solves problem (1), for all $i \in NN$.*

The following equations characterise the maximisation solution. Now, it is useful to expand the expression for the late investment problem, and use the defined variable $\hat{p}$ in order to solve it. So that the problem becomes:

$$\begin{aligned} \max_{s_1^i} \quad & \hat{p} \log\left(\bar{s}_0^i(\mu\rho - 1) + s_1^i(\rho - 1) + \bar{M}_i\right) \\ & +(1-\hat{p}) \log(\bar{M}_i - s_0^i - s_1^i) \\ \text{or} \quad & \max_{s_1^i} \hat{p} \log(\hat{H}) + (1-\hat{p}) \log(\hat{L}), \end{aligned}$$

defining $\hat{H} := \bar{s}_0^i(\mu\rho - 1) + s_1^i(\rho - 1) + \bar{M}_i$ and $\hat{L} := \bar{M}_i - s_0^i - s_1^i$ respectively.

The FOCs give:

$$\hat{p}\hat{L}[\rho - 1] = -(1 - \hat{p})\hat{H} \cdot [-1],$$

which gives:

$$\begin{aligned} s_1^i(s_0^i; R_i, e_i, e_j, R_j, \bar{M}) = \frac{1}{\rho - 1} \big(&\hat{p}[\rho - 1][\bar{M} - \bar{s}_0^i] \\ &-(1 - \hat{p})[\bar{s}_0^i(\mu\rho - 1) + \bar{M}]\big) . \end{aligned} \tag{2.8}$$

First of all, the larger the probability of success, $\hat{p}$, the larger s_1. A larger endowment, $\bar{M}$ allows for a larger investment, making s_1 larger. Finally, a larger early investment, s_0, as well as a larger μ both account for a smaller s_1; this happens because the more the agent is incentivized to invest in Period 2.0, the less he is to do it in Period 2.1, except for the fact that indirectly investing in Period 2.0 comes from a positive signal which might be confirmed in Period 2.1 by the neighbor's signal.

With $s_1^i(s_0^i, R_i, e_i, e_j, R_j)$, now the agent solves for the early investment problem. In the case of one neighbor, the problem looks as follows:

$$\begin{aligned} \max_{s_0^i} \quad & p * \big(q_j \log(s_0^i[\mu\rho - 1] + s_1^i(s_0^i; \hat{p}, R_j = 1)[\rho - 1] + \bar{M}_i) + \\ & (1 - q_j) \log(s_0^i[\mu\rho - 1] + s_1^i(s_0^i; \hat{p}, R_j = 0)[\rho - 1] + \bar{M}_i)\big) + \\ & (1 - p) * \big((1 - q_j) \log(\bar{M}_i - s_0^i - s_1^i(s_0^i; \hat{p}, R_j = 1)) + \\ & q_j \log(\bar{M}_i - s_0^i - s_1^i(s_0^i; \hat{p}, R_j = 0))\big) \\ \text{or} \quad \max_{s_1^i} \quad & p[q_j \log(\bar{H}_1) + (1 - q_j) \log(\bar{L}_1)] + (1 - p)[(1 - q_j) \log(\bar{H}_0) + q_j \log(\bar{L}_0)], \end{aligned}$$

defining $\bar{H}_1 := s_0^i[\mu\rho-1]+s_1^i(s_0^i;\hat{p},R_j=1)[\rho-1]+\bar{M}_i$, $\bar{L}_1 := s_0^i[\mu\rho-1]+s_1^i(s_0^i;\hat{p},R_j=0)[\rho-1]+\bar{M}_i$, $\bar{H}_0 := \bar{M}_i - s_0^i - s_1^i(s_0^i;\hat{p},R_j=1)$, and $\bar{L}_0 := \bar{M}_i - s_0^i - s_1^i(s_0^i;\hat{p},R_j=0)$ respectively.

The FOCs give:

$$\begin{aligned}
&p * \Bigg(\frac{q_j}{\bar{H}_1}(\mu\rho - 1 + [\rho-1]\frac{\partial s_1^i(s_0^i;\hat{p},R_j=1)}{\partial s_0^i}) + \\
&\frac{(1-q_j)}{\bar{L}_1}(\mu\rho - 1 + [\rho-1]\frac{\partial s_1^i(s_0^i;\hat{p},R_j=0)}{\partial s_0^i})\Bigg) + \\
&(1-p) * \Bigg(\frac{(1-q_j)}{\bar{H}_0}(-1 - \frac{\partial s_1^i(s_0^i;\hat{p},R_j=1)}{\partial s_0^i}) + \\
&\frac{q_j}{\bar{L}_0}(-1 - \frac{\partial s_1^i(s_0^i;\hat{p},R_j=0)}{\partial s_0^i})\Bigg) = 0
\end{aligned} \tag{2.9}$$

with $\frac{\partial s_1^i}{\partial s_0^i} = \frac{1}{\rho-1}[-\hat{p}(\rho-1) - (1-\hat{p})(\mu\rho-1)]$.

This equation implicitly defines $s_0^i(R_i, q_i, \{q_j\}_{j\in N(i)})$ as a function of $R_i, \{e_j\}_{j\in N(i)}$, and parameters $(R, \rho, \mu, q_i, \{q_j\}_{j\in N(i)})$. In general it is only possible to solve with numerical methods. Adding more neighbors simply expands on the number of combinations for expected signals. In other words, it requires the same logic, but would make the problem algebraically more complicated to solve, as the expected value for the second period would include 2^n terms, and the variable s_0^i to solve for would always appears in the denominator of each term.

Proposition 1. *Let $q_i, q_j \neq 0$. For a given set of parameter values, $(\bar{M}_i, R, \rho, q_i, \{q_j\}_{j\in N(i)})$ there is a $\bar{\mu}$ above which s_0^j reveals the signal R_j.*

This proposition shows that in equilibrium the modelling of revealing the signal by observing the investment choices of the neighbors and mechanically knowing the signal of the neighbor once it becomes known is equivalent, so it can be simplified to such.

Proposition 2. *For each information level, e_i, belief $\hat{t}_i$, and a given set of parameter values, $(R, \rho, \mu, q_i, \{q_j\}_{j\in N(i)})$, there is an upper and a lower $\hat{M}_i$ cutoff, below which $f_i^* = 0$, and above which $f_i^* = 1$ is optimal regardless of R_i and $\{e_j\}_{j\in N(i)}$.*

More precisely, the education decision for the child, f_i, has a simple cutoff decision rule:

$f_i = 1$ *whenever* $\mathbb{E}[u_{child}(\phi return + w_i(\hat{t}_i, 1) - D_i)] > \mathbb{E}[u_{child}(\phi return + w_i(\hat{t}_i, 0))]$ *and the liquidity constraint is not binding.*

This proposition shows that in equilibrium there is a simple cutoff rule (which depends on the variables of the agents, and parameter values) such that households will choose to invest in human capital for their children as long as their initial wealth is above a given threshold. These results are also aligned with Schelling (1971), where agents act above a certain endogenous variable level or parameter. Proof of proposition 1 and 2 are found in PROOF OF PROPOSITION 1 and PROOF OF PROPOSITION 2.

2.3. Stable network outcome

By assumption, when choosing their willingness to pay and to accept a transfer, agents in the neighborhood assume that they are the last ones to move. That is, they don't internalise the fact that some of their neighbors might actually decide to move after they settle in their neighborhood. Without loss of generality, assume $\#GN(i) < \#GN(j)$.

Definition 7. *The willingness of i to pay to j to switch nodes is based on the compensating variation between nodes. In other words, it is an amount in dollars, x, such that*

$$V(\bar{M}_i, e_i, \{e_j\}_{j \in N(i)}, x) = V(\bar{M}_i, e_i, \{e_k\}_{k \in N(j)}, 0)$$

This definition simplifies the bargaining of the households such that they will always offer the maximum amount of expected returns.

Definition 8. *The willingness of j to accept a transfer from i to switch nodes is based on the compensating variation between nodes. In other words, it is an amount in dollars, y, such that $y \geq x$, and*

$$V(\bar{M}_j, e_j, \{e_k\}_{k \in N(i)}, 0) = V(\bar{M}_j, e_j, \{e_k\}_{k \in N(j)}, x)$$

At this point it is possible to see clearly that the *price of the houses*, that is, the willingness to switch nodes, in particular the willingness to pay of node i, is determined by the expected gain in return resulting from the switch, together with his own information level, the information value that (good) neighbors add, as well as the monetary endowment, as in general a larger endowment gives larger returns. Now it is possible to establish the definition of equilibrium for the whole network in Period 1:

Definition 9. *Total stability in the network is achieved when there is no agent i in the network that can propose an offer to some other node j that makes both i and j better off.*

Although sometimes providing different mechanisms of swapping or moving along the network, or even definitions on stability, papers like Immorlica et al. (2017) have studied conditions on stable outcomes. The main complication of the current framework, however, resides in the vertical heterogeneity of types, in that they have two information levels, e_i[10], together with different endowments, M_i. Therefore, it is necessary to introduce a lighter definition of stability in the network.

Definition 10. *Partial stability in the network is achieved when total stability is achieved or the limit in the number of iterations reaches a maximum.*

The maximum number of iterations can be justified by the fact that people cannot choose to change locations indiscriminately. It also reflects the fact that certain economic decisions have a time constraint. For example, multiple grants, health or academic choices have a deadline for the application, so that the relocation has to happen before that date.

The way to verify that the stability is achieved depends on selecting different random initial location of agents in the given network, and verifying that the ending distribution is converging to a significantly similar network, as measured by the Economic Connectivity. This way, although the algorithm could be path dependent, the partial stability guarantees that while there might be cycles in the network, at least in average the results are consistent and so the simulation is reliable.

[10]Vertical segregation refers to the fact that there is an objectively better type.

Definition 11. *A distribution, D_G of agents in a network (G, A), is (strictly) dominated, or welfare improved, by another distribution, E_G over the same network, whenever the sum of the expected returns of the E_G are (strictly) higher than that of D_G.*

Using this definition, it is possible now to refine the concept of aggregate externality:

Definition 12. *A network distribution has an aggregate negative externality when it is the partially stable outcome, but is dominated by another one.*

Furthermore, it will be useful when discussing the social benefit of the economy, to define an optimality condition on the network:

Definition 13. *A distribution, D_G of agents in a network (G, A), is optimal when there is no other possible distribution, E_G over the same network, such that E_G strictly dominates D_G.*

2.4. Heterogeneous outcome

Different network structures will yield different outcomes. Completely random networks tend to cycle around and do not settle into something stable. Hence it is essential to impose a structure to the network so that it is possible to establish conditions where the heterogeneous (or homogeneous) neighborhood is a stable outcome. A depiction of the simplest environment sets down an initial notion of full heterogeneity in a network.

Consider the case in which all agents have the same endowment $\bar{M}$, and a network with four agents, two low-information and two-high information agents, that are paired with one another as depicted in Figure 2.2.

This heterogeneous is optimal in this case, as the marginal benefit of a good neighbor for a low-information agent clearly outweighs that of the high-information agent.

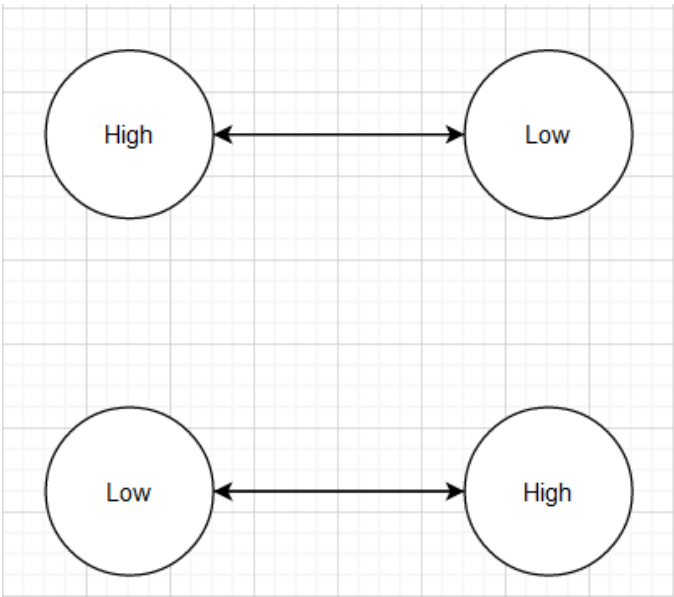


Figure 2.2: Basic heterogeneous network structure.

Then we can ask two questions to find the stability in the network:

1. Can there be a price for the houses such that the completely heterogeneous network (in this case, a low-information agent is always connected with a high and vice-versa) is a stable outcome?

2. Starting with a completely homogeneous network (high-information is connected with high, and low with low), is there a price of the house such that there would be a transfer from a low-information agent to a high-information agent, leading to a heterogeneous network formation? In other words, is there a possible transfer from the low-information agent to the high whenever there is a homogeneous network that would lead to a distribution that strictly dominates?

The answer for both questions is yes. When the endowment is fixed and the same for all agents, it turns out that a heterogeneous network will always be stable. As it will be shown in the following section, the compensating variation of the low information agent is always above that of the high-information agent whenever the initial endowment is the same for all agents. Hence, it is possible to set a price such that both the agents wouldn't be willing to change nodes, provided that they are already in the heterogeneous network, and such that they would be willing to change nodes,

provided that they start in the homogeneous network. Notice, however, that when transfers take place, this affects the endowments of the agents, so that one low-information agent is free riding on the new good neighbor, and one high-information neighbor is simply receiving the externality of a sudden bad neighbor. All this, despite the fact that overall the expected returns of the network increase, as will also be shown in Section Welfare Analysis.

2.5. Homogeneous outcome

From the previous result, a heterogeneous outcome will always be stable for that basic network structure, unless something is altered. Perhaps the most intuitive modification is to provide heterogeneity in the initial endowment, $\bar{M}_i$. Suppose that the endowment is correlated with the information level. Suppose furthermore, without loss of generality, that the monetary endowment is the same across each information level.

Then for a sufficiently large difference in the initial endowment, the high-information agents will have a higher willingness to pay because their expected returns will be way above that of the low-information agents. Thus, a homogeneous outcome would be stable. However, in this case, it is not trivial whether the distribution is optimal, as it is possible that the gains of the high-information agents is sufficiently high without the need of a neighbor, that is, when their signal is precise enough.

I now turn to make a backward analysis of the comparative statics, first of that of the investment decisions from Period 2, and then of the whole stability of the network for period 1, based on the expected returns of the agents.

CHAPTER 3

Comparative Statics

This section describes the key mechanisms of the Period 2 of the model, which provide predictions and quantitative analysis of the investment choices of the household. For example, agents with high-information neighbors choose to delay to invest in order to observe the signals of their neighbors, especially when there is a big benefit in terms of the certainty they can win thereof. This theoretical result is aligned with the descriptive statistic of savings, as shown in section Data , where in general agents that are better connected have greater savings, arguably due to better financial choices.

Similarly, using the definition of willingness to switch nodes, it is possible to quantify the amount of dollars that a house is worth, given a specific set of parameters. This is crucial, as it will be the first empirical question regarding the value of good neighbors, when imputing, as the model does, all the force of inequality to the value of information flows.

Furthermore, as will be shown in Figure 3.8 of subsection Two-Neighbor case, the marginal value of first high-information neighbor is larger than any other. This is because the benefit of a good neighbor is captured by the Bayesian probability $\hat{p}$, that is, an increase in certainty in the precision or accuracy of signals shared by the neighbors. In general, when the difference in accuracy between the low and the high-information agents is relatively large, it is the first good neighbor that significantly increases the accuracy of the signal. In fact, the exact increase in probability can be easily calculated, while the increase in savings and compensating variation can in practice only be solved for, due to the fact that the model requires solving a highly nonlinear equation.

The following plots show the level of investment, expected returns, and utility of the agents with different education levels, signals, and neighbors' education and signal, as the parameters μ, the prime of early investment, or q_{high}, the high-information signal precision, increases.

The first set of plots show the variables and comparative statics of investment for different values of parameters with just one neighbor. The case of one neighbor allows to isolate the changes of

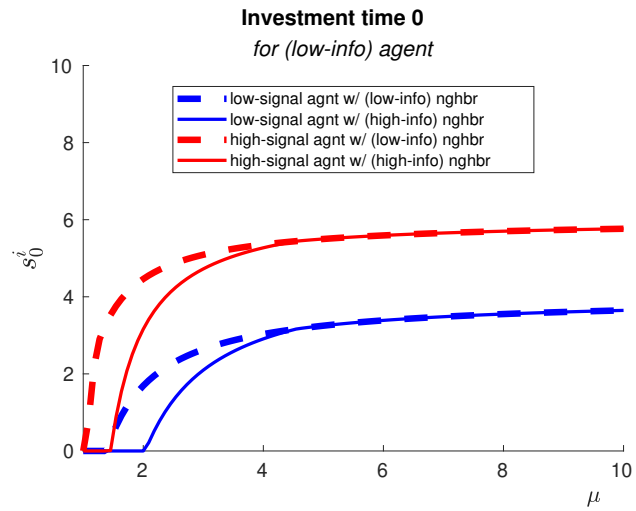
investment due to gains in information (spillovers). In general, it is observed that a low signal agent invests less than a high-signal agent. Now, the relationship between the low/high information neighbor and the agent's signal may result in a low signal agent investing more than a high signal agent, because the high signal agent might benefit from waiting for his signal to be confirmed in the next period.

For Figures 3.1 through 3.4, all agents have the same level of endowment. Reducing or increasing the endowment level would cause the plots to shift down or up respectively.

More importantly, the differences in the expected utilities (or the compensating variation) will drive the mechanism of the housing prices equilibrium, which depends fundamentally on the network structure. This will be further discussed in the subsequent section.

3.1. One-Neighbor case

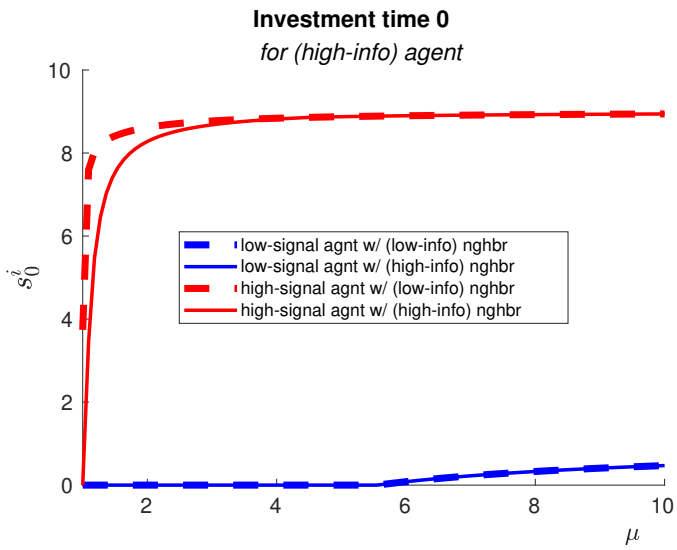
All else equal, agents with better neighbors choose to delay their early investment so as to collect information from neighbors. Figure 3.1 shows the level of investment of the initial period of a low-information agent for different values of the parameter μ, which controls the extra return of early investment. Two observations: as expected the low-signal agent invests less than the high-signal agent, conditional on having the same neighbor. For a given signal (high or low), the agent with a high-information neighbor chooses to invest less than that of a high-information neighbor. That is because the latter can gain some useful information in the next period, so he needs to save a little for the future. In order to get the picture, equation 2.9 is used to solve for early investment, with the parameters shown at the bottom of the picture.



$$\rho = 1.8, R = 1, q_{low} = 0.6, q_{high} = 0.9$$

Figure 3.1: Early investment values for a low-information agent, upon all the combinations of signal and neighbor information level. μ controls for the extra return of early investment.

For a high-information agent, the pattern is similar, as the low-signal agent invests less, conditional on having the same neighbor. Nevertheless, in this case the separation between them is larger. That happens because the signal of the agent is more informative, there is less uncertainty about its accuracy. For a similar reason, the separation between the low and high information neighbor is smaller, because the signal of the agent in itself is more informative. Figure 3.2 shows the level of investment of the initial period of a high-information agent.

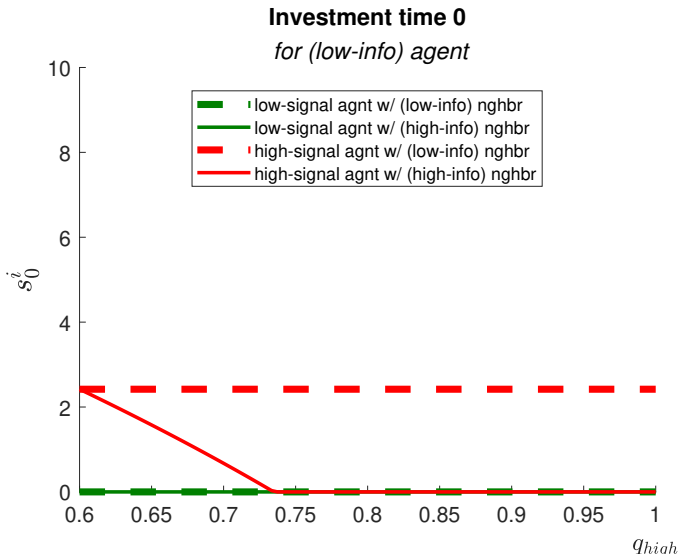


$\rho = 1.8, R = 1, q_{low} = 0.6, q_{high} = 0.9$

Figure 3.2: Early investment level (sub-period 0) for a high-information agent, upon different values of the parameter μ.

As one would expect from equation 2.8, the late investment, s_1, drops when the early investment of sub-period 0, s_0, increases. Figures 3.3 to 3.8 show the level of late investment, expected returns, expected utility and compensating variation of the agents with the different combination of information level, signals and neighbors' information level, as the parameter q_{high} changes, which is the precision of signal of high-informed agents.

When changing the signal precision, regarding early investment, similar to figure 3.1, the high-signal agent decides to invest more than the low-signal agent. Furthermore, an increase in the precision of the signal raises the incentive of the high-information neighbor agent to save for the future, as a waiting strategy. Figure 3.3 shows the level of investment at period zero for this experiment.

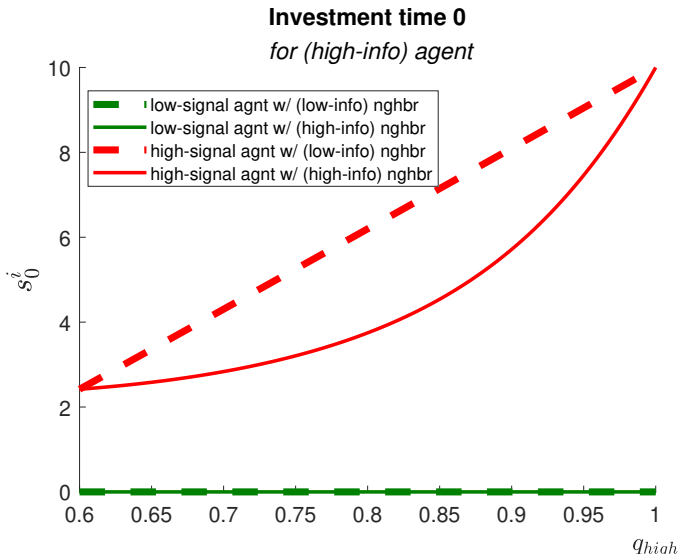


$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure 3.3: Early investment values for a low-information agent, upon all the combinations of signal and neighbor information level, as the value of q_{high} changes, signal precision of the high-information agents.

A low signal is translated into a smaller investment for both agents. Yet, an increase on the precision of the signal has a trade-off for the high-information agent: an increase in the precision yields a larger investment. Nonetheless, whenever he has a high-information agent, he prefers for the neighbor's signal to reveal some information. This latter effect is surpassed when the precision is sufficiently large, so that in the extreme case, when the precision of the signal is perfect, the optimal strategy is to invest all upon a positive signal. That is why Figure 3.4 is slightly different from the previous one. The trade-off for high-information agents is an important phenomenon that will appear with a different face when performing the analysis of the compensating variation, as well as expected returns.

"FIGURES" contains plots of the investment levels as the parameter q_{high} (precision of signal of high-informed agents) increases, for different combinations of μ and ρ parameters.

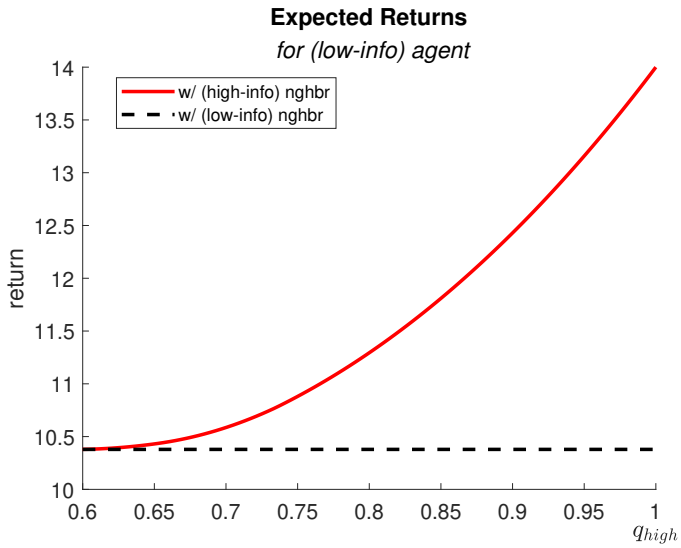


$$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$$

Figure 3.4: Early investment values for a high-information agent, upon all the combinations of signal and neighbor information level, as the value of q_{high} changes, signal precision of the high-information agents.

Using the equations of the investment choices found earlier, one can compute the ex-ante expected return of all the possible combination of agents with one neighbor. Ex-ante in the sense of what the possible returns could be given that nature has not yet chosen the state of the economy. This is a crucial concept, as it allows for the most natural analysis of welfare, as described in the previous section and expanded upon in the following section.

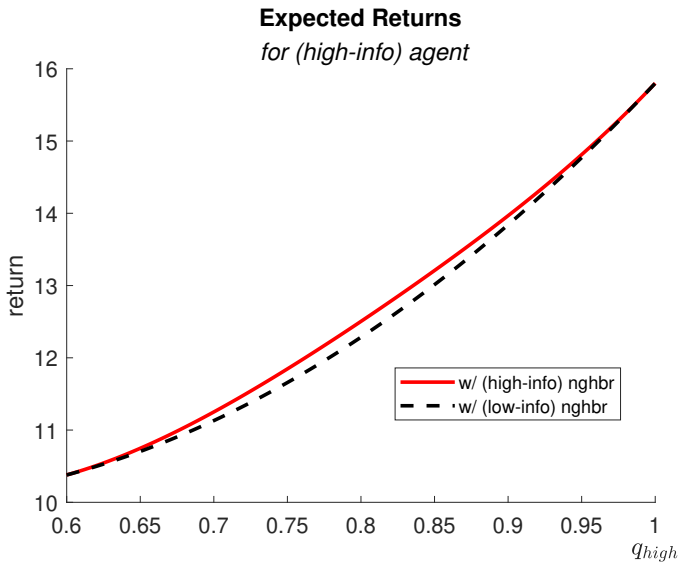
An increase in the signal precision q_{high} does not increase the return of the agent who at the same time is low-informed and has a low-informed neighbor. That is because a change of precision does not affect him whatsoever. Yet, the increase affects the one with a high-informed neighbor. Figure 3.5 shows the effect on the expected return of the low-information agent before the private signals are revealed, considering the optimal strategies for each contingency, and is plotted as the precision of the signal, q_{high}, changes from q_{low} to 1. The expected return of the agent with one good neighbor follows the precision, reflecting the fact that the late investment adjusts accordingly.



$$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$$

Figure 3.5: Ex-ante expected returns for a low-information agent for different values of the parameter q_{high}.

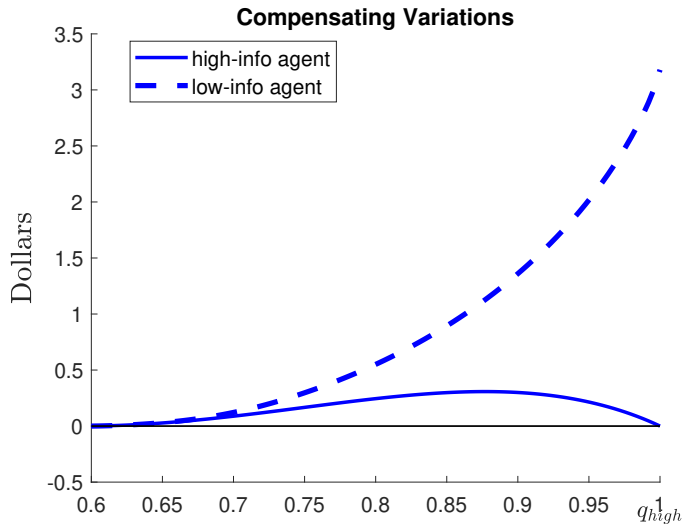
The expected return for the high-informed agent is a close consequence of what happens with investment in time zero, shown in Figure 3.4. The expected return increases as the precision increases, but the gap opens up when it is low, and closes back down when the precision tends to one. Again, the gap opens at first because there is an actual gain of having a high-information neighbor. However, it begins to close once that the precision is large enough that the effect is precluded by the private signal itself. Figure 3.6 shows the corresponding plot.



$$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$$

Figure 3.6: Ex-ante expected return for a low-information agent for different values of the parameter q_{high}.

Figure 3.7 is crucial for the empirical analysis, and sums up the comparative statics for one neighbor. It shows the compensating variation for both a low and high-information agent. That is, aligned with Definition 7 and 8, the plot shows how much money an agent would have to be compensated for giving away his high-informed neighbor, and getting a low-informed neighbor instead. Conversely, it shows how much an agent with a low-informed neighbor would be willing to give in order to gain a high-informed one, or what would be his gain of having one. Note that the compensating variation is in dollars, and it corresponds to an initial monetary endowment of $\bar{M}_i = 10 \quad \forall i$.



$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure 3.7: Compensating variation for the agents: from having a low-informed to a high-informed neighbor.

There are two important effects: for the low-information agent, the benefits increase at a higher rate as the precision increases. For the high-informed agent, the benefits increase at the beginning, until the point in which his own precision matters more than his neighbor's. That is because the precision is sufficiently high that now he can disregard what his neighbor contributes to his return. This last effect follows what had been explained both for investment, as well as for expected returns, namely, that initially there is a gain of good neighbors as the precision increases, but the effect is ameliorated as the effect on the private signal takes over.

3.2. Two-Neighbor case

In this section, the two-neighbor case is analyzed. The main takeaway is that the benefit of a second neighbor is relatively low. That happens because having one neighbor already provides with sufficient accuracy for the late investment, when collecting the signal of the neighbors. Adding another good neighbor marginally improves less the probability that the true state is revealed through the signals.

The "TWO NEIGHBORS" shows plots with the corresponding levels of investment in period 1, as well as the investment in period 0, and expected utility when the high-information level precision

parameter, q_{high} changes. The plots contain two times the amount of plotted lines, because the number of combinations increases geometrically as the number of neighbors increases (curse of dimensionality). As the signal precision grows, the marginal benefit from one to two high-information neighbors for a low-information agent is relatively small compared to the increase from zero to one high-information neighbor, as is possible to observe in Figure 3.8.

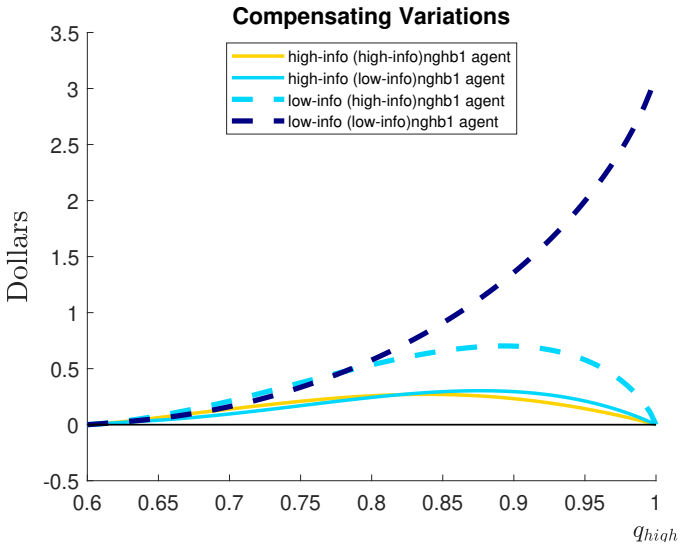


Figure 3.8: Two-neighbor case, compensating variation for the agents: from having a low-informed to a high-informed neighbor.

The compensating variation for the two-neighbor case is in a way similar to that of the one-neighbor case. When an agent has at least one high-information neighbor or when he himself is a high-information agent, there is a trade-off of increasing the signal precision. Hence, all except the low-information with a low-information neighbor agent have a compensating variation that goes to zero when the precision of the high-information agent goes to one. The low-information agent that has one good neighbor values the second one similar to how the high-information agent does. It is not through the private signal, but through the advice received from the good neighbor in the late investment. Therefore, the value of the second good neighbor decreases once the precision is high enough. In the same vein, the compensating variation for the first and second good neighbor for the high-information agent faces a trade-off. When the precision is low enough, having two neighbors is actually slightly beneficial. however, as the precision increases, and in particular once the effect of the private signal kicks in, having a second good neighbor becomes less valuable. Furthermore, for

the empirical analysis, it is necessary to compute not only the benefit of the marginal good neighbor, but also the trade-off between zero to two good neighbors, as such switches will be possible across the network in Period 0, which are not plotted here. Hence, whenever there is more than one neighbor, the compensating variation is indeed a matrix for both types of agents, reflecting the change of adding k good neighbors to the existing ones, such that the existing plus k does not exceed the maximum number of neighbors.

CHAPTER 4

Network Stability Comparative Statics and Welfare Analysis

This section describes the key results of the Period 1 of the model, which provide predictions and the simulation of the neighborhood choice of the agents. Quite intuitively, networks with little or no structure not only don't have a guarantee of convergence to total stability, but also have bigger dispersion of outcome.

Furthermore, as hinted already in a very simple network in Subsection Homogeneous outcome, it will be shown in Figure 4.2 and then with an example in 4.3 of Subsection Two-Neighbor case, that the homogeneous outcome can be the totally stable outcome of Γ, while still be dominated by a (more) heterogeneous distribution.

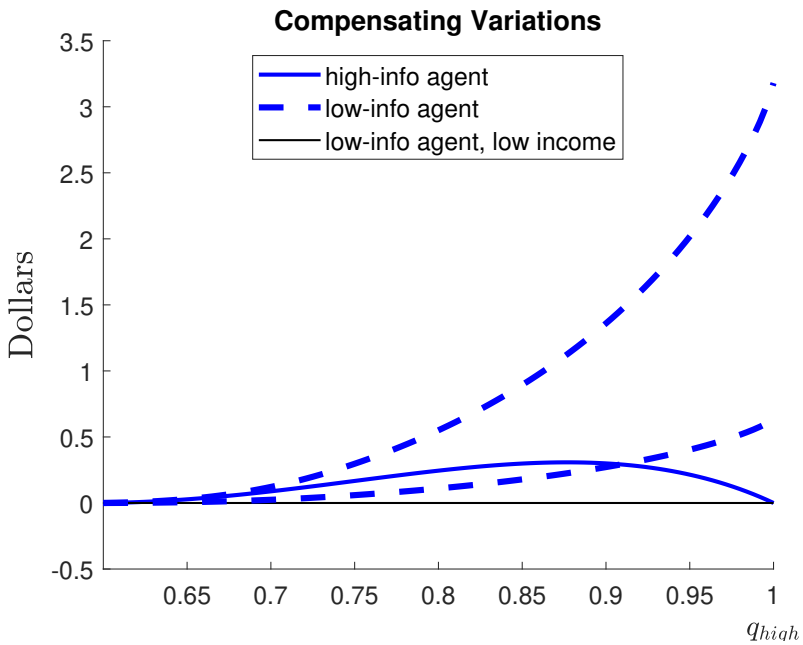


Figure 4.1: Compensating variation for a shift towards a lower-endowment for the low-information agent.

Aligned with the result provided for a simple network structure in Subsection Homogeneous outcome in which the difference in initial endowment is crucial for the stability, Figure 4.1 shows the plot of the Compensating variation for a high and a low information agent. The lower dotted line shows the

new compensating variation for the low-information agent when the monetary endowment is shrunk, so that it is significantly smaller than that of the high-information agent. The Figure shows that in the region of q_{high} where the compensating variation is higher for the high-information agents, their willingness to pay will be higher, hence giving rise to a homogeneous equilibrium, conditional on the network structure being the simple one described in Subsection Homogeneous outcome.

4.1. Welfare Analysis

Welfare in this Section refers to the sum of the utility of the ex-ante expected returns of the agents. To begin with the welfare analysis, consider Figure 4.2. For simplicity, the decision of the household on the children is omitted, but adding it would not have an impact on the analysis. Furthermore, the exogenous network structure of Figure 2.2 is used. The simple average expected utility of the four agents is shown for a completely homogeneous network and for a completely heterogeneous network, regardless of whether they happen to be stability. When the accuracy of the high-information agent is low (close to q_{low}), the homogeneous network is welfare improving. As the precision increases, however, the relationship is reversed, and indeed the gap opens, making the heterogeneous network exponentially welfare improving than the homogeneous. The latter result is more intuitive, as it makes sense that informed agents spill over their knowledge to the less informed. Yet, because their own signal is sufficiently accurate, they benefit little from having neighbors with their own information level. Notice, perhaps counter-intuitively, that there exists a region (low q_{high}) where the heterogeneous outome is a totally stable, and yet the homogeneous network is welfare improving!

An important observation is that, even though the result in subsection Homogeneous outcome is providing with a simple condition for a homogeneous outcome, is does not say anything about the aggregate externality of the network. Indeed, it is efficient for the high-information agents to invest more when they share information among themselves. In order to get a sense of the aggregate externality, it is useful to consider the possibility of having larger spillover effects on low-information agents. It is thus necessary to consider instead of four agents, a larger proportion of low-information agents relative to high- that could potentially benefit from at least one connection with one high-information agent.

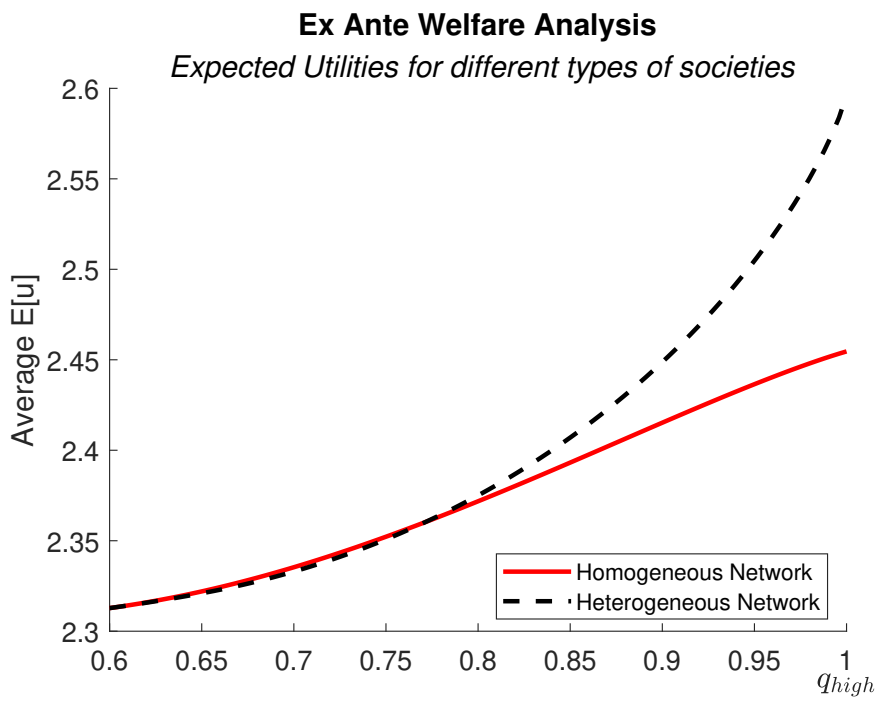


Figure 4.2: Welfare Analysis for the simple 4-agent network.

It is important to remember that in terms of investment, higher is not necessarily translated into better, because the "optimal" decision of the household is to do high levels of investment when the true state is successful, and low levels when the true state is not, which means that ex-ante it is not possible to assert the welfare merely on the investment level, at least not by a simple rule.

Now, given some parameters, heterogeneous or homogeneous societies would be preferred in terms of welfare. The large increases in welfare when $q_{high} \to 1$ depends on the low-information agent gaining from the externality (in a way, free-riding from the good neighbors). However, when the low-information agents have significantly less endowment (like in the case of homogeneous stable outcomes require), homogeneous societies will actually be preferred to heterogeneous ones.

One problem with this analysis is that welfare depends strongly on the endowment level, so in a way the poor matter less! Still, one question arises: how to make at least that many poor matter? To do that, one can consider the following structure, illustrated by Figure 4.3.

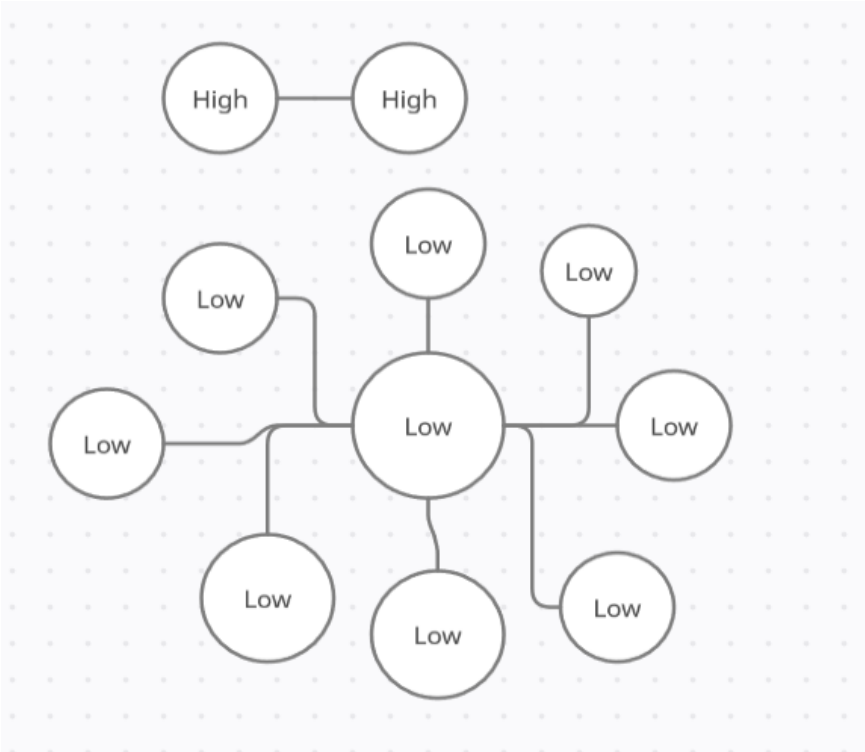


Figure 4.3: Network structure for externality effect.

Figure 4.3 is an illustration of such poverty trap with aggregate externality. Having one low-information agent which is connected to many low-information agents, and separately, two high-information agents, and combining it with a sufficiently small endowment for the low informed agents, then the homogeneous network would be a totally stable outcome. Yet, it would certainly be optimal to relocate one high-information among the low-informed, namely in the center of the network. Allowing for such a network, it is possible to obtain not only the homogeneous network stability, but the additional desired externality.

CHAPTER 5

Measurements

The goal of the empirical analysis is to quantify the compensating value for each type of agent of switching from a neighborhood with an increasing amount of good neighbors. In order to do this, the unobserved parameters, ρ and μ late and early investment prime, and the signal precision, q_{high} and q_{low} have to be estimated. Using those, then the model uses calibrated parameters to simulate the next generation movements and hence changes in Economic Connectedness.

The key components are the two equations of early and late investment, which are minimised with a GMM to match the observed savings. Because the variables are stock, they have to be transformed in a way that it matches the model. Ecological inference has to be used in order to deduce the individual characteristics from the aggregate observations. Once those parameters are estimated, they can be used as an input for the simulation. I begin by describing the selection of the network to perform the estimations on.

5.1. Network Selection

I need to take a stance on the the actual structure used to represent the connections of each agent for the estimation.

As Jackson has pointed out, there are multiple challenges when selecting a network structure. "Specifying the likelihood at a network level then runs into tractability issues, as the number of possible networks is exponential in the number of nodes, and so even with a tiny number of nodes it is impossible to calculate the relative likelihood of different networks." (Jackson (2014a))

Following the herding literature and the threshold models (see Schelling (1971)), one edge represents a proportion of agents of a given socio-economic status. This way, if an agent has three neighbors, for example, each of them represents one third of its connections, so that having one high-information neighbor is analogous to having roughly 33% of connections with high socio-economic status.

As shown in the Network Stability Comparative Statics and Welfare Analysis section, the existence of a totally stable outcome hinges not only on the parameters, but more fundamentally on the network structure itself. The most appropriate network is one that satisfies three main properties: i) on the one hand, it has to be large enough so as to be able to represent a wide range of proportions of high-educated agents; ii) it also has to be able to represent the economic connectedness, as defined earlier in Section Model[11], richly enough when performing the estimation; and iii) to be tractable enough not only to take to data, but to be able to solve for the equilibrium and later on perform the simulation of the third period of the model.

The selected network structure is a 16 node graph, where each agent is connected to four neighbors, known as a regular graph. Such a network, also known as quartic graph is minimally constructed with 5 vertices. Having 16 nodes is not only visually simple to construct with a grid, but it also allows for a sufficiently fine range of proportion of high-low agents (where each agent adds to $1/16 = 6.25\%$, see Figure 5.1).

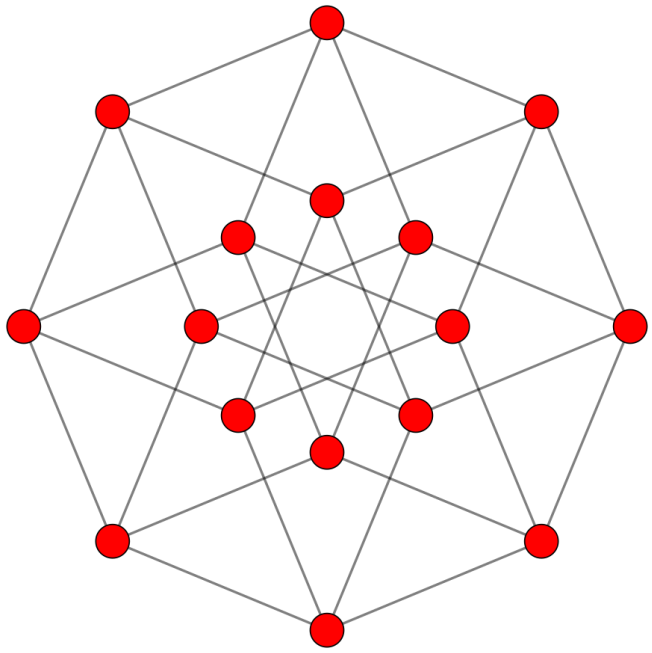


Figure 5.1: The Hypercube Graph Q-4 is 4-regular and has 16 vertices.

[11]Economic Connectedness, as defined in Chetty et al. (2022a) is "two times the share of high-SES friends among low-SES individuals, averaged over all low-SES individuals in the county."

In order to gain a deeper understanding on the graph, a few tests were run to analyse its properties. The main discipline into selecting the distribution of its nodes is as follows:

The proportion of high-information agents in the network is matched with the proportion of people with college degree in the data. The allocation within the network is chosen so that the EC matches that of the data. That is, given a graph $G = (N, E)$, the number of low/high-agents is chosen to be as close as possible to the proportion of the data, and the order of the nodes in N is chosen so that the EC criterion is closest to the county data as possible, using E. It is important to note that the network structure is important and not only the moments of the distribution, as it allows to pin down a more clear structure of how information is transferred, as it excludes the distributions that in aggregate. This is a key difference from traditional work, like that of Fogli and Guerrieri (2019).

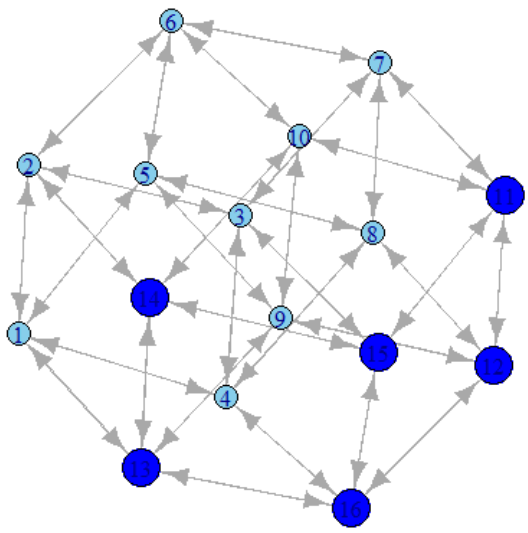


Figure 5.2: 6 Agents in dark blue have high-info level, while 10 light blue are low-information ones.

For example, for an EC target of 0.4 and a proportion of college-degree of 60%, a graph like Figure 5.2 has a 62.5% share of high-information agents, and an EC of 0.5, which satisfies the minimizing criteria out of all the possible permutations of allocation of 10 low-information neighbors in the 16 nodes.

5.2. Data

Three main data sources for the United States are used. These are briefly descirbed below and the key variables for the analysis are highlighted.

Regarding the specific variables used, as well as the years, it is important to note two things: on the one hand, the Opportunity Atlas is only available for 2018. Therefore, all the variables selected from the PSID are around that time. In order to select and use the variables from investment for 2018, the methodology explained at the end of PSID.

5.2.1. PSID

Survey data of a sample of representative households since 1968 are used. The most relevant variable is that of wealth, which includes measures of total savings with and without home equity, loans, assets, and vehicles for the years 2013-2019 every two years. It also has the county level indicator, which is restricted, the 1968 ID indicator, marriage, age, family member (head, child),

As part of the project, a repository was created in order to allow for researchers to easily download, access and manipulate data from the PSID in R.[12]

This is the methodology for the data selection of savings from the PSID unto the model:

There are three main variables from the model: M, s_0, and s_1. The PSID contains data on income and savings with and without home equity of the households for years 2011, 2013, 2015 and 2017 (all prior to the 2018, which corresponds to the Opportunity Atlas). Call such observed variables for savings $\bar{Sg}_i$, for $i \in \{2011, 2013, 2015, 2017\}$.

Define $sav_i = \bar{Sg}_i + \mathbf{Income}_i - \mathbf{cons}_i \quad$ for $i \in \{2011, 2013, 2015, 2017\}$. Then, by construction, it has to be the case that:

[12] https://github.com/moralesmendozar/readPSIDdata → This repository contains R code to read the downloaded data from PSID from Umich on R. It contains instructions on using Stata within R to transform the data from Stata into R (*.rds files), and then how to read it once it is used. It also explains a challenge of variable names.

$$\bar{Sg}_{2017} = f * (sav_{2013}) * \mu * \rho + g * (sav_{2015}) * \mu + (1-g) * (sav_{2015}) * R \tag{5.1}$$

$$\bar{Sg}_{2015} = (1-f) * (sav_{2015}) * R \tag{5.2}$$

It is then possible to solve for f and g.

Finally, we have from the model that:

$$s_0 = f * sav_{2013},$$

$$s_1 = g * sav_{2015}.$$

Finally, M can be simply proxied with sav_{2013}, as it is a stock.

5.2.2. Opportunity Atlas

The Opportunity Atlas has a pretty robust construction of the network connectivity in the United States for 2018, using Facebook, Census and other administrative data to provide a detailed and accessible view of economic outcomes and opportunities at the county level, as well as other levels of aggregation.

For the purposes of the estimation, the most significant variable is that of Economic Connectedness per county. This is particularly significant, as explained in the Ecological inference section. Other variables, such as the standard error of the variable and the children Economic Connectedness, are used in the robustness checks of the simulation.

5.2.3. IPUMS - NHGIS

IPUMS NHGIS (Integrated Public Use Microdata Series National Historical Geographic Information System) is used mostly for two main parameters: total population and the education attainment for individuals of age 25 and older. This allows to find the highly-educated counties, considered as counties above the mean, and also to get the simple proportion of education attainment. Similarly, the variable of dispersion within the county is evaluated using the census-tract dispersion within a county is used for the ecological inference.

Very few counties present a radical difference in education attainment for the range of data from 2006 to 2020, which is suggestive evidence that both the education patterns, as well as the connectivity patterns have not radically changed within that period. In fact, when considering the changes in highly-educated counties for that range, a minimal amount of less than 10 counties changed denomination (high to low or vice versa), depending on the time frame selected. A robustness check was done to verify that there is no significant changes in education attainment for the counties.

The following sections, including Ecological inference, explain in detail the process of inference from the aggregate data for the individual parameters, the estimation itself, and provide the main simulation results for the given 16-node 4-regular network.

5.3. Ecological inference

Given that the data does not provide an individual (or household) measure of economic connectedness, it is important to make an inference based on the county-level aggregate and other individual observations.

Ecological inference in statistics refers to the process of making inferences about individual-level behaviors or characteristics based on aggregate data. It is typically used for binary variables. The challenge for the present estimation lies in accurately deducing individual actions from a vector of probabilities of the number of neighbors, based on the proportion of good neighbors in a network, together with the economic connectedness.

Before estimating the model, it is important to ensure that the network itself is in some way unique. While, depending on the parameters, it is not possible to guarantee that there is a unique isomorphism that satisfies both the proportion of highly informed agents as well as economic connectedness, it is possible to count how many unique isomorphism there are. Furthermore, taking one extra parameter, a moment of the proportion of education inside a county, it is possible to pin down a unique graph that matches the county.

Each county contains 16 nodes and each node is connected to four other. The proportion of high-information neighbors is matched with the proportion of people with college degree in the data, while the allocation in the network is chosen so that the EC matches that of the data. That is, given a sub-graph $G = (N_0, E)$, representing a county, that satisfies the properties described, the number of low/high is chosen to be as close as possible to the proportion of the data, and the order of the nodes in N is chosen so that the EC criterion is closest to the county data as possible. It is important to emphasize that the network structure is fundamental both in terms of the model and for the estimation, and not only the moments of the distribution, as it allows to pin down a structure of how information is transferred.

For example, for an EC target of 0.4 and a proportion of college-degree of 60%, a graph like Figure 5.3 has a 62.5% share of high-information agents, and an EC of 0.5, which satisfies the minimizing criteria out of all the possible permutations of allocation of 10 low-information neighbors in the 16 nodes.

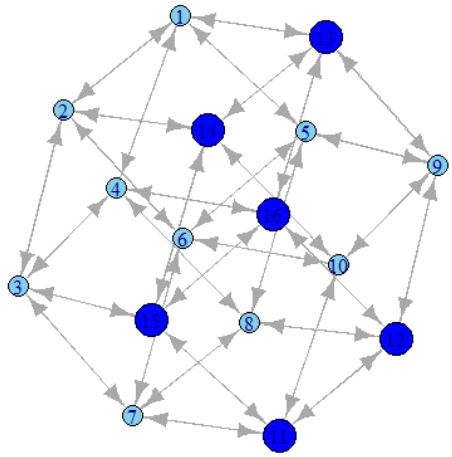


Figure 5.3: The figure shows an example of a randomly allocated 16-node 4-regular network. Agents in dark blue have high-info level, while light blue are low-information ones. The size of the bubble is proportional to the endowment level.

Table 5.1 summarises some of the possible combinations of proportion of low/high agents and EC, as well as the number of probability vectors for the number of good neighbors that arise thereof, depending on the location of the type of agents in nodes. It shows two important things: a) while there is many times different unique non-isomorphic graphs that characterise a pair of parameters, namely economic connectedness and proportion of high-education agents, the count is relatively small; and b) furthermore, the vectors of probabilities that conform them tend to be relatively different in their distribution, meaning that for a given pair, there are some that have few low-informed agents with many high-neighbors, and the others that have rather a similar number for each low-agent.

#low-agents= 0	#possibleGraphs= 1	#vecsProba(H&L)= 1	#ECGraphs= 1
for EC = 0	#unique prob(h|h,l)= 1		
#low-agents= 1	#possibleGraphs= 16	#vecsProba(H&L)= 1	#ECGraphs= 1
for EC = 2	#unique prob(h|h,l)= 1		
#low-agents= 3	#possibleGraphs= 560	#vecsProba(H&L)= 6	#ECGraphs= 3
for EC = 1.33	#unique prob(h|h,l)= 1		
for EC = 1.67	#unique prob(h|h,l)= 2		
for EC = 2	#unique prob(h|h,l)= 3		
#low-agents= 7	#possibleGraphs= 11440	#vecsProba(H&L)= 53	#ECGraphs= 9
for EC = 0.71	#unique prob(h|h,l)= 1		
for EC = 0.86	#unique prob(h|h,l)= 3		
for EC = 1	#unique prob(h|h,l)= 8		
for EC = 1.14	#unique prob(h|h,l)= 15		
for EC = 1.29	#unique prob(h|h,l)= 12		
for EC = 1.43	#unique prob(h|h,l)= 8		
for EC = 1.57	#unique prob(h|h,l)= 4		
for EC = 1.71	#unique prob(h|h,l)= 1		
for EC = 2	#unique prob(h|h,l)= 1		
#low-agents= 16	#possibleGraphs= 1	#vecsProba(H&L)= 1	#ECGraphs= 1
for EC = 0	#unique prob(h|h,l)= 1		

Table 5.1: Number of possible graphs for each parameter.

CHAPTER 6

Calibration

The number of agents, N is only used for the simulations of specific networks, and their ex-post distributions in terms of investment, which are not relevant for the desired questions. In general, it is important to notice that the equilibrium conditions are given for a network with 16 agents, except for the last case, with the negative externality.

The parameters on the returns of the assets, as well as those of the precision signal of the agents are the ones estimated by the equilibrium equations of the model and its correspondence to the data. In the section Comparative Statics, μ is first analyzed as a changing parameter, and after observing that around 1.2, the investment decisions in time zero were relevant, the value was estimated. Also in that section, the parameter ρ was fixed after observing how it affected the distribution of the investment. In general it was chosen at a level which it was not extraordinarily high, but still allowed for some of the effects to be exaggerated in order to study the trade-offs in the relevant variables.

The risk free rate, r (and therefore the risk free factor, R) was simply fixed as 0 ($R = 1$) in order to convey the idea that the gains of successful returns on the project are only given in real terms. This is a normalisation that reflects that all returns of the asset are above that. Changing it to a different value would simply make it more complicated to analyze the results, with no benefit for the analysis.

The nature state probability was originally t fixed at 0.5, making it equally likely for the project to be successful. Modifying it enhances the relative gains or losses with regards to the externality, as it in a way introduces a bias of the probability of the project to be successful. It is matched to the proportion of years in the twentieth century that were a recession, to reflect the notion that without a signal, it is reasonable to expect a bad year with such probability. Finally, the parameter q_{low}, originally fixed at 0.6 to have a sufficiently low probability close enough to 0.5, while still not close

Parameter	Value	Description	Notes	Source
$\bar{M}$	10	Initial endowment of agents		
N	100	Initial number of agents		
t	0.79	Proba of good/bad state	Probability of Recession	
t_i		Talent of kid	Correlation w/Parent = 0.39	Fogli and Guerrieri (2019)
β_w	0.449	Return to college (1990).		Valletta (2018)
D	0.3		Choosing $D = 0.3$ so that $0.6t_i = D$ when ti = 0.5	
ζ	0.96			De Nardi and Yang (2014)
ϕ	0.11			Karagiannaki (2017)
Returns				
R	1			

Table 6.1: Calibrated parameters.

enough to make it indistinguishable from flipping a coin, is estimated together with q_{high}, which was studied in the section Comparative Statics. ζ and ϕ, which are the altruistic parent's discount of utility of the kid and proportion of savings reserved the descendant (common for all agents), are taken from the OLG literature.

Table 6.1 shows the parameters calibrated and borrowed from the literature. According to the previous section, $\bar{M}$ is simply the initial endowment. A value of 10 was assigned as a way of normalisation, and then matched with the model according to the distribution of the savings for each year in nominal dollars.

Parameter	Value	
μ	1.6	prime of early investment
ρ	1.8	prime of (late) investment
q_l	0.65	low-info signal precision
q_h	0.8	low-info signal precision

Table 6.2: Estimated non-observable parameters.

Table 6.2 shows the parameters found in the estimation of the model. The estimated parameters are not too distant from those of the comparative static exercise.

Once the estimates are found, allow for agents to choose neighborhood according to period 1 of the model. If after a number of iterations the model has not converged to something similar to

that of the network matched to the data, this is suggestive evidence that the parameters are not appropriate, and so the estimation has to be revised.

CHAPTER 7

Estimation and Simulation

7.1. Methodology

The algorithm for the simulation is as follows:

1. Randomly allocate the proportion of college-degree agents that satisfy the county level proportion (Erdös-Renyi).

2. With the estimates found using the method described in PSID, minimising the square distance between the observations and the model equations, allow for agents to choose neighborhood according to period 1 of the model.

3. If after a number of iterations the model has not converged to something similar to that of the network matched to the data, this is suggestive evidence that the parameters are not appropriate, and so the estimation has to be revised. Given that the agents will move from county to county, and so the proportion in each of them cannot be guaranteed, it suffices to find that the first moment across counties with similar characteristics matches. That is, counties across the four combinations of low/high information level and low/high connectivity level.

   Provided that the moving of agents is across neighborhood with a simple discipline, allowing the agents to move in succession (and allow given the willingness to pay to randomly give an offer to another node that gives more benefit), the parameters to match are those of the distribution of the counties, across both the education and the connectedness dimensions. This way, the initial distribution will always be consistent with the equilibrium by definition.

7.2. Results

The estimated parameters are used for the simulation, which includes the predictions of period 2. With the parameters, I estimate the compensating value for an agent of living with a marginal

increase of 25% of high-information neighbors.

Table 6.1 shows the parameters calibrated and borrowed from the literature. According to the previous section, $\bar{M}$ is simply the initial endowment. A maximum value of 10 was assigned as a way of normalisation, and then matched with the model according to the distribution of the savings for each year in nominal dollars, which is naturally skewed. Negative values and extremely large values were truncated becaues the model does not accept negative values of savings, and so as not to carry heavy tails for the estimation.

CV (in dollars) for an extra n-good neighbors, low-info agent:				
Current $\#GN$	1-good neighbor	2-good neighbors	3-good neighbors	4-good neighbors
0	\$3200	\$5878	\$7501	\$8437
1	-	\$2578	\$4300	\$6102
2	-	-	\$1956	\$4054
3	-	-	-	\$1770
CV (in dollars) for an extra n-good neighbors, high-info agent:				
Current $\#GN$	1-good neighbor	2-good neighbors	3-good neighbors	4-good neighbors
0	\$5422	\$8245	\$10285	\$11294
1	-	\$4472	\$6946	\$8711
2	-	-	\$4032	\$6725
3	-	-	-	\$3527

Table 7.1: Compensating variation for low-endowment agent and perceived low-talent of child.

Tables 7.1 to 7.3 show the compensating variation of selected types of agents. The model is rich enough that it produces hundreds or thousands of tables similar to these for all different types of agents, with different information levels, endowment levels, signal precision and other parameters.

Table 7.1 shows the compensating variation for an agent with low endowment and perceived low-talent of child. The first decile was chosen to represent "low endowment", which roughly corresponds

to $20,000 savings. The first section of the table contains the compensating variation for a low-information agent. The first column shows the current number of good neighbors, with a maximum of 3, as the following columns show the actual compensating variation for one to four good neighbors. The second part of the table contains the same structure for a high-information agent.

In terms of the values themselves, for an agent with low savings, the model predicts less gains for low-information agents. This is because the endowment is low, and so the gains are bigger for the agents with high precision signal, as they do not need to wait for their neighbors.

Table 7.2 contains the compensating variation for the median household with a perceived high-talent child. One observes a similar pattern as the previous table, with a larger effect on savings, as is natural from having a greater endowment. The first quarter of high-information neighbors (versus none) for a low information agent is estimated to be approximately 16% of the median wealth.

Notice that in general there is diminishing returns for having an extra neighbor, as the Bayes rule for probability kicks in. This is because adding one more neighbor indeed increases the precision of the late signals obtained, but once the precision has been increased, say, to a level of above 90%, the amount of precision that can be increased is significantly smaller. However, the increase in precision is still good enough to boost an extra return in savings such that the compensating variation is large.

Finally, Table 7.3 shows the compensating variation of agents in the upper side of the savings distribution, and with a high perceived talent of their child. These have the values reversed for high and low-information agents: the value of a good neighbor for a low-information agent is higher, as it reflects the fact that they have higher endowment, and the gains from a good neighbor is higher therefore.

The estimation is used for a simulation of the wealth mobility in the network, for a predicted decrease in Economic Connectedness – the fraction of high-informed friends among low-informed individuals – of 10%, compared to a random network. A network is more homogeneous (heterogeneous) when the agents are more (less) connected at the same information level.

CV (in dollars) for an extra n-good neighbors, low-info agent:				
Current $\#GN$	1-good neighbor	2-good neighbors	3-good neighbors	4-good neighbors
0	\$22724	\$38324	\$53569	\$36825
1	-	\$20320	\$35309	\$40974
2	-	-	\$17258	\$25425
3	-	-	-	\$15426
CV (in dollars) for an extra n-good neighbors, high-info agent:				
Current $\#GN$	1-good neighbor	2-good neighbors	3-good neighbors	4-good neighbors
0	\$30165	\$57615	\$83255	\$98897
1	-	\$29561	\$55840	\$73902
2	-	-	\$26309	\$50188
3	-	-	-	\$24205

Table 7.2: Compensating variation for median-endowment agent and perceived high-talent of child.

CV (in dollars) for an extra n-good neighbors, low-info agent:				
Current $\#GN$	1-good neighbor	2-good neighbors	3-good neighbors	4-good neighbors
0	\$180450	\$312142	\$478012	\$568012
1	-	\$216540	\$450650	\$572748
2	-	-	\$251186	\$408880
3	-	-	-	\$306447
CV (in dollars) for an extra n-good neighbors, high-info agent:				
Current $\#GN$	1-good neighbor	2-good neighbors	3-good neighbors	4-good neighbors
0	\$120300	\$224961	\$294735	\$384960
1	-	\$144360	\$244260	\$343728
2	-	-	\$168468	\$282840
3	-	-	-	\$185314

Table 7.3: Compensating variation for high-endowment agent and perceived high-talent of child.

CHAPTER 8

Concluding Remarks

Endogenous network formation and the impact of Social Capital on wealth accumulation is fundamental when considering the recent decrease in intergenerational mobility.

I present an iterated game network model based on the herding literature, where agents choose their neighbors based on the information they can extract from them, and I derive from it conditions for externalities that arise due to neighborhoods better informed than others. To my knowledge there is no such model in the literature, although it is similar in spirit to some I mention in the literature review. It provides a theoretical framework for the Chetty et. al (2018) line of research. Understanding the marginal benefits of information sharing across networks provides an incentive-based explanation as to why homogeneous or heterogeneous networks exist and it allows to make an estimate of the marginal benefit of having better neighbors, and on how good neighborhoods endogenously arise.

The main contribution is a novel method for estimating an economic network, performing Ecological Inference. It also introduces endogenous decisions of the players on their neighborhoods to an iterated game with saving technology and bequests. This results in both theoretical and quantitative contributions to the growing literature on intergenerational mobility.

In terms of the model results, the comparative statics analysis calculates the advantage of having increasingly informed neighbors, using the compensating variation due to a neighbor with high information. Using that equation, the range of unobservable parameters for which there is a homogeneous outcome that does not maximize returns is identified.

The study proceeds to assess the worth of each additional quarter of high-information neighbors for agents with low and high levels of information. In quantitative terms, it's estimated that the welfare compensating value for a low-information household (characterized as an agent with a less precise signal) residing in an area where 25% of the neighbors are high-information, as opposed to

none, is roughly 16% of the median savings.

To arrive at this figure, the paper first estimates the non-observed parameters using a Generalized Method of Moments. The network's configuration plays a crucial role in these estimations. An algorithm is systematically used to conduct ecological inference on the agents, with their connections only observed at the county level. Moreover, simulations using the estimated parameters within this network structure forecast a ten percent reduction in Economic Connectedness – the proportion of high-information contacts among low-information individuals – for the ensuing generation, relative to a baseline of a randomly formed network.

In terms of future work, a direct research question that arises from this paper is what happens when extending the framework to an infinite horizon. Is there any steady state in the distribution of the network? Another potential future avenue of research for this project is to add an endogenous decision of the agents on the level of information they wish to acquire.

APPENDIX A

POSTERIOR PROBABILITY

Consider the case of having only one neighbor, I write the equation for the posterior probability $\hat{p}$, without loss of generality, with a positive signal for both i and j:

$$\hat{p} = P_{rob}\left(state = H | R_i, q_i, \{e_j, s_0^j, b_0^j\}_{j \in N(i)}\right)$$

$$\begin{aligned} P_{rob}\left(state = H | R_i = 1, q_i, R_j = 1, q_j\right) &= \frac{P_{rob}\left(R_i = 1, R_j = 1 | state = H, q_i\right) P_{rob}\left(state = H\right)}{P_{rob}\left(R_i = 1, R_j = 1\right)} \\ &= \frac{q_i \cdot q_j \cdot t}{q_i \cdot q_j \cdot t + (1 - q_i) \cdot (1 - q_j) \cdot (1 - t)}. \end{aligned} \tag{A.1}$$

APPENDIX B

PROOF OF PROPOSITION 1

Proposition 1 is equivalent to showing that there is a separating equilibrium in which players with the same information level e_i who differ in signals R_i make a different level of investment.

Let i and j be two different agents who have $e_i = e_j$. Furthermore, assume without loss of generality that the number of good neighbors for each is the same, as having a different number of neighbors would change the equilibrium condition in a way that would further enhance the difference in investment. Let $R_i = 0$ and $R_j = 1$.

We wish to show that $s_0^i(R_i, q_i, \{q_j\}_{j \in N(i)}) \neq s_0^j(R_j, q_j, \{q_k\}_{k \in N(j)})$. It is important to note that the players are symmetric in every sense, so that the function is not dependent on i or j. Furthermore, given that $e_i = e_j$, we have that $q_i = q_j$. Finally, because the number of good neighbors is assumed to be the same, one can write the equation as

$$s_0^i(0, q_i, \{q_j\}_{j \in N(i)}) \neq s_0^i(1, q_i, \{q_j\}_{j \in N(i)}).$$

From looking at the maximisation problem it is clear that

$$s_0^i(1, q_i, \{q_j\}_{j \in N(i)}) \geq s_0^i(0, q_i, \{q_j\}_{j \in N(i)}).$$

Given that $q_i > 0$, one has that $p > 0$ as defined in Definition 2. Then again, from looking at the maximisation problem, for μ large enough, we have that $s_0^i(1, q_i, \{q_j\}_{j \in N(i)}) > 0$. There is a trivial case where $s_0^i(0, q_i, \{q_j\}_{j \in N(i)}) = 0$. For the non-trivial case, it remains to be proven that $s_0^i(1, q_i, \{q_j\}_{j \in N(i)}) \neq s_0^i(0, q_i, \{q_j\}_{j \in N(i)})$. Now, because the equation is highly non-linear, but continuously differentiable on s_0^i, a change in R_i will only change the loading parameter through p on the FOC. From inspecting the FOC,

$$
\begin{aligned}
p * \Bigg(\frac{q_j}{\bar{H}_1}(\mu\rho - 1 + [\rho - 1]\frac{\partial s_1^i(s_0^i; \hat{p}, R_j = 1)}{\partial s_0^i}) + \\
\frac{(1 - q_j)}{\bar{L}_1}(\mu\rho - 1 + [\rho - 1]\frac{\partial s_1^i(s_0^i; \hat{p}, R_j = 0)}{\partial s_0^i})\Bigg) + \\
(1 - p) * \Bigg(\frac{(1 - q_j)}{\bar{H}_0}(-1 - \frac{\partial s_1^i(s_0^i; \hat{p}, R_j = 1)}{\partial s_0^i}) + \\
\frac{q_j}{\bar{L}_0}(-1 - \frac{\partial s_1^i(s_0^i; \hat{p}, R_j = 0)}{\partial s_0^i})\Bigg)
\end{aligned}
$$

for μ large enough, $\frac{\partial s_1^i(s_0^i;\hat{p},R_j=1)}{\partial s_0^i}$ becomes negligible with respect to μ in the first terms. Now, because all else remaining constant, larger values of p implies larger values of s_0^i, and because of the continuously differentiability over s_0^i, we conclude that

$$
s_0^i(1, q_i, \{q_j\}_{j \in N(i)}) > s_0^i(0, q_i, \{q_j\}_{j \in N(i)}),
$$

which is the desired result.

APPENDIX C

PROOF OF PROPOSITION 2

The expected return of the asset is trivially monotonic on the endowment level, M_i, all else constant. Unless the utility functions of the parent and child are different, and because they constitute simply a monotonic transformation of the return, the return is maximised both when the household simply maximises it, or when it performs the whole maximisation problem.

Then, given a linear function $w(\hat{t}_i, f_i)$ on f_i, it is clear that $f_i^* = 1$ will be optimal whenever

$$\mathbb{E}[u_{child}(\phi return + w_i(\hat{t}_i, 1) - D_i)] > \mathbb{E}[u_{child}(\phi return + w_i(\hat{t}_i, 0))].$$

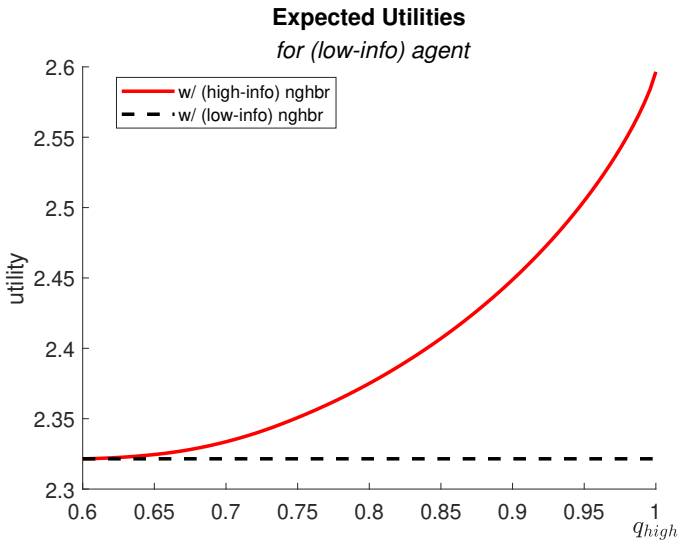
Hence, the proposition holds.

APPENDIX D

FIGURES

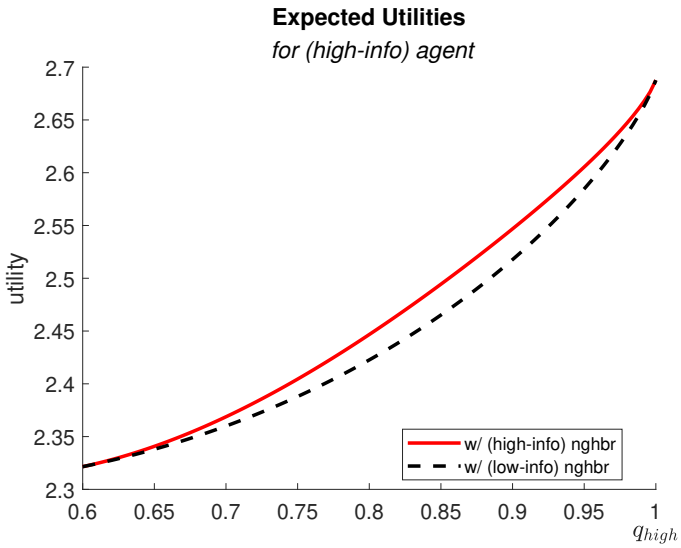
Figures D.1 to D.4, show Period 1 Investment levels for different values of μ, when $\rho = 1.8$.

What happens in Figures D.5 and D.6 are a mirror of what happens for the expected return, with a different scale, due to the logarithmic transformation.



$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure D.5: Ex ante expected utility for a low-information agent for different values of the parameter q_{high}

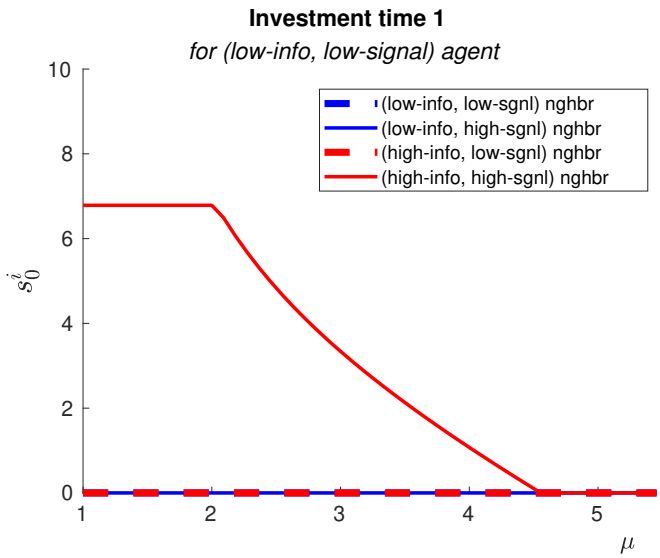


$\rho = 1.8, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure D.6: Ex ante expected utility for a high-information agent for different values of the parameter q_{high}

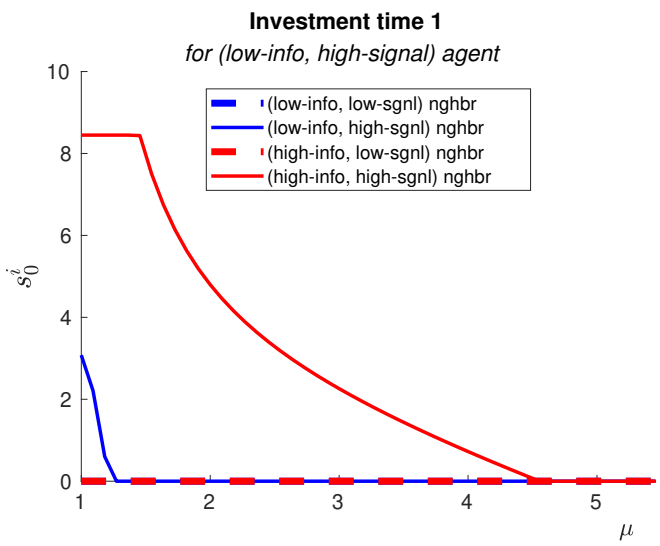
Figures D.7 to D.10 show Period 0 Investment levels for different values of q_{high}, with $\rho = 2.2$ or $\mu = 7$.

Figures D.11 to D.17 show expected returns and utilities, as well as compensating variations for different values of q_{high}, with $\rho = 2.2$ or $\mu = 7$.



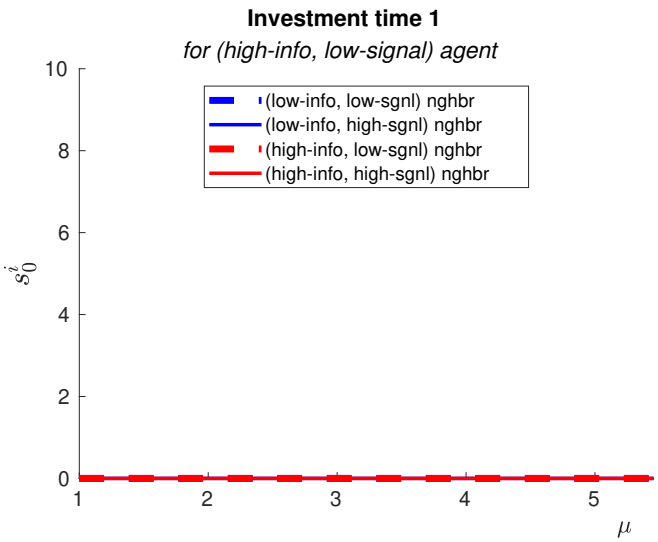
$\rho = 1.8, R = 1, q_{low} = 0.6, q_{high} = 0.9$

Figure D.1: level of investment of the period 1 of a low-information low-signal agent for different values of the parameter μ



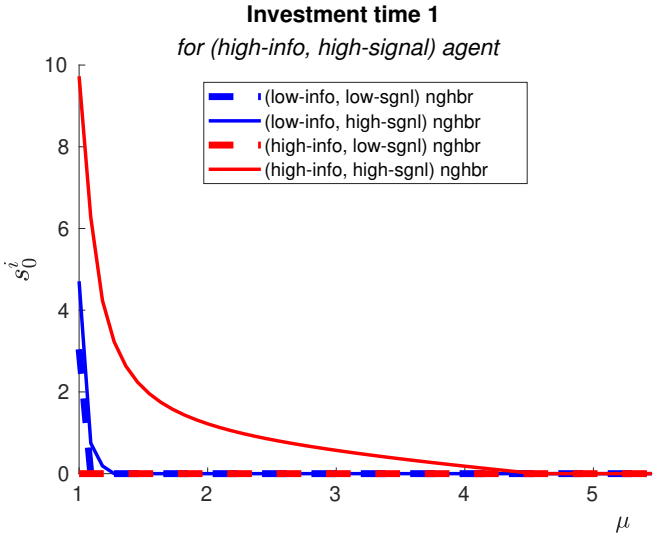
$\rho = 1.8, R = 1, q_{low} = 0.6, q_{high} = 0.9$

Figure D.2: level of investment of the period 1 of a low-information high-signal agent for different values of the parameter μ



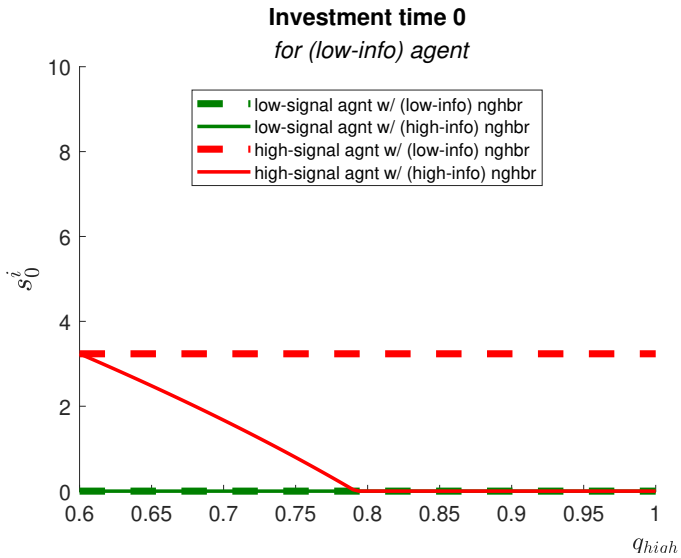
$\rho = 1.8, R = 1, q_{low} = 0.6, q_{high} = 0.9$

Figure D.3: level of investment of the period 1 of a high-information low-signal agent for different values of the parameter μ



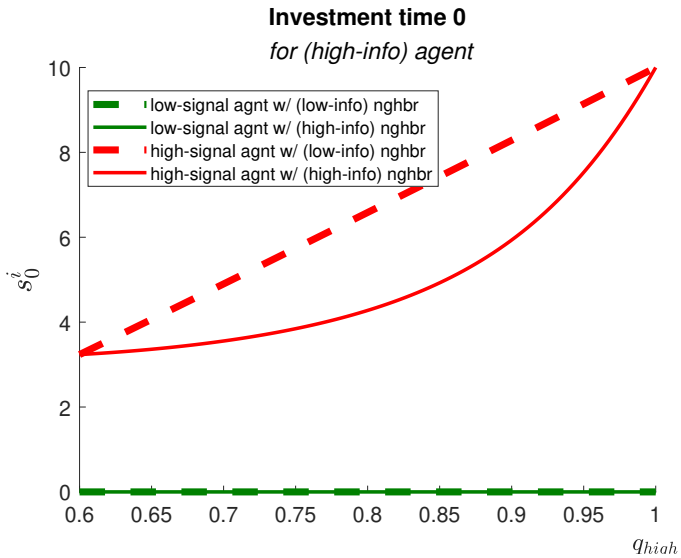
$\rho = 1.8, R = 1, q_{low} = 0.6, q_{high} = 0.9$

Figure D.4: level of investment of the period 1 of a high-information high-signal agent for different values of the parameter μ



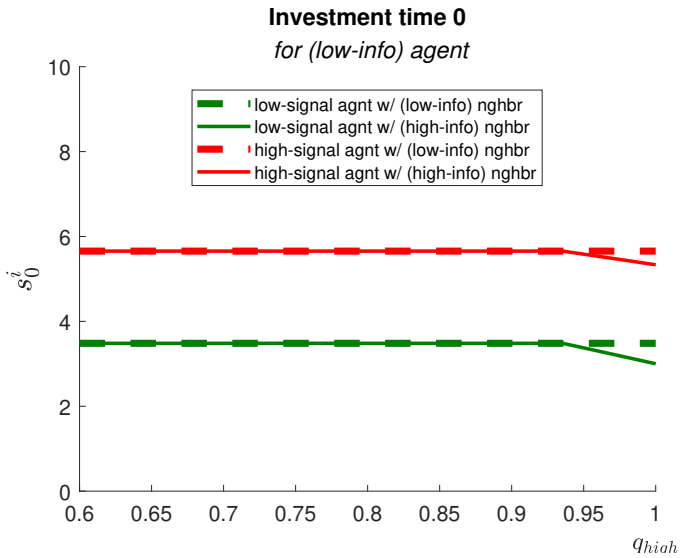
$\rho = 2.2, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure D.7: level of investment of the initial period of a low-information agent for different values of the parameter q_{high}



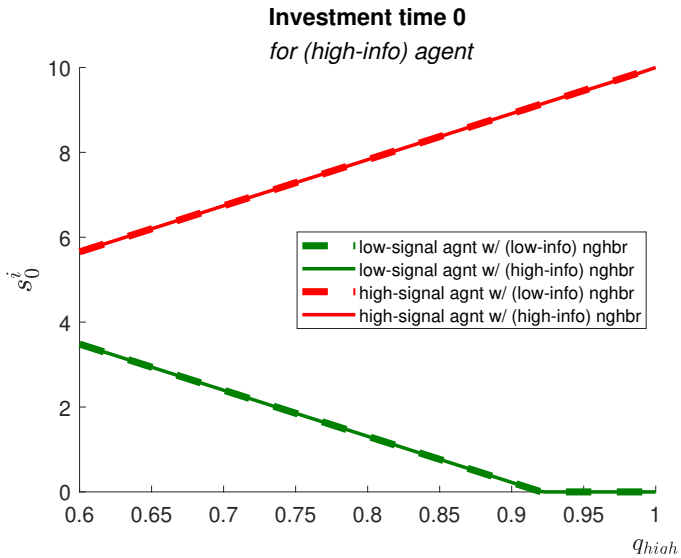
$\rho = 2.2, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure D.8: level of investment of the initial period of a high-information agent for different values of the parameter q_{high}



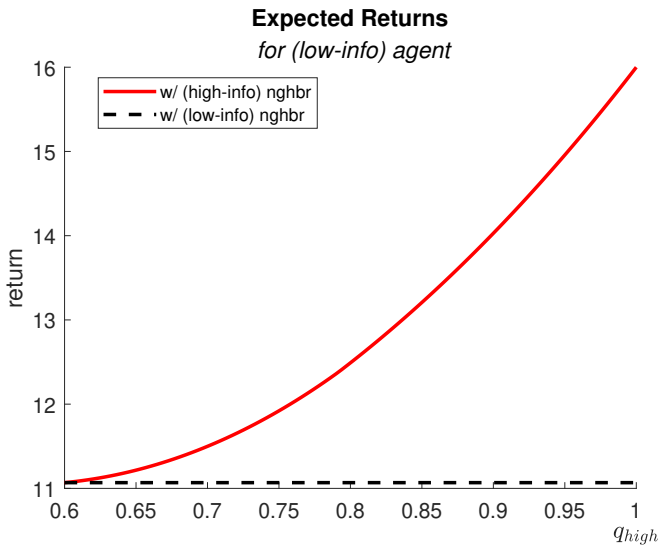
$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.9: level of investment of the initial period of a low-information agent for different values of the parameter q_{high}



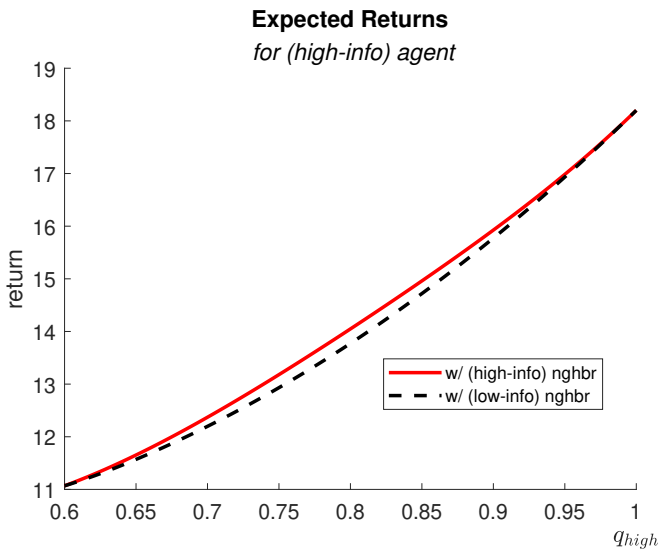
$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.10: level of investment of the initial period of a high-information agent for different values of the parameter q_{high}



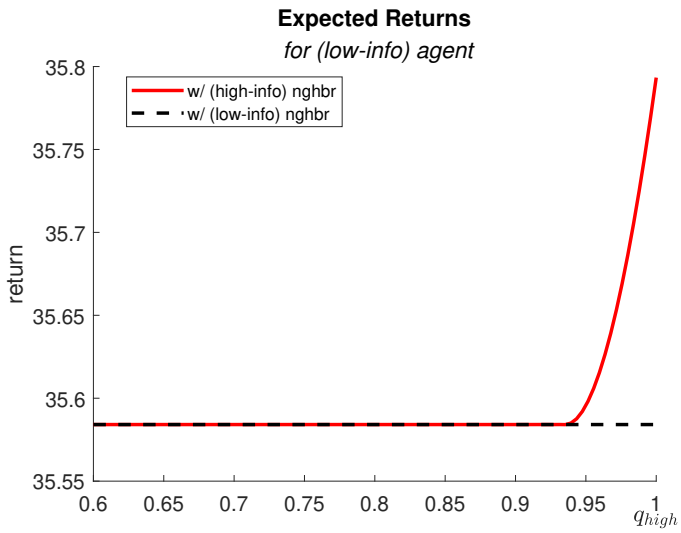
$\rho = 2.2, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure D.11: Ex ante expected return for a low-information agent for different values of the parameter q_{high}



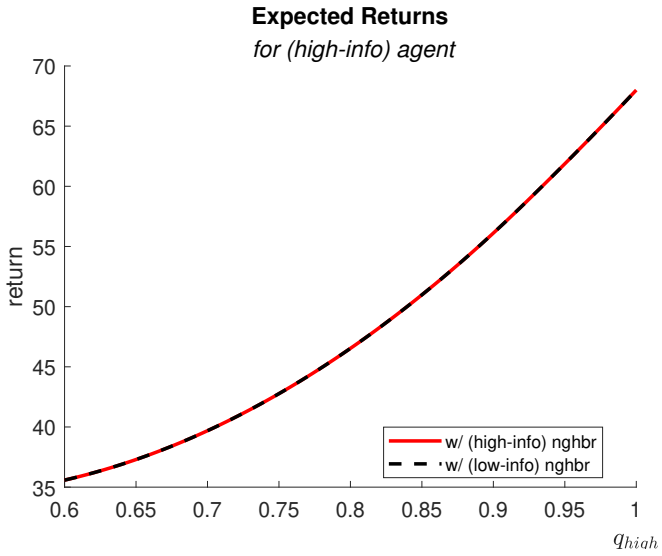
$\rho = 2.2, \mu = 1.2, R = 1, q_{low} = 0.6$

Figure D.12: Ex ante expected return for a high-information agent for different values of the parameter q_{high}



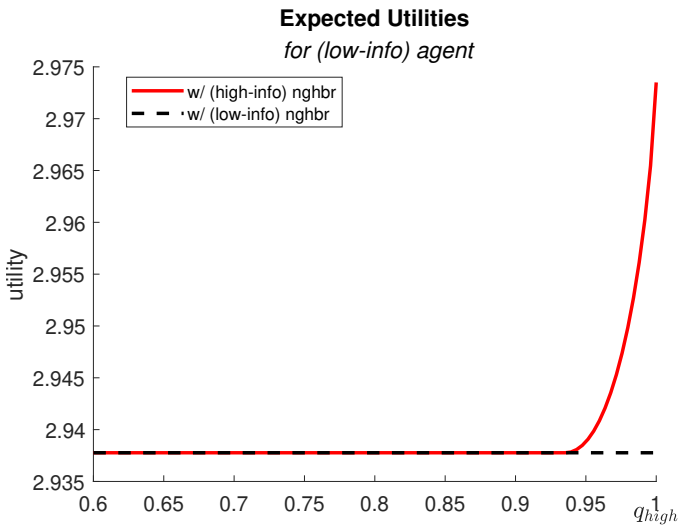
$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.13: Ex ante expected return for a low-information agent for different values of the parameter q_{high}



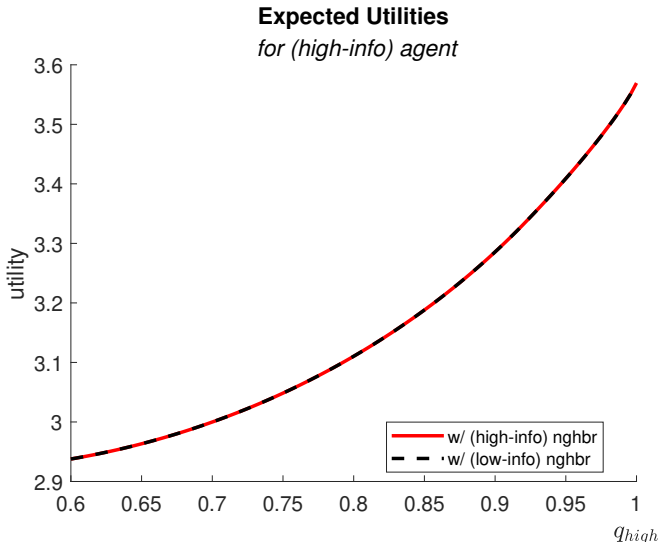
$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.14: Ex ante expected return for a high-information agent for different values of the parameter q_{high}



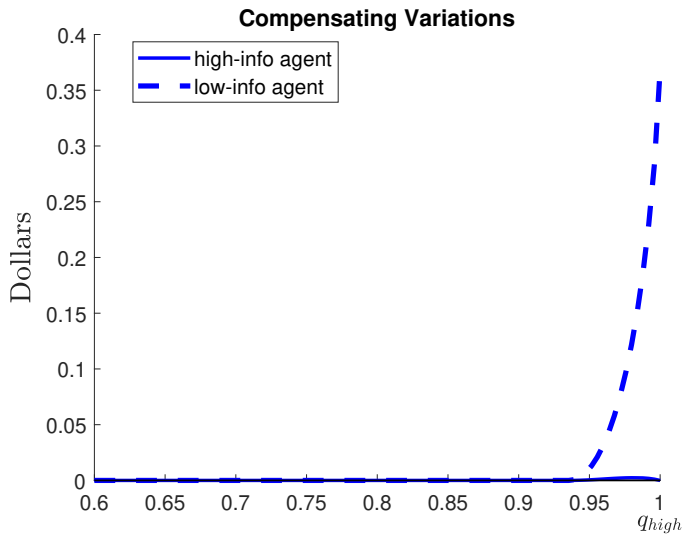
$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.15: Ex ante expected Utility for a low-information agent for different values of the parameter q_{high}



$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.16: Ex ante expected return for a high-information agent for different values of the parameter q_{high}



$\rho = 1.8, \mu = 7, R = 1, q_{low} = 0.6$

Figure D.17: Compensating variation for the agents: from having a low-informed to a high-informed neighbor, when $\mu = 7$.

APPENDIX E

TWO NEIGHBORS

Figures E.1 to E.8 contain plots of Investment in period 1, Expected Utilities and Returns, as well as Compensating Variations and Welfare Analysis for the two-neighbor case, for for different values of μ and q_{high}.

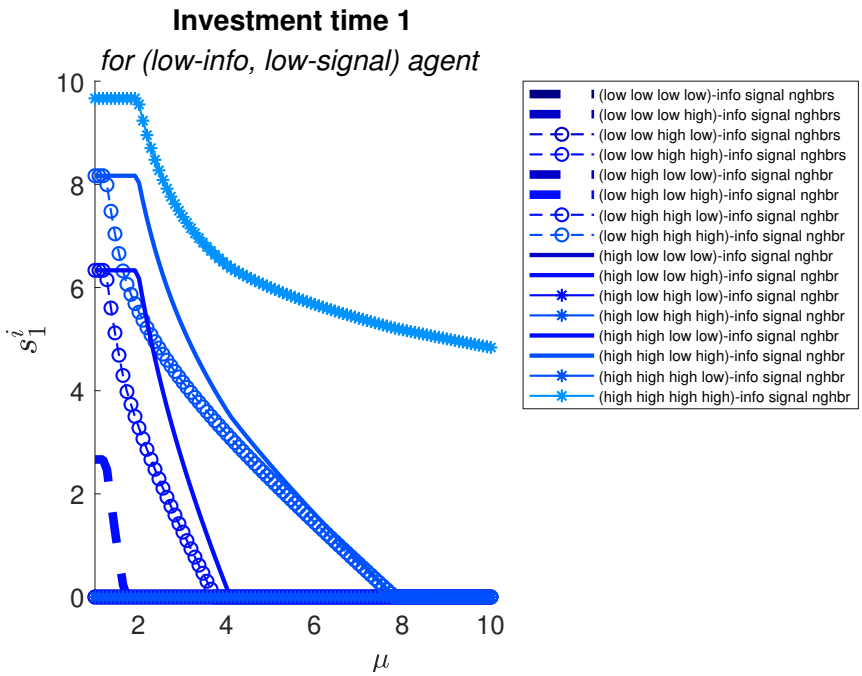


Figure E.1: Two-neighbor, late investment of a low-information low-signal agent for different values of the parameter μ.

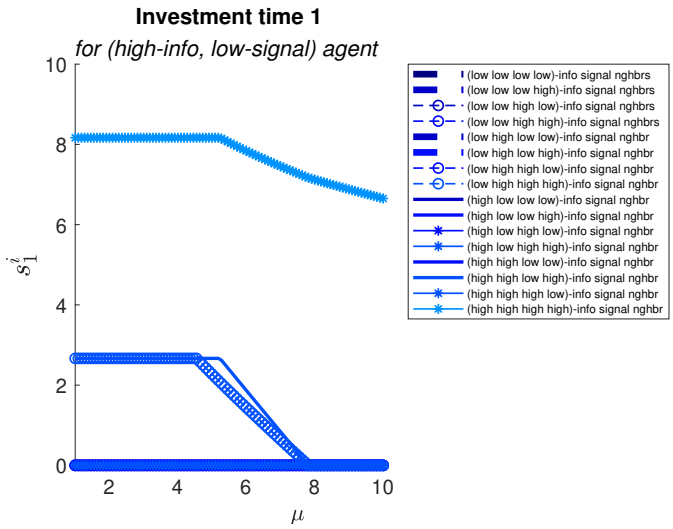


Figure E.3: 2-neighbor, level of investment of the period 1 of a high-information low-signal agent for different values of the parameter μ

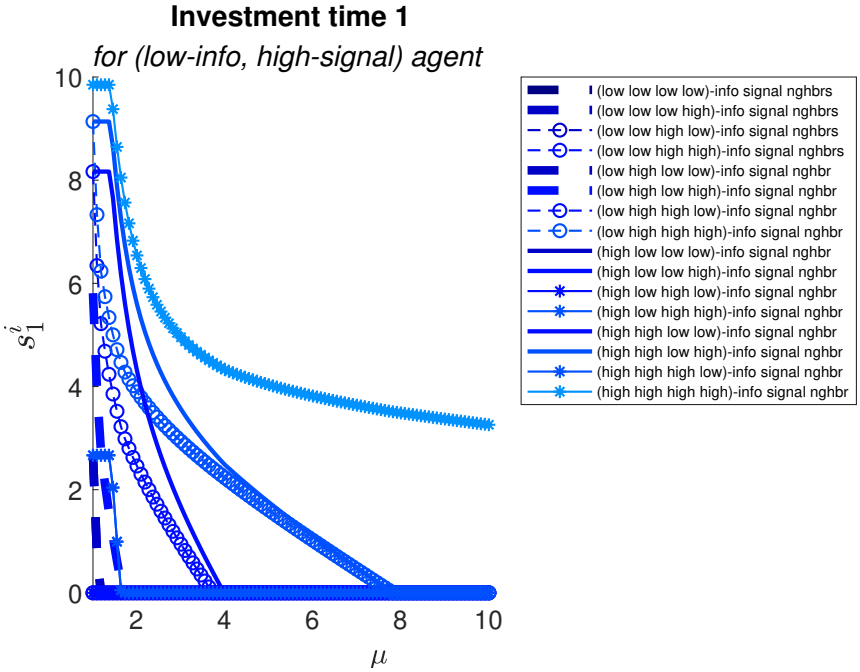


Figure E.2: Two-neighbor, late investment of a low-information high-signal agent for different values of the parameter μ.

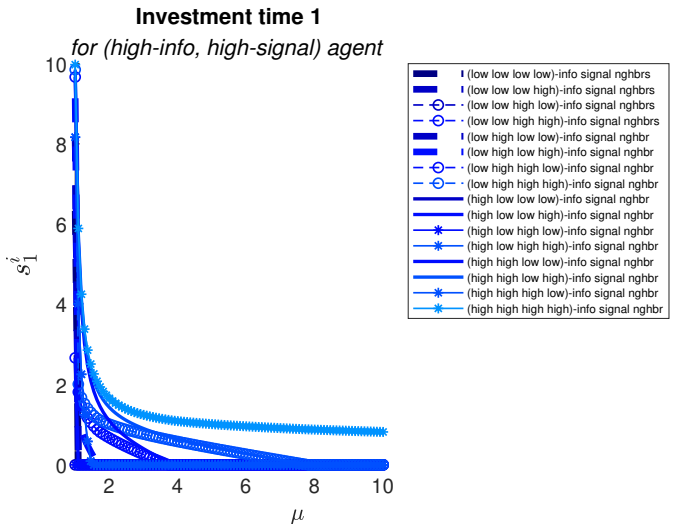


Figure E.4: 2-neighbor, level of investment of the period 1 of a high-information high-signal agent for different values of the parameter μ

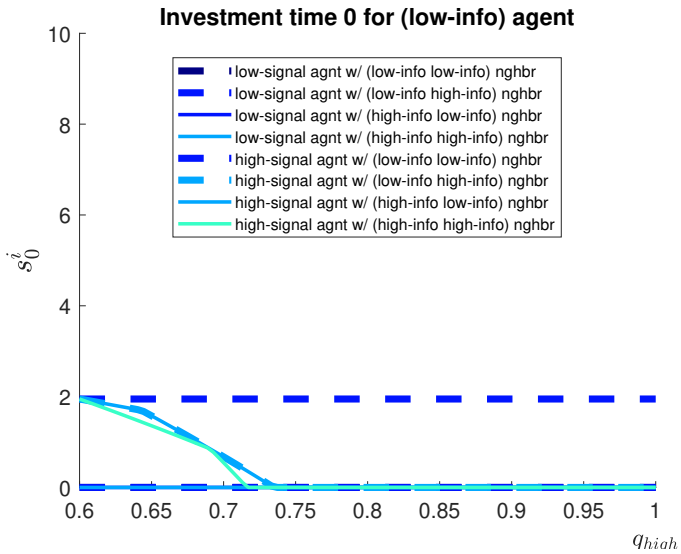


Figure E.5: level of investment of the initial period of a low-information agent for different values of the parameter q_{high}

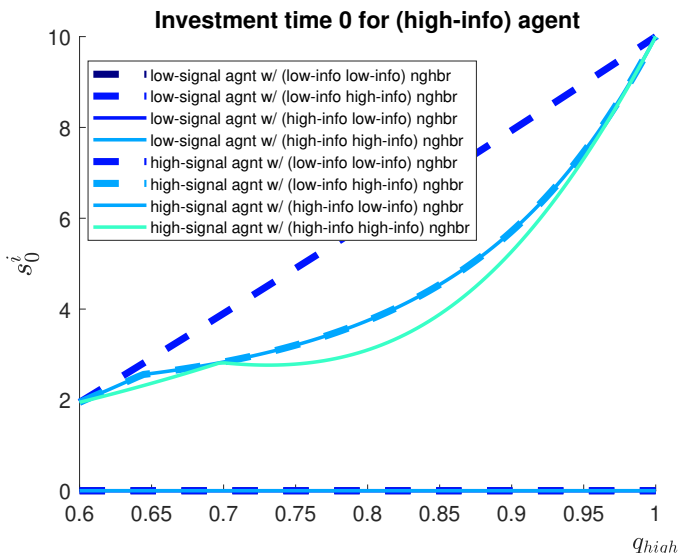


Figure E.6: level of investment of the initial period of a high-information agent for different values of the parameter q_{high}

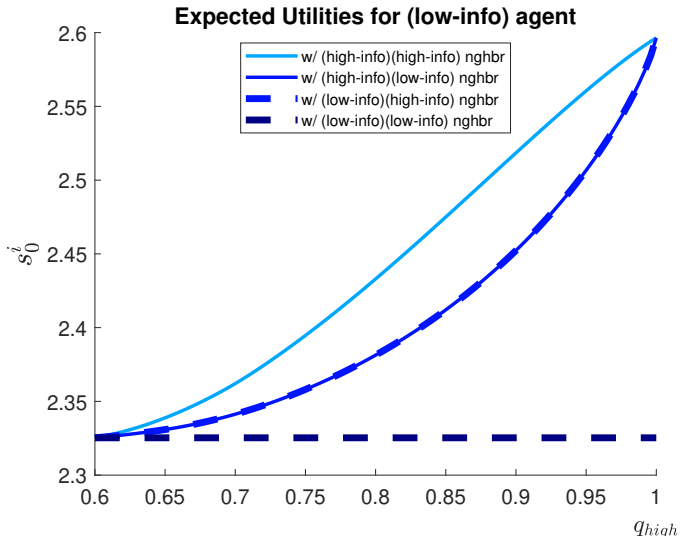


Figure E.7: Ex ante expected utility for a low-information agent for different values of the parameter q_{high}

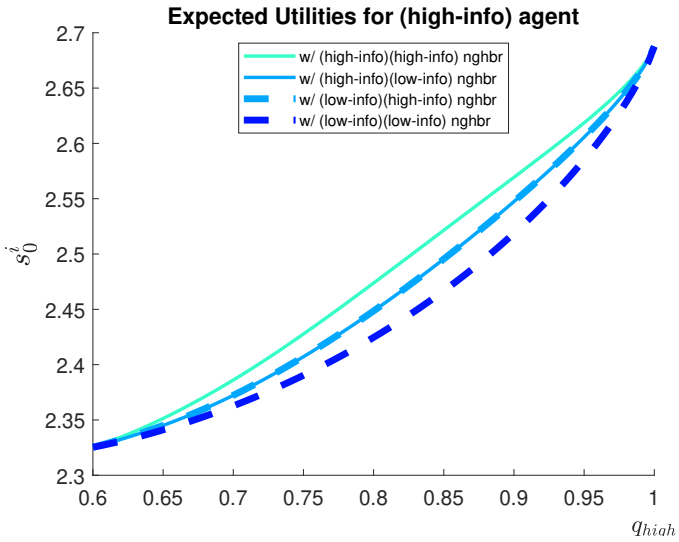


Figure E.8: Ex ante expected utility for a high-information agent for different values of the parameter q_{high}

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