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GENDER, SOCIAL NETWORKS AND PERFORMANCE

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ABSTRACT

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Keywords: Networks, Peer Pressure, Gender, Labor Market Outcomes

JEL Classification: D85, Z13, J16

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"Loose connections are the connections you need. It's the No. 1 rule of business."

Sallie Krawcheck, owner of the global women's network *85 Broads*[1]

1 Introduction

Gender differences in labor market outcomes remain striking. In the US, women's earnings in 2012 were on average 80.9% of men's earnings.[2] Even though part of it can be explained by occupational sorting, *within* occupations wage gaps are considerable. Management occupations, such as financial manager and chief executive, are particularly affected, whereas healthcare support and administrative occupations show much smaller gaps.[3] Similar patterns were found for the UK, where full-time working women in the financial sector earn 55% less than full-time male workers – a gap twice as large as the gap in the economy as a whole.[4] What these high-wage-gap occupations have in common is that they are characterized by a large amount of uncertainty, commonly measured by earnings variability. Earnings of both executives and financial managers are largely based on performance pay and thus not constant. Women's lower earnings in these occupations are mainly due to large differences in performance pay and bonuses, suggesting that men perform better.[5] At the same time, and possibly as a logical consequence, more men than women sort into occupations with high earnings volatility.[6] But why do women perform relatively poorly in "high-risk" occupations and avoid them?

In this paper, we offer a novel answer to this question, which is based on social network heterogeneity between men and women.[7] We argue that men's network structures allow them to perform better in uncertain environments compared to women and our model clarifies why this is the case. This approach is motivated by our novel empirical finding that men's and women's social networks differ. We show in the AddHealth Data Set that women have fewer friends than men, that is they have a lower *degree*, but their

[1] Krawcheck at Marie Claire's luncheon for the *New Guard*, November 2013.

[2] See the report of the U.S. Bureau of Labor Statistics, http://www.bls.gov/cps/cpswom2012.pdf

[3] See BLS-Reports (2013), http://www.bls.gov/cps/cpswom2012.pdf

[4] Wage differences are considerable even when controlling for hours of work (full time) and type of job. See the report by the Equality and H.R.Commission (2009).

[5] Again, see the report by the Equality and H.R.Commission (2009).

[6] See Dohmen and Falk (2011).

[7] Common explanations for these patterns are discrimination against women in male-dominated environments, or differences in preferences and risk aversion. See Eckel and Grossman (2008) for an overview of the literature that finds women to be more risk averse than men. Other explanations involve differences in bargaining strength, which can account for part of the gender wage gap (Card et al. (2013)) as well as future fertility concerns which leads women to self-select in different occupations (Adda et al. (2011)).

friends are more likely to be friends among each other, implying a higher *clustering coefficient*.[8] Thus, women have smaller but tighter networks, whereas men have larger but looser ego networks. We argue that the network patterns among friends carry over to the informal network structures at the workplace, an assumption in line with Burt (2011) and supported by case studies (Brands and Kilduff (2013)).

We argue that tight and loose networks provide different types of social capital: a tight network fosters trust or peer pressure among agents, as it prevents them from shirking. This is because they fear repercussions not only from the individual they affect directly with their behavior but also from other members of their network. As a result, closed networks help overcome free-riding problems (Coleman (1988a)).[9] But network closure comes at a cost.[10] Networks with high closure do not allow individuals to access as much information and other low-value resources as networks with lower closure. Being in a loose network with links to individuals that are not connected themselves is particularly valuable for information acquisition. This is what the literature has referred to as the "strength of weak ties" (Granovetter (1973)).[11] We are interested under what circumstances tightly connected female networks and thus high peer pressure are more important for *performance on the job* and in what environments the opposite is the case.[12] We develop a theory where networks provide both access to information as well as peer pressure and outline the implications of different network structures on wages.

In our model, workers repeatedly form partnerships to complete projects. Project success positively depends on the partners' efforts. Effort is unobservable and only the project outcome is public information. If the project is completed successfully, the project payoff is shared between the team members. Because output is split but costs are not, there is a team moral hazard problem at work. As a result, the project partners exert inefficiently low effort.[13] We will show how networks can help attenuate this moral hazard

[8]We are using data of teenagers, not of men and women who are already employed. We do this as we are interested in the informal networks, not the formal ones. To the best of our knowledge there does not exist a sufficiently big data set that contains information on *informal* networks at the workplace.

[9]Specifically, closed networks mitigate free-riding problems through the creation of norms and punishment systems. Coleman (1988b) stresses the importance of this mechanism for diamond traders in New York.

[10]All of this literature assumes that individuals have a fixed budget of time.

[11]These two types of social capital can also be related to the concepts of bonding versus bridging social capital defined in Putnam (2000).

[12]We do not aim to address the question of job *search*, as has been done, for example, in Arrow and Borzekowski (2004), Calvo-Armengol and Jackson (2004), Calvó-Armengol and Jackson (2007), but we are interested in how the network structure matters once the job has been found.

[13]See Holmstrom (1982) for moral hazard problems in teams.

problem by increasing effort.

We are interested in the effort levels of the project partners as a proxy for their performance and specifically in the factors influencing this choice. First, the choice of effort depends on *information* about the value of the project, which can be high or low, depending on the state of the world. Workers receive signals about the state through their network and form expectations about the project value. These expectations influence effort. The more signals and thus information a worker has, the more precise is his belief about the state of the world. This allows for a better judgment as the optimal effort is state dependent. Second, effort positively depends on the amount of *peer pressure* individuals face.

How much information a worker has and how much peer pressure he faces depends on his network structure. Workers with a higher degree hold more information, as they receive a higher number of signals about the state of the world. In turn, workers with higher clustering face more peer pressure through the following mechanism: a failed project leads to discord between the project partners. But this discord also affects their common friends, that is their disagreement spreads through the entire group – an idea based on the *structural balance theory*.[14] Since an intact friendship is necessary for a successful project, repercussions of a failure are worse for a worker with high clustering compared to someone with a looser network. Therefore, higher clustering leads to higher effort in order to be on good terms with future potential project partners.[15]

Our model allows the ranking of networks by their benefit for job performance. We show under which circumstances a network with higher clustering is more beneficial for performance and ultimately wages and when a network with a higher degree is more advantageous. Our main findings are as follows: A higher degree is more beneficial for performance in volatile environments, where the uncertainty about the project value is considerable, which is particularly true when (i) overall information (that is information coming from sources unrelated to the network) is scarce, (ii) when signals are noisy and (iii) when project rewards differ significantly across the two states. In these cases, uncertainty about the state of the world and associated rewards is large and the benefits of a purely information-based, loose network outweigh the benefits of a closed network that

[14] This is a concept first proposed by Heider (1946) who has spawned a field of research that remains active until today. For an overview on the numerous works on structural balance theory, see Easley and Kleinberg (2010), chapters 3 and 5.

[15] Note that in our model links are never cut and disagreement is considered to be only short term.

leads to more peer pressure. In turn, peer pressure leads to higher effort and thus project completion in environments characterized by certainty where additional information has no value. In general, someone with more information can better fine-tune his effort to the expected project reward, exerting high effort only when there is something at stake. In turn, a worker facing high peer pressure exerts extra effort even if the project reward is expected to be low.

Effort choices directly translate into wages. Someone with higher clustering earns more than someone with higher degree when uncertainty about the state is negligible (in both states of the world). Such a worker also has a comparative advantage in jobs whose outcomes are more certain compared to jobs with less certain outcomes. Finally, we show that, due to the dynamic effect of clustering, there is a strong persistence of wage patterns across time, consolidating early career wage gaps.

We then model a man's network as one that is characterized by a relatively high degree and a woman's network as one that is characterized by relatively high clustering. We provide a mechanism of how this social network heterogeneity relates to differences in labor market outcomes of men and women and show that our theory is consistent with a variety of empirical facts: (1) Wage gaps within occupations are large and especially within those occupations that characterized by uncertainty, such as the financial sector or the film industry.[16] (2) More men than women choose occupations with high earnings volatility (Dohmen and Falk (2011)). In our model, this would happen even though both men and women are risk-neutral and thus have the same attitude towards risk. The reason is that women have a comparative advantage in job environments characterized by little uncertainty. (3) Having women in the network is particularly beneficial high up in the organizational hierarchy (Lalanne and Seabright (2011)). In light of our model, we expect that having women in the network is particularly beneficial when information is abundant. We argue that this is the case at higher levels of the organizational hierarchy when networks have grown large rather than in low positions that are commonly held at the beginning of the career. (4) During recessions (i.e. when returns are low) men's unemployment exceeds women's unemployment (Albanesi and Sahin (2013)). Our model predicts that, incentivized by peer pressure, women put over-effort despite low expected

[16] See, for instance, http://www.bls.gov/cps/cpswom2012.pdf or Equality and H.R.Commission (2009), which will be discussed in depth.

rewards whereas men are more selective in their effort choice. Women's higher effort does not hinge on the fact that they have different expectations, but will emerge even with the same predicted reward. (5) The beginning of the career is the crucial period for the emergence of a wage gap (Babcock and Laschever (2003), Gerhart and Rynes (1991), Martell et al. (1996)). In our model, an initial wage gap is strongly persistent because women are deprived of more project opportunities over time due to their high clustering. This makes it difficult for them to catch up.

In sum, we expect that, based on their loose networks, men outperform women in work environments that are characterized by uncertainty but yield high expected returns – conditions that are typical for a large number of jobs in business and research. Our predictions are in line with what various business leaders consider conventional wisdom: Loose instead of deep connections are the key to success in business.

Related Literature We contribute to the work on the gender wage gap (a review of gender wage differences can be found in Blau and Kahn (2000)). Common explanations for this gap are discrimination (Black and Strahan (2001), Goldin and Rouse (2000), Wenneras and Wold (1997)) and differences in abilities and preferences which result in occupational self-selection (Polachek (1981)). Differences between men and women have also been found in their competitiveness (Gneezy et al. (2003), Gneezy and Rustichini (2004)), risk aversion (for a summary, see Eckel and Grossman (2008)), in their ability in bargaining (Card et al. (2013)) and in terms of future fertility concerns (Adda et al. (2011)). We suggest a new disparity between men and women, their network structure, as a source of wage disparity.

We also add to the limited amount of network literature that evaluates the trade-off between network density and the network span. This trade-off has first been analyzed in Karlan et al. (2009) where individuals use their network to borrow goods. They focus on the trust generated in networks and find that higher closure increases trust and enables agents to borrow high value goods. But network closure reduces access making less easy to borrow frequently low value goods. Although the impact of network closure on economic outcomes is analyzed in both Karlan et al. (2009) and our work, the theoretical frameworks and applications are entirely different. In our setting, networks do not generate trust but transmit information and provide peer pressure and both features impact performance on the job. Dixit (2003) also discusses the trade-off between sparse and closed networks in a trade setting. He focuses on the role of self governance, as an alternative to official institutions, in trading relationships. Trading with more distant individuals offers higher gains, but information flows about cheating are decreasing in this distance. There is a clear trade-off between networks that have a high closure, that is a local bias in trade, and networks that span a larger distance but this trade-off differs from ours which focusses on information and peer pressure.

Our work also contributes to a growing literature on the effects of peer pressure. Kandel and Lazear (1992) incorporate peer pressure in their model through a simple function, where peer pressure depends on own effort, the effort of peers as well as other actions of the agents that do not affect firm output directly. Their finding is that peer pressure induces individuals to exert higher effort, which leads to a higher profit for the firm. They argue that firms can create peer pressure by establishing norms and mutual monitoring. In the case of mutual monitoring, the crucial issue is to define the relevant group, that is the team, the department or the entire firm. We put forward an alternative source of peer pressure (i.e., the social network), define the relevant group (i.e., friends and common friends) and provide a novel mechanism of how peer pressure operates.

The paper proceeds as follows: In Section 2, we document empirically that men's and women's networks differ. In Section 3, we develop the general model, which we then solve for the static case in Section 4 and for the dynamic case in Section 5. Section 6 connects our predictions on gender differences in labor market outcomes to a variety of empirical facts. Section 7 discusses our equilibrium selection. Section 8 concludes.

2 Gender Differences in Networks

A main assumption of our model is that women have a higher clustering coefficient than men, but that men have a higher degree than women. This assumption is based on our findings from the AddHealth data set that male and female networks differ.

The AddHealth data set contains data on students in grades 7-12 from a nationally representative sample of roughly 140 US schools in 1994-95. Every student attending the sampled schools on the interview day is asked to compile a questionnaire (in-school data) on respondents' demographic and behavioral characteristics, education, family background and friendships. The AddHealth website describes surveys and data in detail.

This sample contains information on 90,118 students.[17]

Why AddHealth? Our main reason for using a dataset of *students* instead of employees in a firm is to circumvent the problem that networks can be shaped by the work environment. For instance, if men and women prefer to have friends of the same gender, some male-dominated work environments would cause women to have smaller networks. Moreover, if we were using data of firms or occupations we would be concerned that individuals with certain network types sort into those occupations and firms for which their network type is most beneficial. However, at the school level there is no such selection bias or constrained availability of same-sex individuals. We can therefore estimate male and female network structures more accurately with this data set.

Further, it is well documented that individuals are more likely to name others as their friends if these have a higher social status, see Marsden (2005). At the workplace social status is connected to a higher position in the hierarchy and therefore to formal power. However, here we think of a link between individuals as a friendship instead of trying to have a connection with someone superior. Additionally, as higher status is connected to formal power, it is difficult to distinguish between formal and informal networks. We believe that this is less of a problem at school as by definition the networks formed there are informal. There might be some misreporting in the sense that popular children will also be named as friends by individuals who would just like to be associated with them. But we believe that there is less of an incentive for high school students to be strategic about their friendship nominations than for employees. A possible reason is that superiors might be able to access this nomination data and therefore employees have an incentive to name them. In contrast, from the design of AddHealth it is clear that students will not have access to the nomination data.

We are interested in these network characteristics of men and women as *exogenous types*, comparable to different ability or skill types commonly used in the literature, where this network type is stable over time. Burt (2011) provides evidence for the existence of different network types from a multi-role game in a virtual world.[18] He finds that people

[17] For more information on the AddHealth data set, see http://www.cpc.unc.edu/projects/addhealth.

[18] This is a video game where players can play different roles and the different roles require different network structures. For some roles it is better to be linked to individuals, who are connected, for others having friends who are not connected is more beneficial. In other terms, it can be good or bad to have a high

build a similar type of network, e.g., a network that is more or less closed, where friends are more or less likely to be connected, independently of what is required for the role.[19] Based on this, we argue that boys' and girls' networks at school, closely resemble the ones they will form as adults both in their private and work life in terms of *closure*.[20]

Friendship Network The friendship network constructed from the AddHealth data is a directed network, based on friendship nominations.[21] For this network, we compute both directed and undirected clustering coefficients as well as in-, out- and overall degree.[22]

The clustering coefficient is computed as the ratio of the number of links between a node's neighbors to the total possible number of links between the node's neighbors, both for the directed and undirected network. To give an illustrating example, the clustering coefficient in a star network is zero whereas it is one in a ring network with three nodes. The in-degree denotes how often an individual was named, the out-degree gives how many friends this individual named and the degree is the sum of in- and out-degree.

We focus on the subsample of students that are older than 17 since they are closest to the working age, which is the age we are interested in.[23] We do a t-test of the standardized variables and consider the differences between boys and girls. The results are given in Table 1. We find that boys of this age have a lower clustering coefficient, independently of whether we consider the directed or undirected one, and also a higher in-, out- and overall degree than girls.

Male and Female Networks Beyond AddHealth To the best of our knowledge, differences in the clustering coefficient between men and women have not been documented in the literature with the exception of Brands and Kilduff (2013). They have a sample

clustering coefficient.

[19] About a third of network variance is consistent with individuals across roles, but the correlation coefficient between the network formed and the network type is above 0.5.

[20] Unfortunately, there does not exist much further evidence of how persistent network types are or, in general, of how persistent differences between girls and boys are, i.e. whether this improves over time or not. A notable exception is Sutter and Rützler (2010) who show that gender differences in competitive behavior emerge as early as age three and are quite persistent over time. The girls who exhibited a more competitive behavior earlier on, were more likely to be less competitive later on, those who were less competitive remained so. Therefore, the gender differences became more pronounced later in life.

[21] For more details on the friendship networks, see the Appendix.

[22] For the undirected clustering coefficient we assume that a link exists if at least one of the individuals named the other one as a friend.

[23] Our results for the entire sample are given in the Appendix.

Table 1: Difference in Network Characteristics Men-Women

	Age > 17
Cl. Coeff. (dir.)	-0.0677***
	(0.0144)
Cl. Coeff.	-0.0618***
	(0.0145)
In Degree	0.0222*
	(0.00965)
Out Degree	0.0208**
	(0.00669)
Degree	0.0259***
	(0.00749)
Observations	28259

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, Standard errors in parentheses.

of 33 employees, 16 men and 17 women. They calculate the constraint as well as the out-degree of the workers, where constraint is the extent to which an individual's friends are also friends among each other (Burt (1992)). Constraint is therefore closely related to the clustering coefficient. They find that men have a significantly lower constraint and higher out-degree, which is in line with our findings. Additionally, Fischer and Oliker (1983) look at the number of friends individuals have. They show that women have a lower number of friends than men, in particular at the workplace. We use part of the table from Fischer and Oliker (1983), p. 127, to document this. Their sample consists of

	Under 36, unmarried, no children	Under 36, married, no children	Under 36, married, children	36-64, married, no children	36-64, married, children
Men	2.8	3.4	3.1	2.3	2.0
Women	2.5	2.1	0.9	1.4	1.4
Men (N)	113	50	70	63	54
Women(N)	76	51	98	67	60

Table 2: Friendships with Coworkers, see Fischer and Oliker (1983), p. 127

employed men and women. They find that the number of friendships with co-workers differs greatly between them. For individuals under 36, who are unmarried and do not have children, the gender difference in the number of friends at the workplace is small:

men have on average 2.8 friends, women 2.5. But this difference increases, when men and women under 36 and married, with or without children, are compared. Without children, men have on average one more friend than women, with children they even have two more friends at the workplace. Therefore, our finding that older girls have a lower degree than older boys does not suddenly reverse, but is also documented for man and women at the workplace across all age groups.

Other studies also find network differences across gender. That girls and boys have different types of networks has been shown by Eder and Hallinan (1978) and is also documented in a survey by Belle (1989). The emphasis in this literature is on dyadic and triadic relationships, whereas we focus on the entire network. Gender differences in networks for adults have been shown by Kürtösi (2008), Tattersall and Keogh (2006) and Marsden (1987). These studies stress the number of friends and the content of relationships but do not contain precise information on gender differences in the network structure. Nevertheless, they show that women form closed groups and emotional ties, whereas men's networks are sparser and characterized by instrumental ties, supporting our findings.

Taking our estimation results together with the evidence in the literature, we feel confident to assume that men's and women's network types differ with women having a higher clustering coefficient but lower degree than men. This points to a new dimension of heterogeneity between men and women, which might help explain the gender wage gap and differences in occupational sorting. We do not have a causal argument since there might be an underlying factor that causes these network differences but also impacts labor market outcomes directly. Identifying the source of network differences is beyond the scope of this paper. Nor do we want to argue that differences in social networks is the whole story behind wage and performance gaps as well as occupational sorting. However, we do believe that networks play an important role and our model clarifies how these network differences can matter for job performance and wages.

In our setting, a higher clustering coefficient leads to higher peer pressure and a higher degree leads to more information. Both of these features are valuable and we characterize environments under which peer pressure is more beneficial and contrast them to settings where access to information is more important. We then obtain theoretical predictions for when we would expect men to perform better than women, which we connect in Section 6 to observed disparities in labor market outcomes. Our first step is to develop a model that translates clustering into peer pressure and the degree into access to information, highlighting our main theoretical mechanism.

3 Model

We consider an undirected network g of N workers. Two of those workers, $i, j \in N$, are selected in each period t. We focus here on a two period model, $t \in \{1, 2\}$, to keep our set up as simple as possible but note that it is straightforward to extend our setting to more periods. Once two workers are selected they have to complete a project. Whether they are successful depends on their exerted effort, their network structure and past project outcomes. In order to highlight how each of these factors matter we first consider the game that is played in each period t.

1. Worker Selection At the beginning of each period, two workers are drawn at random from the set of workers to complete a project. These workers can be linked directly, where a link between i and j, denoted by $g_{ij} = g_{ji} = 1$, implies a good relationship between coworkers. We assume that two workers can only complete their project successfully if there exists a direct link between them. If there is no link between two selected workers, their project fails with certainty, leading to zero payoff.[24] The number of links of worker i, his degree, is denoted by d_i. Then, the probability of being selected for a project and being partnered with a directly connected worker is given by (see Appendix)

$$s_i = \frac{2d_i}{N(N-1)}.$$

This probability is proportional to the degree of an individual, that is workers with higher degrees will be selected more often into potentially profitable projects.[25]

2. Information Every period is marked by a state of the world, θ, which can be high or

[24] A link or rather a good relationship between workers makes them better team partners. To simplify, we set the payoff of projects between unlinked workers to zero.

[25] This is in line with Aral et al. (2012), who study project performance in a recruiting firm. They find that peripheral nodes, i.e. nodes that are not well connected, do fewer projects per unit of time than central nodes.

low

$$\theta = \begin{cases} \theta_h & \text{with probability} \quad q \\ \theta_l & \text{with probability} \quad 1-q. \end{cases}$$

It is drawn after project teams are formed and is not observable to the workers. In the high (low) state, the project value is $2v_h$ ($2v_l$), with $v_h > v_l$. We assume that the payoff of the project is split equally among the project partners.[26]

In the following, we show how a worker's network structure affects his information about the state of the world. Each worker obtains a signal $x_i \in \{0, 1\}$ about the state, where $x_i = 1$ indicates the high state. Signals are informative in the sense that $Pr(x_i = 1|\theta_h) = p > \frac{1}{2}$ and $Pr(x_i = 1|\theta_l) = 1 - p$.[27]

Each worker receives one signal directly, but can also observe the signals of all workers he is directly or indirectly connected to. Note that the entire network might or might not be connected (where *connected* means that there are no isolated nodes). We denote the overall number of signals a worker receives by n_i. We allow for $n_i > N$ and interpret the additional signals (i.e. the signals beyond the number of workers in the network N) as basic information everyone possesses, which enables us to vary the baseline amount of information below.

Based on the observed signals, a worker can compute a sufficient statistic y_i, which is the number of high signals out of all observed signals, that is $y_i \in \{0, 1, \ldots, n_i\}$. Note that for two (directly or indirectly) connected workers, i and j, $y_i = y_j$.[28]

As our focus is on the effects of ego-networks, we distinguish between the number of signals a worker obtains from himself and his direct friends, $n_{int,i} = d_i + 1$ and the signals he obtains indirectly from external sources, $n_{ext,i}$, with $n_i = n_{int,i} + n_{ext,i}$.[29]

Based on y_i, the posterior probability of being in the high state, $Pr(\theta_h|y_i)$, is computed via Bayesian updating and thus having a higher number of signals gives a more precise

[26]We impose the equal split assumption as we aim for a model in which agents are perfectly symmetric except for their network. This allows to show the effects of network structures in the cleanest way possible.

[27]Put differently, if $\theta = \theta_h$, each signal $x_i \sim$ Bernoulli(p) and if $\theta = \theta_l$, this signal is $x_i \sim$ Bernoulli($1 - p$).

[28]To be precise, let $n_{max} = max_i n_i$. Then $y_i, i = 1, ..., N$ takes values on $Y = \{0, 1, \ldots, n_{max}\}$.

[29]Ego networks consist of a focal node (*ego*) and the nodes to whom ego is directly connected to (*friends*) plus the ties, if any, among the friends.

posterior. The project value, $\pi(y_i)$, is then given by

$$\pi(y_i) = Pr(\theta_h|y_i)v_h + (1 - Pr(\theta_h|y_i))v_l.$$

To summarize, the network structure matters as a higher degree gives a higher number of internal signals, which in turn affects the expectation about the project value.

3. Choice of Effort The paired workers simultaneously choose what effort, $e_i \geq 0, \forall i$ to exert on the project. This effort is costly with all workers facing the same cost function $c(e)$. We assume quadratic costs $c(e) = ke^2$, where $k > 0$. Given that the project certainly fails if the two project partners are not connected, we focus on the effort choice of two directly linked project partners. Effort makes project success more likely. The probability that the project is completed is given by the success probability function $f(e_i, e_j) \in [0, 1)$. In order to ensure that $f(e_i, e_j)$ is strictly smaller than one, we assume that effort is bounded, $e_i \in E = [0, e_{max}]$ where $f(e_{max}, e_{max}) < 1$.[30] This implies that success cannot be guaranteed. We impose the following assumptions on the success function.

Assumption 1. *Success Probability Function $f(e_i, e_j)$:*

(a) *Symmetry: e_i and e_j enter $f(e_i, e_j)$ symmetrically.*

(b) $f_1(e_i, e_j) = f_2(e_j, e_i) > 0$

(c) $f_{11}(e_i, e_j) = f_{22}(e_j, e_i) < 0.$

(d) *Strict Supermodularity:* $f_{12}(e_i, e_j) = f_{21}(e_i, e_j) > 0.$

(e) $f(e_i, 0) = f(0, e_j) = 0.$

(f) $f(\lambda e_i, \lambda e_j) = \lambda f(e_i, e_j)$, $\lambda e_i, \lambda e_j \leq e_{max}$.

The effort levels of the workers are complements. We focus on complements as the natural benchmark for a team problem since with substitutes a worker should complete the project by himself, circumventing the team moral hazard problem. Additionally, if one team member chooses zero effort, the project fails for sure. We assume further that the success probability function exhibits constant returns to scale. We know that $e_i \in [0, e_{max}]$. If $\lambda \in [0, 1]$, then $\lambda e_i \leq e_{max}$, and for $\lambda > 1$ we impose the additional restriction that $\lambda e_i \leq e_{max}, \forall i$. After effort has been chosen, the project outcome – success or failure – is realized.

[30] By choosing an appropriate bound on v_h, we can guarantee an interior solution $e \leq e_{max}$.

These three stages occur in both periods. What differs across periods is information (i.e. the signals workers obtain) and the effect of peer pressure (which impacts effort only if today's project outcome matters for tomorrow's). Effort depends on information through the sufficient statistic y. It depends on peer pressure because publicly observable past project outcomes affect current relationships between workers, especially when the network is characterized by high clustering. We now outline the peer pressure channel and how past project outcomes matter rather informally, formal details are in the Appendix.

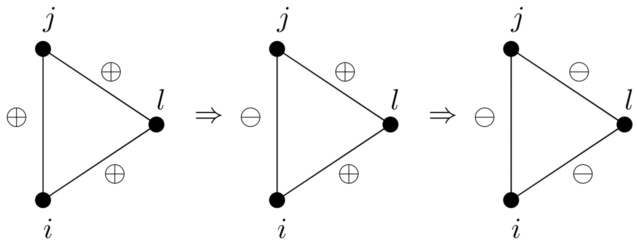
We assume that a failure has an impact if the same team partners are chosen in two consecutive periods. We believe it is intuitively plausible that a project failure leads to discord among team partners and their relationship turns 'bad'. The failure has to be justified, which is disagreeable and affects their relationship. We further argue that this discord between team partners also spreads to common friends. This idea is based on the well-established *structural balance theory*. According to this theory, triads of friends are only stable as long as the relationships are balanced. Suppose that i, j and l are all directly connected. Initially, all their relationships are 'good'. Then, i and j work on a project together that fails, turning their relationship into a bad one. But a triad with one bad relationship and two good ones is unstable. This instability is resolved by the workers taking sides. To simplify our analysis, we assume that *all* relationships in a triad will be bad after a project failure.[31] This is why project failures affect workers with high clustering more than those with low clustering. They are deprived of more future project opportunities. This sequence of events is depicted in Figure 1, where a plus (minus) signifies a good (bad) relationship.[32]

Each project failure induces some bad relationships, whereas a project success means that all directly connected workers remain in good terms. We denote the quality of the relationship by $\gamma \in \{\gamma_b, \gamma_g\}$, that is the relationship can be good or bad. The relationship between i and j is bad after a project failure in the previous period if either (1) i and j were teamed in the previous period or (2) i or j were teamed with a common friend in the

[31] Our assumption is a simplification of the following idea: Given a project failed, a worker faces with a positive probability more than one negative connection if he and the project partner had common friends, but only has one negative connection if the project failed with someone he does not have a common friend with.

[32] Note that discord does not imply that links are cut. If there is no link between two workers, then they never get along. Once a link exists, we interpret this as two individuals getting along in principle. Thus, a bad link is transitory. Also, information is still transferred if the link is bad but is not if the link was cut.

Figure 1: Structural Balance Theory



previous period. Otherwise, i and j have a good relationship. We assume that in period one the relationship between any two workers is good.

This relationship quality between two directly connected workers constitutes a state, $\gamma \in \Gamma$, and we can define a pure public strategy $\sigma(\gamma, y) : \Gamma \times Y \to E$, which maps from the relationship state and the signals into the action space.

Due to our restriction to public strategies, the equilibrium concept applied is that of a public perfect equilibrium. We index the variables in the second period by *prime*.

Definition 1. *A public perfect equilibrium (PPE) is a profile of public strategies σ that for any state $\gamma, \gamma' \in \Gamma$ and for any signal realization $y, y' \in Y$ specifies a Nash equilibrium for the repeated game, i.e. in the first period, $\sigma(\gamma_g, y)$ is a Nash equilibrium and in the second period $\sigma'(\gamma', y')$ is a Nash equilibrium.*

In our setting a higher degree leads to more signals, allowing for a more precise belief about the project value. Higher clustering, on the other hand, makes a bad relationship after a project failure more likely and therefore incentivizes effort through peer pressure. This is the basic trade-off we are focussing on. We will show in more detail how peer pressure influences effort choices in the dynamic setting but, before doing so, we want to discuss the static case, where only information matters. After presenting the full model and our results, we will justify our equilibrium selection, comparing the workers' payoffs from choosing this strategy to the payoffs of other strategies.

4 Static Decision Problem

In the static setting, worker i chooses effort to maximize his expected payoff, given by

$$\max_{e_i \in E} f(e_i, e_j)\pi(y) - c(e_i). \tag{1}$$

Recall that $y_i = y_j = y$ since each worker observes not only his own signal but also the signals of all workers he is (in)directly connected to, so we write $\pi(y)$. Given our assumptions on $f(\cdot,\cdot)$ and $c(\cdot)$, the first order condition of (1) is both necessary and sufficient for a maximum. The same holds true for worker j. Based on the first order approach, we can determine the pure strategy public perfect equilibria of the game where, to simplify notation, we define $e(y)$ to denote the optimal strategy based on y.

Proposition 1 (Public Perfect Equilibria Static Game)**.** .

1. *Every public perfect equilibrium is symmetric such that $e_i(y) = e_j(y) = e(y)\ \forall y$.*
2. *For each y, there exist exactly two pure public perfect equilibria.*

$$\begin{aligned} &\textit{(a) Zero effort:} && e(y) = 0 \\ &\textit{(b) Strictly positive effort:} && e(y) = \frac{f_1(1,1)\pi(y)}{2k} \end{aligned} \tag{2}$$

.

All proofs are in the Appendix. Given the symmetry in our setting, in particular, the symmetry of success function $f(\cdot,\cdot)$, identical cost functions $c(\cdot)$ and equal split of the payoff, both workers will always exert the same effort in equilibrium. We further show that the one-period problem has two pure strategy PPE. There always exists a PPE where both project partners exert zero effort independently of signal realizations. It is a best response to choose zero effort given the other worker has chosen zero effort as $f(e_i, 0) = f(0, e_j) = 0$. Each team member has to exert at least some effort for the project to be successful. But there also exists a PPE with strictly positive efforts. The uniqueness of the positive effort equilibrium follows from supermodularity and constant returns to scale property of $f(\cdot,\cdot)$, as well as the convexity of the cost function. In particular, we obtain a closed form expression for effort when taking into account symmetry across team members, where k is the multiplicative constant in the cost function and where $f_1(1,1)$ is a constant as well.

We are now interested in how network characteristics influence equilibrium effort through the information channel in the static model. All else equal, a worker with a higher degree receives more signals about the state of the world. We want to know how effort varies with the number of signals.

It follows from (2) that effort positively depends on the project value $\pi(y)$. We focus on how the *expected* project value, $E(\pi(y))$, varies with the number of signals as this is the channel through which information affects effort. If additional signals increase the expected project value, then expected effort, $E(e(y))$, increases as well. A worker has an incentive to work harder if he believes the payoff for his work to be higher.

We first show that $\pi(y)$ has the martingale property, meaning that it is unaffected by the number of signals, which follows from Bayes' Rule. This is not true once we condition on the state. To emphasize that a worker receives n signals, we denote the project value by $\pi(y_n)$ instead of $\pi(y)$.

Lemma 1 (Information and Expected Project Value)**.** $\pi(y_n)$ *satisfies the martingale property:* $\pi(y_n) = E(\pi(y_{n+1})|y_n)$. *However, given that the state is realized, a worker with more signals holds a more accurate posterior belief about the state of the world and thus about the project value:*

$$v_h > E\left(\pi(y_{n+1})|\theta_h\right) > E\left(\pi(y_n)|\theta_h\right) \qquad v_l < E\left(\pi(y_{n+1})|\theta_l\right) < E\left(\pi(y_n)|\theta_l\right).$$

The impact of an additional signal vanishes, if uncertainty vanishes, i.e. $E\left(\pi(y_n)|\theta\right) = E\left(\pi(y_{n+1})|\theta\right)$, *if either (i)* $v_l \to v_h$ *(ii)* $p \to 1$, *(iii)* $q \to 1$ *if* $\theta = \theta_h$, $q \to 0$ *if* $\theta = \theta_l$, *or (iv)* $n_{ext} \to \infty$.

An additional signal does not contain further information about the state of the world, given the state of the world has *not* been realized, that is $E\left(\pi(y_n)\right) = E\left(\pi(y_{n+1})\right)$. But once the state of the world has been realized, this is no longer true. Since signals are informative, the more signals are available the more accurate is the posterior belief about the state of the world. The expected project value increases in the number of signals if the state of the world is high and decreases in the number of signals if the state of the world is low. This implies that, given the high state of the world, a worker with more information expects a higher project value compared to a worker with less information. If the low state has been realized, the reverse is true.

The expected project value becomes *independent* of the number of overall signals n when the uncertainty of the underlying environment vanishes. This can happen for four reasons: (i) There is no difference between high and low project values. (ii) The signals are completely informative.[33] (iii) A worker's prior reflects complete certainty about the

[33] In fact, the expected project value also becomes independent of the number of overall signals n when signals are completely uninformative $p \to 0.5$.

state of the world. (iv) Moreover, if overall information becomes abundant, which happens when the number of external signals, n_{ext}, becomes large, then in the limit, all agents know the state of the world with certainty even if the number of signals obtained through their ego-networks, n_{int}, differs. The expected payoff converges to the high (low) value when the state is high (low). In sum, the effect of additional information on the expected project value is reinforced when the uncertainty of the underlying environment is considerable and dies out when uncertainty vanishes.

Taking Lemma 1 together with equation (2), we can shed light on the effect of information on expected effort, summarized by the following proposition.

Proposition 2 (Information and Expected Effort)**.** *A worker with more information, i.e. with a higher degree, exerts on average more (less) effort when the state of the world is high (low) compared to a worker with less information. The impact of additional signals on effort vanishes as the underlying uncertainty vanishes.*

A worker with a higher degree and thus more signals holds more accurate information about the state of the world. In the high state, he exerts on average higher effort compared to a worker with lower degree. The opposite is true for the low state. Intuitively, workers with more accurate information, i.e. more signals, can better fine-tune their effort to the expected project reward.

5 Dynamic Decision Problem

Having discussed the static game, we can now analyze the agents' effort choices and how they depend on their network characteristics in a dynamic setting. Here, not only agents' *degree* but also their *clustering* matters for their actions as they adjust their effort to their relationship quality, namely $\forall\ y'$

$$\sigma'(\gamma_g', y') > 0 \qquad \text{and} \qquad \sigma'(\gamma_b', y') = 0.$$

This implies that, when two workers have a bad relationship, they exert zero effort. We know from the static game that zero effort constitutes a PPE in every period, regardless of the signals. In turn, when two team partners have a good relationship they exert strictly positive effort. In what follows, we focus on the dynamic decision problem that pins down the high effort PPE in both periods. We are interested in what determines this choice.

The dynamic maximization problem of team partner i reads

$$\max_{e_i, e_i'} \quad -c(e_i) + f(e_i, e_j)\left(\pi(y) + \beta s_i E\left(f(e_i', e_k')\pi(y') - c(e_i')\right)\right)$$
$$+ (1 - f(e_i, e_j))\left(0 + \beta s_i (1 - r_{ij}) E\left(f(e_i', e_k')\pi(y') - c(e_i')\right)\right) \qquad (3)$$

where the expectation is taken over all possible signal realizations in period two. Problem (3) is dynamic since workers choose today's effort not only based on the current project payoff but also based on the second period expected payoff, taking into account that today's project outcome matters for tomorrow's through its impact on relationships. Therefore, this expected payoff of workers i and j, who are teamed up in period one, depends not only on second period performance but also on

(i) the probability of being selected next period, s_i and s_j, defined in the section on worker selection,

(ii) the probability of *first period* project success, $f(e_i, e_j)$, or failure, $1 - f(e_i, e_j)$, as well as

(iii) the probability that in the next period they are doing a project with someone who would be affected by today's project failure, *given* that they are chosen for a project, r_{ij} and r_{ji}, with r_{ij} given by

$$r_{ij} \equiv \frac{1 + \sum_{k, k \neq i, k \neq j} g_{ik} g_{jk}}{d_i} = \frac{C_{ij}}{d_i}. \qquad (4)$$

The term $\sum_{k, k \neq i, k \neq j} g_{ik} g_{jk}$ denotes the number of common friends of i and j and therefore C_{ij} is a proxy for their common friends. Equation (4) gives the probability of workers having a bad relationship after a failure. They are only affected by their failure if they are chosen to do a project together again or with a common friend in the second period.

We solve problem (3) by backward induction, starting in the second period. Clearly, the second period problem is identical to the static problem.[34] Recall that the high effort level is given by

$$\sigma_i'^*(\gamma_g', y') \equiv \arg\max_{e_i'} V_i(\gamma_g', y') = \arg\max_{e_i'} [f(e_i', e_j')\pi(y') - c(e_i')], \qquad (5)$$

[34] As j and k belong to the same set, namely the friends of i, we can replace k in the second period by j.

where $\sigma_i'^*(\gamma_g', y')$ is the optimal second period effort level if the project partners have a good history and observe signals y' (see equation (2) for the solution to this problem). From here onwards, we denote this equilibrium effort by $e_i'(y) \equiv \sigma_i'^*(\gamma_g', y')$. Moreover, we denote the maximized second period payoff by $V_i^*(\gamma_g', y')$. Then, the maximization problem of agent i in the first period reads

$$\max_{e_i} \quad f(e_i, e_j)\pi(y) - c(e_i) + \beta s_i(f(e_i, e_j) + (1 - r_{ij})(1 - f(e_i, e_j)))EV_i^*(\gamma_g', y') \tag{6}$$

Similar to the static problem, we show that there exists a unique PPE in which both team partners exert positive effort. The solution to (6) is given by $e_i(y) \equiv \sigma_i^*(\gamma_g, y)$.

Proposition 3 (Public Perfect Equilibria Dynamic Game)**.** .

1. *Both project partners always exert the same effort in any PPE, that is effort is symmetric.*
2. *In both periods, there exists a unique PPE in which both team partners exert strictly positive effort,* $\forall y, y'$

$$\begin{aligned} e_i(y) = e_j(y) =& \frac{f_1(1,1)(\pi(y) + \beta srEV^*(\gamma_g', y'))}{2k} \\ e_i'(y') = e_j'(y') =& \frac{f_1(1,1)\pi(y')}{2k} \end{aligned} \tag{7}$$

We already know from Proposition 1 that in the second period there exists a unique PPE with strictly positive effort, which is symmetric. But also in the first period, effort levels are symmetric. This is because two workers can only have the same number of common friends, implying that $s_i r_{ij} = \frac{C_{ij}}{\frac{1}{2}(N-1)N}$ is constant across project partners and, thus, $\beta s_i r_{ij} EV_i^*(\gamma_g', y') = \beta srEV^*(\gamma_g', y')$.[35] Moreover, for $y = y'$ first period effort is higher than second period effort, stemming from the dynamic effort-enhancing effect of clustering: Having common friends creates particularly strong incentives for effort, reducing the team moral hazard problem that causes effort to be inefficiently low.

Again, we are interested in how the agents' network characteristics affect effort. We first discuss the effect of *degree*, which impacts effort through the information channel.

[35] In the last period, T, the network structure does not matter, as there is no threat of bad relationships in the future, and thus effort levels are symmetric as information is symmetric. In $T-1$, when calculating the expected value of T the workers know that the effort levels will be symmetric in T. As sr is also symmetric, this implies that effort levels are again symmetric. However, this symmetry breaks down in $T-2$. Then, when calculating the expected value, the workers need to also take into account with whom they will be teamed up and the sr symmetry will no longer hold.

We then turn to the effect of *clustering*, which influences effort through peer pressure.

Taking expectations over first period signals in (7), it follows that information impacts expected effort through the expected first period project value, $E(\pi(y))$, and second period value, $EV^*(\gamma_g', y')$. Both have a positive effect on effort. Recall from our discussion on the static game that $E(\pi(y))$ positively (negatively) depends on the number of signals if the state is high (low). To see how the expected value, $EV^*(\gamma_g', y')$, depends on the number of signals and thus information, we first establish that $V^*(\gamma_g', y')$ is a convex function of the second period project value, $\pi(y')$ (which, in turn, is a martingale). To simplify notation, we write $EV^*(y')$ instead of $EV^*(\gamma_g', y')$.

Lemma 2 (Information and Second Period Expected Value)**.** *$V^*(y_n')$ is a submartingale. And, thus, a worker with more signals has a higher second period expected value:*

$$E(V^*(y_n')) < E(V^*(y_{n+1}')),$$

The impact of an additional signal vanishes, if uncertainty vanishes, i.e. $E(V^*(y_n')) = E(V^*(y_{n+1}'))$, if either (i) $v_l \to v_h$ (ii) $p \to 1$ (iii) $q \to 1$ if $\theta = \theta_h$, $q \to 0$ if $\theta = \theta_l$, or (iv) $n_{ext} \to \infty$.

To gain some intuition into this result first suppose that the additional signal is high. This implies that effort increases, that the project value increases and that the overall payoff, $V^*(y)$, increases as well. If the additional signal is low, then effort decreases, the project value decreases and the overall payoff is lower. But due to the convexity of the payoff, an additional positive signal has a stronger effect than an additional negative signal. Therefore, having an additional signal increases the expected value in the second period unless uncertainty vanishes. As in the static game (see Lemma 1), here additional information has no impact if (i) there is no variance in the project value across states, (ii) if signals are completely informative, (iii) if the prior is correct, or (iv) if overall information becomes abundant. Intuitively, information only matters under uncertainty.

In turn, the effect of peer pressure, $s_i r_i$, on first period effort (through clustering) is straightforward and unambiguously positive.

We summarize the effect of information and peer pressure (and thus of the agents' network characteristics) on first period effort in the next proposition.

Proposition 4 (Information, Peer Pressure and Expected First Period Effort)**.** *More information, i.e. a higher degree, unambiguously increases expected first period effort only if the state* *is high. Furthermore, higher peer pressure, i.e. higher clustering, increases expected first period effort independently of the state of the world. Finally, unless uncertainty vanishes, a worker with more information but less peer pressure better adjusts his effort to the expected project value compared to a worker with less information and more peer pressure.*

The proof follows immediately from Lemmas 1 and 2 and equation (7) and is therefore omitted. Both network characteristics, high degree and high clustering, affect first period effort and thus project completion. A higher *degree* improves information about the state of the world. This information is particularly beneficial when the true state is high and, at the same time, when the agents' uncertainty about the state is considerable. In this case, additional signals induce the agents to put significantly more weight on the high state, translating into higher effort. (The same logic also applies to second period effort, given by the static case in Proposition 2.)

In turn, *clustering* positively impacts first period effort through a dynamic peer pressure effect. This channel is *independent* of the true state of the world and the underlying uncertainty. Peer pressure induces higher effort because a potential project failure today puts more friendships and thus future project opportunities in jeopardy. Since workers with more information are more selective with their effort choice (depending on the state) and workers facing peer pressure increase their effort no matter the expected payoff, it follows that workers with a higher degree are better able to fine-tune their effort to the project reward than workers with higher clustering. This means that their difference of efforts across states, $E(e(y)|\theta_h) - E(e(y)|\theta_l)$, is larger, which follows directly from (7).

We now turn to the agents' wages, which are tightly linked to their effort choices. Denote the probability of having a good relationship with the second period project partner given first period state by

$$Pr(\gamma_g'|\theta) \equiv E[f\left(e(y), e(y)\right) + (1 - r_i)(1 - f\left(e(y), e(y)\right))|\theta] = E(e(y)|\theta) r_i f(1, 1) + 1 - r_i.$$

We define first and second period wages conditional on the state as follows:

Definition 2 (Equilibrium Wages)**.** *First and second period wages for a given state are respec-*

tively defined as

$$w_i(\theta) \equiv E[f\left(e(y), e(y)\right) v|\theta] = E(e(y)|\theta) f(1,1) v(\theta) \tag{8}$$

$$w_i'(\theta, \theta') \equiv s_i Pr(\gamma_g'|\theta) E[f\left(e'(y'), e'(y')\right) v'|\theta'] = s_i Pr(\gamma_g'|\theta) E(e'(y')|\theta') f(1,1) v(\theta') \tag{9}$$

where $\theta, \theta' \in \{\theta_l, \theta_h\}$ *is the realized first (second) period state.*

These are *expected* wages because even though positive effort is exerted there is no guarantee for project success. The wages reflect that the agents obtain their share of output in case the project is successful. We define these wages *given* that a certain state of the world has materialized. The expected wage across states can then be easily computed, e.g. $E(w_i) = qw_i(\theta_h) + (1-q)w_i(\theta_l)$.

Notice that the structure of both periods' wages is the same, only that in the second period, one also has to take into account the probability of being selected for a project with someone the agent is on good terms with (i.e. the probability of having a good friendship history with the project partner, given by $Pr(\gamma_g'|\theta)$). Since friendship histories matter, the second period expected payoff depends not only on contemporaneous effort but also on first period effort.

Both periods' wages are increasing in effort, highlighting the tight link between the agents' actions and their rewards. As a consequence, Propositions 2 and 4 on the effects of network characteristics on effort give insights into how degree and clustering affect the agents' wages. We summarize these results in the next proposition.

Proposition 5 (Information, Peer Pressure and Wages)**.** *More information, i.e. a higher degree, unambiguously increases first and second period wages only if the state is high in both periods. The effect vanishes as uncertainty vanishes. In turn, peer pressure, i.e. higher clustering, increases the first period wage independently of the state but has an ambiguous effect on second period wage.*

These results follow from Propositions 2 and 4 and wage Definition 2. Information (and thus a high degree) leads to a significant boost in effort and wages if the underlying state of the world is high because agents want to reap the benefits of a high project value.[36] Through the effort channel, information only increases wages if there is uncertainty about the state of the world. In turn, when the agent faces a dynamic decision

[36] If the state is low, it is ambiguous whether clustering or degree leads to a higher wage.

problem (i.e. in the first period), higher clustering unambiguously increases effort and wages through peer pressure, independent of the state and underlying uncertainty. Only in the second period, the effect on wages is ambiguous: Peer pressure leads to higher first period effort (increasing $Pr(\gamma_g'|\theta)$), but many common friends also make a non-intact relationship with the second period team partner more likely (decreasing $Pr(\gamma_g'|\theta)$).

While this discussion has focussed on comparative statics effects of a single network characteristic holding other network characteristics fixed, we now turn to the more interesting but also more involved case of comparing two types of workers: one with higher degree but lower clustering (denoted as D-worker) and one with lower degree but more clustering (denoted as C-worker).

Proposition 6 (Trade-Off Between Information and Peer Pressure). *Suppose that $v_l = 0$. (i) Wage Dynamics: If a C-worker has a lower first period wage than a D-worker, then he also expects a lower wage in the second period, even if second period uncertainty vanishes. This wage gap arises even if both workers perform equally well in the first period. (ii) Comparative Advantage: If $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are sufficiently concave in information n, signal precision p, or the prior belief q, C-Workers hold a comparative advantage in environments with less uncertainty, that is, $\frac{E(w^C)}{E(w^D)}$ increases as uncertainty becomes smaller.*

We make these statements precise in the Appendix where all the formal conditions are provided. Our model predicts a strong impact of early career wages on the future wage trajectory through peer pressure, which puts workers with high clustering but low information into disadvantage. Notice that wage gaps between C-workers and D-workers arise even if they exert the same effort in the first period. Moreover, if these wage gaps exist in the first period, they persist in the second period even if they perform equally well (i.e. even if uncertainty vanishes in the second period).

Our model also predicts that workers with higher clustering and less information have a *comparative advantage* in environments characterized by less uncertainty compared to workers with less clustering and more information. That is, the ratio of expected wages of C-workers to D-workers increases when uncertainty diminishes, which happens when either the amount of overall information, n, increases, when signals become more informative (for p sufficiently large), or when the prior belief q becomes more correct.[37] This is consistent with our previous predictions: Clustering gains importance as uncertainty vanishes.

Our framework allows us to rank networks according to effort choices and wages for different underlying environments. We now connect our theoretical predictions with our empirical finding that men have a higher degree and women more clustering.

6 Performance of Men versus Women

In this section, we use our model to analyze how peer pressure and information influence performance and wages of men versus women. We show that these results are consistent with various observed gender differences in labor market outcomes. Previously, we showed that women have a higher clustering coefficient and a lower degree than men, that is, they face more peer pressure but are less informed. We therefore want to compare agents with these features. To do so, we fix the number of links and nodes in the network, so additional clustering comes at the cost of a lower degree and vice versa. Thus, there is a trade-off between degree and clustering which then translates into a trade-off between peer pressure and access to information and it is not a-priori clear which network characteristic is more conducive to project success and wages.

In what follows, we use our model to predict in which environments men outperform women and show that these predictions are in line with the following empirical facts.

1. Wage and performance gaps between men and women are especially large within occupations and tasks characterized by uncertainty like in the financial sector, film-industry and basic research.

In most developed countries, the gender wage gap is still large. In the US in 2012, for instance, women's earnings were 80.9% of men's earnings.[38] Part of it can be explained by differences in occupational choices where women select into low-paying occupations while men go into high-paying jobs. However, even *within* occupations wage gaps are considerable. Notably, some occupations are more affected than others. In the

[37]In the Appendix, we show that the ratio $\frac{E(w^C)}{E(w^D)}$ is *strictly* increasing as uncertainty decreases. Hence, the result clearly holds for positive but small v_l. In simulations, we also allow for $v_l >> 0$: When project values, v_l and v_h, become more similar across states, then the ratio of expected wages of C-workers to D-workers increases. See Figure 2 in the Appendix.

[38]See http://www.bls.gov/cps/cpswom2012.pdf

US, the within-occupational wage gap is pronounced in management occupations, especially for financial managers and chief executives where female earnings are respectively 70.3% and 76% of male's, as well as in business and financial operations occupations where women earn 74% of men's earnings. In contrast, the wage gap is much smaller in healthcare support and administration where women's earnings are respectively 90.2% and 89.9% of men's.[39] A similar pattern was found in the UK, where full-time working women in the financial sector earn 55% less than full-time male workers – a gap twice as large as the gap in the economy as a whole.[40] In addition, the evidence suggests that women's lower earnings in financial management and executives occupations are especially due to large differences in performance pay and bonuses.[41]

Another well-studied sector where gender inequalities persist is the film industry (Lutter (2012) and Lutter (2013)). This industry is highly project-based where tasks involve little routine work and have uncertain outcomes. Ferriani et al. (2009) argue that the film market requires constant adjustment to new work environments since film ventures operate under constant uncertainty and have to foresee ex-ante whether the project opportunity is valuable. Women in this sector generate lower box revenues from movies, which is a direct measure of performance.

Last, an area well-known for gender disparities is the market for patents. Hunt et al. (2012) document that women in the US are much less likely to be granted a patent than men, with women holding only 5.5% of commercialized patents. This is not due to women's underrepresentation in science and engineering degrees but due to their underrepresentation in patent-intensive fields of study as well as patent-intensive job tasks like design and development. Again, patents can be seen as measures of performance.

This implies that the gender wage gap is particularly pronounced in occupations or tasks characterized by a large amount of uncertainty, commonly measured by earnings variability. Income is based on success which is difficult to foresee. Earnings of executives and financial managers are largely based on performance pay. Similarly, the success of research (and patents) as well as movies is difficult to foresee at the time of production.

Our model provides a new mechanism why men outperform women under uncer-

[39] See BLS-Reports (2013), http://www.bls.gov/cps/cpswom2012.pdf

[40] Wage differences are considerable even when controlling for hours of work (full time) and type of job. See the report by the Equality and H.R.Commission (2009).

[41] See the report by the Equality and H.R.Commission (2009).

tainty. The main prediction is that men's network structure is conducive to information acquisition which is more valuable in such environments than the undifferentiated effort-enhancing effect of women's peer pressure.

Our network-based view finds support in various empirical studies on financial and management occupations, the film industry and patenting. Forret and Dougherty (2004) analyze the impact of networking activities on career outcomes (promotions, total compensation and perceived career success) of male and female MBA graduates over 35 years in the U.S. Those graduates take on positions in management, finance, marketing and other professional jobs – occupations characterized by relatively large amounts of earnings variability. They find that only for men, network activities positively affect career outcomes. The authors speculate that the reason for this finding is that women network less effectively. We propose a theory *why* women's networks are less effective in these settings.

As far as the film industry is concerned, Ferriani et al. (2009) argue that information is crucial to identify potentially successful scripts and to assemble the right project team. Based on the finding that producers who are more central in their network (i.e., have more access to information) are more likely to increase the box revenue from a movie, the authors conclude that social networks provide crucial access to information. In a similar vein, Lutter (2013) documents that women with loose information-based networks perform better in the film-industry than women with dense networks, supporting our hypothesis that information is the key to success in uncertain environments.

With regards to research and development, Gabbay and Zuckerman (1998) document that in basic research, which is typically characterized by complex, uncertain tasks, scientists benefit from sparse networks with many holes, whereas in applied research, which is typically characterized by non-complex, certain tasks, scientists benefit from dense networks. Supporting this view, Ding et al. (2006b) argue that an important reason for the gender wage gap in patenting is that women's networks are less effective: In relying more on close relationships, they lack reach to industry contacts.

Our theory offers a unified explanation for these findings. In uncertain environments, information is crucial for success and men hold more of this type of social capital than women. We show next that this argument also provides a rationale for why occupational choices differ across gender.

2. More men than women choose occupations with high earnings volatility.

Dohmen and Falk (2011) show that men rather than women select into "risky" jobs that are characterized by performance pay and high earnings volatility. They explain this finding, arguing that men and women face *the same* mean-variance trade-off with regards to wages in all occupations but differ in their attitude towards risk (with men being less risk-averse). We offer an alternative explanation, which is based on comparative advantage. Our model predicts that women have a comparative advantage in environments characterized by lower uncertainty.

In such environments, women put relatively more effort than men, translating into relatively higher earnings, compared to more uncertain environments. In turn, in uncertain environments, men tend to face more income dispersion but are compensated for this risk by higher expected wages. We do not model occupational choice explicitly but this argument suggests that women would select into environments with low uncertainty whereas the opposite is true for men. Notably, this holds even though both men and women are risk-neutral and hence do not differ in their risk attitudes.

3. Having women in the network is particularly beneficial high up in the organizational hierarchy.

Lalanne and Seabright (2011) document empirically that having females in the network is beneficial to both male and female executives but not to agents at lower levels in the organizational hierarchy. We believe that networks at high levels of the hierarchy are considerably larger than at lower levels. Hence, information is particularly scarce at the beginning of the career but abundant at the executive level. The more information there is, the lower is the uncertainty about the true state, making men's additional information less valuable. To the contrary, women bring closure to the network, which is particularly beneficial once a sufficient amount of information is available. Therefore, in line with Lalanne and Seabright (2011), our model predicts that at management levels, it is especially profitable to have women in the team because, in environments saturated with information, women's peer pressure kicks in more strongly than men's additional information.

Walker et al. (1997) provides additional support for this view, arguing that sparse networks are most important at the beginning of the network formation process. They analyze the changing value of social capital over the life cycle of inter-firm networks and find that being at a position that bridges a structural hole is more valuable at early stages of network formation, since most tasks of the early networks are informational. However, as the network becomes established, densely connected network relationships and closure become more valuable than brokerage opportunities. In a similar vein, Ferriani et al. (2009) show that producers in the film industry who are more central in the network (i.e., have more access to information) are more likely to increase the box revenue from a movie but that returns to centrality become smaller the more central the producer is. Our theory sheds light on the diminishing returns to network reach (i.e. to degree) and provides a mechanism for why the different types of social capital that emerge from tight and lose networks are complementary.

4. During recessions men's unemployment exceeds women's unemployment.

Albanesi and Sahin (2013) find that this is true even when controlling for sectors. Employers seem to have a preference for keeping woman on their workforce during recessions, a pattern our model can help understand. Our model predicts that women do particularly well when rewards are low, which we believe is the case in economic downturns. Men's additional information leads to a particular advantage if the state of the world is high. In this case, they are more certain than woman that the true state is high, leading to extra effort. The opposite is true in the low state where men assign a higher probability to the low state than women, leading to lower effort. In turn, women take into account that project failures hit them particularly hard because, due to more common friends, failures destroy more second period project opportunities. This effect pushes up women's effort *independently* of the state of the world.

We thus argue that women perform relatively better than men in recessions because they remain productive even if rewards are low. In contrast, men are more selective in their effort choice and better adjust their effort to the expected project value. They put low effort for low value.

5. The beginning of the career is the most decisive period for the gender wage gap formation.

Several studies point out the importance of the gender wage gap at early stages of the career for the future wage path (Babcock and Laschever (2003), Gerhart and Rynes (1991), Martell et al. (1996)). Bertrand et al. (2010a) document that, already 5 years into the career, the gender wage gap among MBAs in the US is substantial and keeps growing thereafter. Napari (2006) shows that in Finland, early years after labor market entry have the largest impact on gender wage differences. Thereafter, the wage gap simply persists. Similar findings are documented for Germany, where the entry wage gap is already 25% (Kunze (2003)).

Our model predicts a strong impact of the performance at the beginning of the career on the future income trajectory of men relative to women. This is because the second period wage does not only depend on the contemporaneous project outcome but also on first period performance. This effect is particularly important for women. Due to their higher clustering, they would lose more second period project opportunities in case of first period project failure even if first period performance is equal across gender. Moreover, a first period wage gap would persist even if there is no uncertainty in the second period. The reason is that women are more likely to be teamed up with someone who punishes them for a previous failure by exerting low effort.

7 Equilibrium Selection

In our analysis, we have selected the equilibrium that induces workers to play high effort if their relationship is good and zero effort if their relationship is bad. Alternatively, agents could choose to play the static high effort PPE each period, independently of their relationship. Another possibility is to select zero effort independently of past project outcomes and signals.[42] We evaluate these different equilibria according to their expected payoffs. We find that if workers always choose the payoff maximizing equilibrium, then the zero effort equilibrium will never be played. Men will do even better in volatile environments, whereas women keep their advantage in environments with little uncertainty, leaving our predictions of Section 6 unchanged.

In order to see this, we define the individual payoffs from choosing the static high

[42]Obviously, there are other equilibria, such as whenever a project fails, all relationships in the network turn bad and then all players choose zero effort. Another possibility is that a good relationship leads to zero effort and a bad relationship to positive effort. We find these equilibria hard to justify and therefore use the static PPE as a benchmark. Further, endogenizing the equilibrium selection is beyond the scope of this work.

effort PPE and from our proposed strategy, respectively:

$$W_i^{stat} = s_i(1+\beta)E\left[f(e'(y), e'(y))\pi(y) - c(e'(y))\right], \tag{10}$$

$$\begin{aligned} W_i^{dyn} =& s_i E\left[f(e(y), e(y))\pi(y) - c(e(y))\right] \\ &+ s_i \beta E\left[(1 - r(1 - f(e(y), e(y))))\right] E\left[f(e'(y'), e'(y'))\pi(y') - c(e'(y'))\right]. \end{aligned} \tag{11}$$

The equilibrium we select yields a higher payoff than the static PPE whenever $W_i^{dyn} > W_i^{stat}$. To simplify notation, we let $EV_1 = E\left[f(e(y), e(y))\pi(y) - c(e(y))\right]$ and $EV_2 = E\left[f(e'(y'), e'(y'))\pi(y') - c(e'(y'))\right]$. Welfare under our strategy, W_i^{dyn}, is higher than welfare in the static high effort PPE, W_i^{stat}, whenever

$$EV_1 - EV_2 > \beta r(1 - E[f(e(y), e(y))])EV_2 \tag{12}$$

So, if $EV_1 - EV_2 > 0$ and $E[f(e(y), e(y))]$ is sufficiently large, then welfare is higher under our strategy.[43] An example for which equation (12) holds is given in the Appendix.

Notice that $E[f(e(y), e(y))]$ is large if effort is high under any signal realization. Effort does not vary greatly with the different signal realizations if the project values across states are similar, implying little uncertainty in the environment. We have shown that women exert higher effort than men in these environments, see Proposition (4).

If agents always play the strategy that yields the highest payoff, then in an environment with high uncertainty the static high effort PPE will be selected, whereas in an environment with low uncertainty and relatively high payoffs, our proposed strategy is implemented. But this implies that the differences between men and women, which we discussed in Section 6, remain unchanged. Women would do even worse than men in uncertain environments than under our strategy and perform the same in situations with low uncertainty and high payoffs.

Last, notice that the payoff maximizing equilibrium might not be selected. If a worker exerts positive effort, but his team partner shirks and only exerts zero effort, then he will face a loss. So, if there is a possibility of miscoordination it might be better to always choose zero effort. Whether the expected payoff maximizing equilibrium or the zero

[43] Note that $EV_1 - EV_2 > 0$ might not always be the case, although $e > e'$. To see this we consider the example given in Table 6 in the Appendix, where $EV_1 < EV_2$. The reason is that workers choose very high effort in the first period even if the project does not yield a payoff in order to avoid having a bad relationship in the second period.

effort equilibrium is selected is related to the question of whether the payoff or the risk dominant strategy will be played. The evidence for this is mixed at best (Van Huyck et al. (1990), Cooper et al. (1990), Cooper et al. (1992)).

We believe that it is plausible to assume that workers risk to choose the high effort which can potentially result in a loss when they trust their project partner after a good history and that they go for the strategy that ensures a nonnegative profit after a loss and thus bad history.

8 Conclusion

We identify a new dimension of heterogeneity between men and women, namely differences in their networks structure, and connect these differences to discrepancies in their labor market outcomes. We first establish that men have a higher degree than women, whereas women have a higher clustering coefficient. Based on this, we build a model that sheds light on the relative advantages of having a male network (high degree, low clustering) versus a female network (low degree, high clustering). A higher clustering coefficient implies higher peer pressure, whereas a higher degree improves access to information. Both peer pressure and access to information can attenuate a team moral hazard problem in the workplace. But whether peer pressure or access to information is more important depends on the work environment. We find that, in environments where uncertainty is high, information is crucial and, therefore, men outperform women. This uncertainty can either stem from large payoff variability, moderately informative signals, a small number of overall signals or little prior knowledge about the state of the world.

Our findings are in line with large gender wage gaps in occupations characterized by uncertainty and with the fact that more men than women choose occupations with high earnings volatility, where volatility can be interpreted as uncertainty. Additionally, it is documented that having women in the network is beneficial once there is an abundance of information. Our model suggests that this is due to women adding network closure which is more beneficial under these circumstances than additional information. Further, it is documented that women have a higher employment rate in recessions when rewards are low, which our model would also predict. Last, our model is consistent with empirical findings of how the gender wage gap changes over the career paths, with a strong impact of the early career wage gap on future wage trajectories of men and women.

We propose a novel, network-based explanation for gender differences in labor market outcomes. We see this approach complementary to other explanations, such as differences in preferences, risk aversion, bargaining behavior and discrimination. Ideally, we would like to test our theory empirically in order to quantify the impact of network differences on wages. However, data requirements are significant. We would need a dataset of informal networks *at* the workplace. We are aware of no such dataset at this moment and leave this question for future research.

It is beyond the scope of this paper to analyze the source of network differences between men and women. There could be an underlying trait that makes women choose more closed networks, such as risk aversion, which also leads them to choose different occupations. But the network structure could also emerge due to differences in games boys and girls play. Whereas boys tend to play in big groups, girls are encouraged to socialize in a different manner already from an early age onwards. So the question is whether friendship formation is guided by an innate trait or a trait that is learned.

Last, at its current stage, we do not use our model to study the optimal composition of a team. The optimal team composition should depend on the network structures of the team members. We believe that this is an interesting extension of our research, which we aim to address in future work.

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Data Appendix

Friendship Networks

The friendship information in the AddHealth data set is based upon actual friends nominations. Students were asked to name up to 5 male and female friends. Students named friends both from the school they attend as well as friends from outside the school. Some of the friends, who do not attend the same school attend a sister school[44] and can still be identified. The other friends cannot be identified and are dropped subsequently from the sample.[45]

Descriptive Statistics AddHealth

Table 3: Differences in Degree and Clustering for Men and Women

	Male Students				Female Students			
	Mean	Std Dev.	Min	Max	Mean	Std Dev.	Min	Max
Cl. Coeff.	0.117	0.195	0	1	0.130	0.195	0	1
Cl. Coeff. (dir.)	0.0876	0.151	0	1	0.0996	0.154	0	1
In Degree	3.597	3.554	0	37	3.917	3.482	0	34
Out Degree	3.417	3.660	0	10	4.100	3.651	0	10
Degree	7.014	5.921	0	44	8.017	5.970	0	43
Age	15.08	1.719	10	19	14.92	1.702	10	19
Size/1000	1.196	0.678	0.0290	2.982	1.200	0.686	0.0290	2.982
Observations	54881				53240			

Estimation Results

We estimate whether gender has a significant influence on degree as well as on the clustering coefficients. We standardize all of our measures in order to improve the interpretability of our results. Further, we normalize the age by subtracting 16. In all our regressions, we also control for school, which serves to capture location effects as well as time differences from when the data was collected. Note that we are not interested in determining which other factors influence these network characteristics, as is done e.g.

[44] A sister school is a school in the same community. So, if in a community there is a high school and a middle school, then the high school is the sister school of the middle school and the middle school is the sister school of the high school.

[45] Overall, less than 10% of the observations are dropped. We believe this to not be a problem as we are interested in a proxy for the friendship network *at* the workplace, not for the entire friendship network of individuals.

in Conti et al. (2013).[46] The purpose of this estimation is only to show that men's and women's networks differ. Our results are given in Table 4.

We find that girls have a significantly higher clustering coefficient, independently of how the clustering coefficient is measured. Both younger and older girls have a higher clustering coefficient, i.e. this characteristic does not change as students grow older. Girls also have a higher in and out degree as well as overall degree. But older girls have a lower absolute degree, out degree and in degree than younger girls, i.e. unlike with the clustering coefficients this property changes as girls mature. However, the degree does not change much for boys as they grow older. When just taking into consideration the oldest students, i.e. those aged 18 and 19, which are the students we are most interested in as we are interested in the network properties of men and women, girls have a lower in, out and overall degree.[47]

Technical Appendix A

Derivation of s_i

The probability that one agent is chosen is given by $Pr(K) = \frac{N-1}{\frac{1}{2}N(N-1)} = \frac{2}{N}$, and the probability that this agent i is linked to the suggested project partner j, given that he is selected by $Pr(g_{ij} = 1|K) = \frac{d_i}{N-1}$. Then, the probability of being chosen *and* being partnered with a friend is

$$s_i \equiv Pr(g_{ij} = 1 \wedge K) = Pr(g_{ij} = 1|K)Pr(K) = \frac{2d_i}{N(N-1)}.$$

Relationship Quality

We outline here formally how a project outcome affects the relationships of workers. As mentioned previously, whether the project of workers i and j was a success, S, or a failure, F is publicly observable and denoted by $\omega \in \Omega = \{S, F\} \times \{1, 2, \ldots, N\}^2$. As an

[46] Conti et al. (2013) take the in-degree of high school students and find that wages 35 years are influenced by how often students were named as friends. They argue that a high in-degree is a measure of social skills, of how good someone is in building positive personal relationships and in adjusting to a certain environment and situation. They also provide evidence that the in-degree manages to capture something other than personality, by controlling for personality traits. Similarly, we use the network as a measure of social skills that can still impact outcomes later on.

[47] As we have standardized the clustering coefficients as well as degrees, the coefficients can be interpreted in terms of standard deviations.

Table 4: Differences in Degree and Clustering for Men and Women

	Cl. Coeff. (dir.)	Cl. Coeff. (dir.)	Cl. Coeff.	Cl. Coeff.	In Degree	In Degree	Out Degree	Out Degree	Degree	Degree
Female	0.110***	0.0729***	0.0922***	0.0612***	0.107***	0.146***	0.186***	0.193***	0.178***	0.205***
	(0.00565)	(0.0107)	(0.00563)	(0.0106)	(0.00683)	(0.0144)	(0.00609)	(0.0123)	(0.00634)	(0.0131)
Age-16	0.00440	-0.000773	0.00456	-0.000780	-0.0173***	0.00629	-0.0500***	-0.0375***	-0.0410***	-0.0193***
	(0.00249)	(0.00292)	(0.00252)	(0.00296)	(0.00271)	(0.00335)	(0.00247)	(0.00304)	(0.00255)	(0.00313)
Size/1000	0.0310	0.0235	-0.0170	-0.0224	0.0420	0.0329	0.0339	0.0240	0.0457	0.0342
	(0.0634)	(0.0631)	(0.0750)	(0.0748)	(0.0571)	(0.0578)	(0.0839)	(0.0831)	(0.0714)	(0.0707)
Female*Age 16-17		0.0668***		0.0594***		-0.102***		-0.0443***		-0.0878***
		(0.0111)		(0.0110)		(0.0121)		(0.0108)		(0.0113)
Female*Age 18-19		-0.0360		-0.0126		-0.356***		-0.214***		-0.342***
		(0.0253)		(0.0258)		(0.0221)		(0.0230)		(0.0225)
Female*Size/1000		0.0122		0.00858		0.0148		0.0169		0.0192*
		(0.00901)		(0.00896)		(0.00991)		(0.00911)		(0.00936)
Constant	0.0767	0.0842	0.186	0.190	-0.242*	-0.210	0.165	0.189	-0.0410	-0.00819
	(0.127)	(0.126)	(0.151)	(0.150)	(0.114)	(0.116)	(0.169)	(0.168)	(0.144)	(0.142)
Additional Controls: School Fixed Effects										
Observations	84792	84792	84792	84792	84792	84792	84792	84792	84792	84792
R^2	0.198	0.199	0.205	0.205	0.132	0.134	0.170	0.170	0.205	0.207

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

example, if $\omega = S12$, this means that a project was successfully completed by workers 1 and 2. We condition also on the workers who carried out the project as we do not only care about whether the project was successful but also about the workers who were involved. Each project failure induces some bad relationships in the network g. The network that contains the links that signify a bad relationship is denoted by $g_b \subset g$. The specific network g_b that arises after Fij, that is a project failure between workers i and j, where $g_{ij} = 1$, is given by $g_b(Fij) = \{\{ij, il, jl\}|g_{il} = 1 \wedge g_{jl} = 1, \forall l\}$. Workers i and j have a bad relationship with each other if their joint project fails. But a worker l, who is connected to both i and j also has a bad relationship with both of them. Denote by $g_g(Fij) = g \backslash g_b(Fij)$ the good relationships in the network g. Let $\gamma_g \in g_g$ and $\gamma_b \in g_b$. Further, for any i, j $g_g(Sij) = g$.

Equilibrium Selection

An example for which equation (12) holds is given in Table 5. We assume $f(e_i, e_j) = \sqrt{e_i, e_j}$ and $c(e_i) = \frac{1}{2}e_i^2$. In this example, men exert on average lower effort than women, in both states of the world. This is not surprising given that the project value in both states of the world is fairly similar.

Table 5: Welfare Parameters

v_l	v_h	p	q	β	d^W	d^M	C^W	C^M	N
1.5	1.6	0.75	0.5	0.9	2	3	2	1	4

Technical Appendix B: Proofs

Proof of Proposition 1: Static Decision Problem

Given the assumptions on $f(.,.)$, there always exists an equilibrium where both project partners exert zero effort. It therefore remains to be shown that there exists exactly one equilibrium with $e_i = e_j > 0$.

We first show symmetry. From the first order conditions we obtain

$$\frac{f_1(e_i, e_j)}{f_2(e_i, e_j)} = \frac{c'(e_i)}{c'(e_j)} \tag{13}$$

Suppose, by contradiction, that effort levels are not symmetric and assume that $e_j > e_i$. Due to convexity of the cost functions, the RHS of (13) is smaller than one. Due to concavity and supermodularity of the effort function, we have $f_1(e_i, e_j) > f_2(e_i, e_j)$, which is why the LHS is larger than one, which gives the contradiction.

Further, there is exactly one equilibrium where both workers exert strictly positive effort. It suffices to show that the FOCs (which under symmetry become a function of one variable) have one zero under the condition that effort is strictly positive.

$$f_1(e, e)\pi(y) = c'(e) \tag{14}$$

Due to our assumption of constant returns to scale, $f_1(e, e)$ is constant in e. By our assumption of quadratic costs, the first derivative of the cost function $c'(e)$ is linear in e and starts in the origin. Hence, the two functions have a unique intersection, implying one symmetric equilibrium with strictly positive effort.

Proof of Lemma 1:

$\pi(y)$ has the martingale property:

$$\pi(y_n) = Pr(\theta_h|y_n)v_h + (1 - Pr(\theta_h|y_n))v_l$$

Define $\psi_n \equiv Pr(\theta_h|y_n)$. We know that the stochastic process $\{\psi_n\}$ is a martingale as

$$E(\psi_{n+1}|y_n) = E(E(\psi|y_{n+1})|y_n) = E(\psi|y_n) = \psi_n,$$

where the second equality follows from the *tower property* of conditional expectations. Then,

$$\begin{aligned} E(\pi(y_{n+1})|y_n) &= E(\psi_{n+1}v_h + (1 - \psi_{n+1})v_l|y_n) = E(\psi_{n+1}v_h|y_n) + E((1 - \psi_{n+1})v_l|y_n) \\ &= \psi_n v_h + (1 - \psi_n)v_l = \pi(y_n) \end{aligned}$$

Properties of $E\left(\pi(y_n)\right)$ and $E\left(\pi(y_n)|\theta\right)$:

1. The number of signals do not matter for $E(\pi(y))$ due to the martingale property of

$\pi(y)$,

$$E(\pi(y_{n+1})) = E(E(\pi(y_{n+1})|y_n)) = E(\pi(y_n)).$$

2. We note that the posterior is given by

$$\begin{aligned} Pr(\theta_h|y) &= \frac{Pr(y|\theta_h)Pr(\theta_h)}{Pr(\theta_h)Pr(y|\theta_h) + Pr(\theta_l)Pr(y|\theta_l)} = \frac{qp^y(1-p)^{n-y}}{qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y} \\ &= \frac{1}{1 + \frac{1-q}{q}\left(\frac{1-p}{p}\right)^{2y-n}} \end{aligned} \tag{15}$$

To simplify notation we define $\tilde{p} \equiv \frac{1-p}{p}$, $\tilde{q} \equiv \frac{1-q}{q}$ and $\hat{y} \equiv 2y-n$. Then, $\psi_n = Pr(\theta_h|y) = \frac{1}{1+\tilde{q}\tilde{p}^{\hat{y}}}$.

We are interested in showing that

$$E\left(\pi(y_{n+1})|\theta_h\right) > E\left(\pi(y_n)|\theta_h\right) \tag{16}$$

$$E\left(\pi(y_{n+1})|\theta_l\right) < E\left(\pi(y_n)|\theta_l\right) \tag{17}$$

We will show that equation (16) holds and leave the proof of equation (17) to the reader. We can rewrite equation (16) and we obtain

$$(v_h - v_l)E\left((\psi_{n+1} - \psi_n)|\theta_h\right) > 0$$

As $(v_h - v_l) > 0$, by assumption, it remains to be shown that $E\left(\psi_{n+1} - \psi_n|\theta_h\right) > 0$. Given $\theta = \theta_h$, $\psi_{n+1} = \frac{1}{1+\tilde{q}\tilde{p}^{\hat{y}+1}}$ with probability p and $\psi_{n+1} = \frac{1}{1+\tilde{q}\tilde{p}^{\hat{y}-1}}$, with probability $(1-p)$. We can show that

$$\begin{aligned} & \frac{1}{1+\tilde{q}\tilde{p}^{\hat{y}}} < \frac{p}{1+\tilde{q}\tilde{p}^{\hat{y}+1}} + \frac{1-p}{1+\tilde{q}\tilde{p}^{\hat{y}-1}} \\ \Leftrightarrow \quad & p\tilde{p}^2 + (1-p) - \tilde{p} < \tilde{q}\tilde{p}^{\hat{y}}(p + (1-p)\tilde{p}^2 - \tilde{p}) \end{aligned}$$

Note that $p\tilde{p}^2 + (1-p) - \tilde{p} = 0$. Then, $0 < \tilde{q}\tilde{p}^{\hat{y}}(p + (1-p)\tilde{p}^2 - \tilde{p})$, which holds for $p > \frac{1}{2}$ and concludes the proof.

Additional signals do not matter in the following cases:

(i) For $v_l \to v_h$,

$$\lim_{v_l \to v_h} E\left(\pi(y_n)|\theta_h\right) = \sum_{y=0}^{n} \frac{(n)!}{y!(n-y)!}\left(p^y(1-p)^{n-y}\right)v_h = (p+1-p)^n v_h = v_h,$$

where the second step follows from the binomial formula. The expression is independent of n and therefore additional signals do not matter. Similarly, this also holds for $E\left(\pi(y)|\theta_l\right)$.

(ii) Assume $p \to 1$. Then,

$$\begin{aligned}
\lim_{p\to 1} E\left(\pi(y_n)|\theta_h\right) &= \lim_{p\to 1}\sum_{y=0}^{n} \frac{(n)!}{y!(n-y)!}\left(p^y(1-p)^{n-y}\right)\left(\frac{qp^y(1-p)^{n-y}v_h + (1-q)p^{n-y}(1-p)^y v_l}{qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y}\right)\\
&= \lim_{p\to 1}\frac{(n)!}{n!(n-n)!}\left(p^n(1-p)^{n-n}\right)\left(\frac{qp^n(1-p)^{n-n}v_h + (1-q)p^{n-n}(1-p)^n v_l}{qp^n(1-p)^{n-n} + (1-q)p^{n-n}(1-p)^n}\right)\\
&= \lim_{p\to 1} p^n\left(\frac{qp^n v_h + (1-q)(1-p)^n v_l}{qp^n + (1-q)(1-p)^n}\right) = v_h,
\end{aligned}$$

and analogue for $\theta = \theta_l$.

(iii) Assume $q \to 1$. Then,

$$\lim_{q\to 1} E\left(\pi(y_n)|\theta_h\right) = \sum_{y=0}^{n} \frac{(n)!}{y!(n-y)!}\left(p^y(1-p)^{n-y}\right)v_h = (p+1-p)^n v_h = v_h$$

which is independent of n. Similarly for $q \to 0$ and $E\left(\pi(y)|\theta_l\right)$.

(iv) Note that $y \sim$ Binomial$(np, np(1-p))$ if $\theta = \theta_h$ and $y \sim$ Binomial$(n(1-p), np(1-p))$ if $\theta = \theta_l$. Then, $\lim_{n\to\infty}(y-(n-y)) = \infty$ if $\theta = \theta_h$ and $\lim_{n\to\infty}(y-(n-y)) = -\infty$ if $\theta = \theta_l$. To see this note that $y-(n-y) = 2y-n$. By the central limit theorem, as $n \to \infty$,

$$\begin{aligned}
\text{if}\quad \theta = \theta_h \quad y \xrightarrow{p} np \quad &\Rightarrow \lim_{n\to\infty}(2np - n) = \infty\\
\text{if}\quad \theta = \theta_l \quad y \xrightarrow{p} n(1-p) \quad &\Rightarrow \lim_{n\to\infty}(2n(1-p) - n) = -\infty.
\end{aligned}$$

Then, $\lim_{n\to\infty} Pr(\theta_h|y) = 1$ if $\theta = \theta_h$ and $\lim_{n\to\infty} Pr(\theta_h|y) = 0$ if $\theta = \theta_l$ as

$$\lim_{n\to\infty} Pr(\theta_h|y) = \lim_{n\to\infty}\frac{1}{1+\frac{1-q}{q}\left(\frac{1-p}{p}\right)^{2y-n}}$$

We have already shown that $Pr(\theta_h|y)$ is increasing in n if $\theta = \theta_h$ and decreasing in n if $\theta = \theta_l$. Thus we can apply the Monotone Convergence Theorem, which implies that $\lim_{n\to\infty} E(Pr(\theta_h|y)v_h) = E(\lim_{n\to\infty} Pr(\theta_h|y)v_h)$. From this it follows that $\lim_{n\to\infty} E\left(\pi(y)|\theta_h\right) = v_h$ and $\lim_{n\to\infty} E\left(\pi(y)|\theta_l\right) = v_l$.

Proof of Lemma 2:

$V^*(y')$ is a Submartingale: We can express $V^*(y')$ as a function of $\pi(y')$, and write

$$V^*(y') \equiv g(\pi(y')) \tag{18}$$

As $\pi(y')$ is a martingale, we know that when g is a convex function, then $g(\pi(y'))$ is a submartingale whenever $E(V^*(y'_n)) < \infty$, which is always fulfilled as $0 \leq E(V^*(y'_n)) < v_h \; \forall n$.

Note that the equilibrium effort depends the expected project payoff through the signals, or $e'('y)$. We mostly omit this dependence here in order to keep notation simple but write simply e'.

Applying the envelope theorem repeatedly, the first and second derivative of g are given by

$$\begin{aligned}
\frac{\partial g(\pi(y))}{\partial \pi(y)} &= f_2(e',e')\pi(y')\frac{\partial e'}{\partial \pi(y')} + f(e',e') \\
\frac{\partial^2 g(\pi(y'))}{\partial \pi(y')\partial \pi(y')} &= [f_{22}(e',e') + f_{12}(e',e')]\pi(y')\left(\frac{\partial e'}{\partial \pi(y')}\right)^2 + f_2(e',e')\pi(y')\frac{\partial^2 e'}{\partial \pi(y')\partial \pi(y')} + f_2(e',e')\frac{\partial e'}{\partial \pi(y')} \\
&\quad + (f_1(e',e') + f_2(e',e'))\frac{\partial e'}{\partial \pi(y')} \\
&= f_2(e',e')\pi(y')\frac{\partial^2 e'}{\partial \pi(y')\partial \pi(y')} + f_2(e',e')\frac{\partial e'}{\partial \pi(y')} + (f_1(e',e') + f_2(e',e'))\frac{\partial e'}{\partial \pi(y')}
\end{aligned}$$

From first order condition of the static problem, evaluated at the equilibrium effort, we can compute

$$\begin{aligned}
\frac{\partial e'}{\partial \pi(y')} &= \frac{f_1(e',e')}{c''(e')} > 0 \\
\frac{\partial^2 e'}{\partial \pi(y')\partial \pi(y')} &= \frac{(f_{11}(e',e') + f_{21}(e',e'))\frac{\partial e'}{\partial \pi(y)}}{c''(e')} = 0
\end{aligned}$$

It follows that

$$\frac{\partial^2 g(\pi(y'))}{\partial\pi(y')\partial\pi(y')} = f_2(e',e')\frac{\partial e'}{\partial\pi(y')} + (f_1(e',e') + f_2(e',e'))\frac{\partial e'}{\partial\pi(y')} > 0,$$

which implies that $V^*(y'_n)$ is a submartingale.

Properties of $E(V_n^*) = \sum_{y=0}^{n} \frac{n!}{(y)!(n-y)!}(qp^y(1-p)^{n-y}+(1-q)p^{n-y}(1-p)^y)\left(f(e',e')\pi(y) - c(e')\right)$

(i) $v_l \to v_h$.

We are interested in

$$\lim_{v_l\to v_h} E(V_n^*) = \lim_{v_l\to v_h}\sum_{y=0}^{n}\frac{n!}{(y)!(n-y)!}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y)\left(f(e'(y'),e'(y'))\pi(y') - c(e'(y'))\right)$$

where $e'(y')$ is the equilibrium effort for given y'. As the other terms are constant in v_l, all that matters is

$$\begin{aligned}\lim_{v_l\to v_h}\left(f(e'(y'),e'(y'))\pi(y') - c(e'(y'))\right) &= \lim_{v_l\to v_h} f(e'(y'),e'(y'))\lim_{v_l\to v_h}\pi(y') - \lim_{v_l\to v_h} c(e'(y'))\\ &= \lim_{v_l\to v_h} f(e'(y'),e'(y'))v_h - \lim_{v_l\to v_h} c(e'(y'))\end{aligned}$$

Note that $\lim_{\pi(y')\to v_h} e'(y') = e'_{v_h}$, i.e. the effort converges to some constant as $\pi(y') \to v_h$ since $e'(y')$ is a linear function of $\pi(y')$ (see (2)). Also, due to constant returns to scale, $f(e'(y'),e'(y')) = e'(y')f(1,1)$ and thus $\lim_{e'(y')\to e'_{v_h}} f(e'(y'),e'(y')) = e'_{v_h}f(1,1)$, which again is constant in n. As $f(.,.)$ is continuous, i.e. $f(e'_{v_h},e'_{v_h}) = e'_{v_h}f(1,1)$, we know that $\lim_{\pi(y')\to v_h} f(e'(y'),e'(y')) = e'_{v_h}f(1,1)$. The argument is similar for $c(.)$. Then, we can write

$$\lim_{v_l\to v_h}\left(f(e'(y'),e'(y'))\pi(y') - c(e'(y'))\right) = b_{v_l},$$

where b_{v_l} is constant and thus independent of n. Therefore, as v_l converges to v_h, the expected second period value converges to a constant and is independent of the number of signals,

$$\lim_{v_l\to v_h} E(V_n^*) = b_{v_l}.$$

(ii) $p \to 1$ for $\theta \in \{\theta_h, \theta_l\}$.

Note that

$$\lim_{p\to 1} \pi(y) = v_h \quad \text{if} \quad n - 2y < 0$$

$$\lim_{p\to 1} \pi(y) = qv_h + (1-q)v_l \quad \text{if} \quad n - 2y = 0$$

$$\lim_{p\to 1} \pi(y) = v_l \quad \text{if} \quad n - 2y > 0$$

As $\pi(y)$ converges to some constant (and, of course, the same holds for $\pi(y')$), so does $(f(e'(y'), e'(y'))\pi(y') - c(e'))$. We denote by $V^*(v_h)$ $(V^*(v_l))$ [$V^*(v)$] the limit when $\pi(y)$ converges to v_h (v_l) [$qv_h + (1-q)v_l$].

Note further that if $n-2y < 0$, $\lim_{p\to 1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = \lim_{p\to 1} qp^y(1-p)^{n-y}$. Then we know that

$$\lim_{p\to 1} = \begin{cases} q & \text{if} \quad y = n \\ 0 & \text{otherwise} \end{cases}$$

If $n - 2y > 0$, $\lim_{p\to 1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = \lim_{p\to 1}(1-q)p^{n-y}(1-p)^y$. It follows that

$$\lim_{p\to 1} = \begin{cases} 1-q & \text{if} \quad y = 0 \\ 0 & \text{otherwise} \end{cases}$$

Last, if $n - 2y = 0$, $\lim_{p\to 1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = \lim_{p\to 1} p^y(1-p)^{n-y} = 0$, as $y, n > 0$ From this it then follows that

$$\lim_{p\to 1} E(V_n^*) = qV^*(v_h) + (1-q)V^*(v_l),$$

which is independent of n.

(iii) $q \to 1$.

Notice that,

$$\lim_{q\to 1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = p^{n-y}(1-p)^y,$$
$$\lim_{q\to 1}\pi(y) = v_h.$$

It follows that $\lim_{q\to 1} E(V_n^*)$ is a constant and independent of n.

Next, $q \to 0$.

$$\lim_{q\to 0}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = p^{n-y}(1-p)^y,$$
$$\lim_{q\to 0}\pi(y) = v_l,$$

and $\lim_{q\to 0} E(V_n^*)$ is constant.

(iv) Abundance of Information: $n_{ext} \to \infty$.

We want to show that

$$\lim_{n\to\infty} E(V_n^*) = E(V^*).$$

We know that for each n, $E(V_n^*) \leq E(V_{n+1}^*)$ as V_n^* is a submartingale and that $E(V_n^*) \leq v_h$ for all n. By the monotone convergence theorem, we know that a finite limit exists, which we denote by $E(V^*)$.

Proof of Proposition 6: Trade-Off Between Information and Peer Pressure

We assume that a D-worker has a higher degree and hence more signals n_{int} and has clustering $(sr)^D$. In turn, a C-worker has a lower degree and thus a lower number of signals (and therefore $s^D > s^C$) but higher clustering and therefore $(sr)^C > (sr)^D$. Further, assume $v_l = 0$.

(i) Wage Dynamics:

Claim 1: $w^D(\theta) > w^C(\theta) \quad \Rightarrow \quad E(w'^D) > E(w'^C)$.

From definition (2), it follows that the second period expected wage across states is defined as

$$E(w') = qw'(\theta, \theta'_h) + (1-q)w'(\theta, \theta'_l) = qw'(\theta, \theta'_h)$$

where the second equality is due to $v_l = 0$ and where we dropped the subindex i for convenience. Also, recall

$$w'(\theta, \theta'_h) \equiv sPr(\gamma'_g|\theta)E(e'(y')|\theta_h)f(1,1)v_h$$

where $Pr(\gamma'_g|\theta) \equiv E(e(y)|\theta)rf(1,1)+1-r$. Suppose that in the first period $w^D(\theta) > w^C(\theta)$, implying $E(e(y)^D|\theta) > E(e(y)^C|\theta)$. Moreover, by assumption, $s^C < s^D$ and $(sr)^C > (sr)^D$. Hence, $[sPr(\gamma_g|\theta)]^D > [sPr(\gamma_g|\theta)]^C$. Last, by Proposition 2, $E(e'(y')^D|\theta'_h) > E(e'(y')^C|\theta'_h)$ and therefore $w'^D(\theta, \theta'_h) > w'^C(\theta, \theta'_h)$. Thus, $w^D(\theta) > w^C(\theta)$ implies $E(w'^D) > E(w'^C)$, which proves the claim.

Claim 2: (a) $w^D(\theta) = w^C(\theta) \Rightarrow E(w'^D) > E(w'^C)$.

(b) $w^D(\theta) > w^C(\theta) \Rightarrow E(w'^D) > E(w'^C)$ even if $E(e'(y')^D|\theta'_h) = E(e'(y')^C|\theta'_h)$.

(a) Even if $w^D(\theta) = w^C(\theta)$ and thus $E(e(y)^D|\theta) = E(e(y)^C|\theta)$, we have $[sPr(\gamma_g|\theta)]^D > [sPr(\gamma_g|\theta)]^C$ due to $s^C < s^D$ and $(sr)^C > (sr)^D$. Also, by Proposition 2, $E(e'(y')^D|\theta'_h) > E(e'(y')^C|\theta'_h)$ and therefore $w'^D(\theta, \theta'_h) > w'^C(\theta, \theta'_h)$. It follows: $w^D(\theta) = w^C(\theta) \Rightarrow E(w'^D) > E(w'^C)$.

(b) We use a similar argument as in (a). Even if uncertainty vanishes in the second period, that is even if the D-worker loses his informational advantage, implying $E(e'(y')^D|\theta'_h) = E(e'(y')^C|\theta'_h)$, it holds that if $w^D(\theta) > w^C(\theta)$ then $E(w'^D) > E(w'^C)$, because $[sPr(\gamma_g|\theta)]^D > [sPr(\gamma_g|\theta)]^C$.

(ii) Comparative Advantage:

We want to show that $\frac{E(w^C)}{E(w^D)}$ increases in n, q and $p > p^*$ if $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are sufficiently concave in n, q and p, respectively. First notice that, assuming $v_l = 0$,

$$\frac{E(w^C)}{E(w^D)} = \frac{qw^C(\theta_h)}{qw^D(\theta_h)} = \frac{[E(\pi(y)|\theta_h)]^C + \beta(sr)^C[EV^*(\gamma_g', y')]^C}{[E(\pi(y)|\theta_h)]^D + \beta(sr)^D[EV^*(\gamma_g', y')]^D} \tag{19}$$

where we used the definition of wages and the expression for equilibrium effort (7). We want to show that (19) is increasing as uncertainty vanishes. To illustrate the argument, we show this for the case of increasing n (strictly, speaking we let n_{ext} increase). We adopt the following notation

$$\begin{aligned}
[E(\pi(y)|\theta_h)]^C &= E(\pi(y_n)|\theta_h) \\
[E(\pi(y)|\theta_h)]^D &= E(\pi(y_{n+1})|\theta_h) \\
[EV^*(\gamma_g', y')]^C &= EV^*(y_n') \\
[EV^*(\gamma_g', y')]^D &= EV^*(y_{n+1}') \\
(sr)^C &= \overline{sr} \\
(sr)^D &= \underline{sr}
\end{aligned}$$

We will show that (19) is increasing in n, that is,

$$\frac{E(\pi(y_n)|\theta_h) + \beta\overline{sr}EV^*(y_n')}{E(\pi(y_{n+1})|\theta_h) + \beta\underline{sr}EV^*(y_{n+1}')} > \frac{E(\pi(y_{n-1})|\theta_h) + \beta\overline{sr}EV^*(y_{n-1}')}{E(\pi(y_n)|\theta_h) + \beta\underline{sr}EV^*(y_n')} \tag{20}$$

if $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are sufficiently concave, i.e. if

$$EV^*(y_n')^2 > EV^*(y_{n-1}')EV^*(y_{n+1}') \tag{21}$$

$$E(\pi(y_n)|\theta_h)^2 > E(\pi(y_{n+1}|\theta_h))E(\pi(y_{n-1})|\theta_h) \tag{22}$$

$$\frac{EV^*(y_n')}{EV^*(y_{n-1}')}\frac{E(\pi(y_n)|\theta_h)}{E(\pi(y_{n+1})|\theta_h)} > \frac{\overline{sr}}{\underline{sr}} > \frac{EV^*(y_{n+1}')}{EV^*(y_n')}\frac{E(\pi(y_{n-1})|\theta_h)}{E(\pi(y_n)|\theta_h)}. \tag{23}$$

To show this, rearrange (20) to get:

$$[E(\pi(y_n)|\theta_h)]^2 - E(\pi(y_{n+1})|\theta_h)E(\pi(y_{n-1})|\theta_h) +$$
$$\underline{sr}\,\overline{sr}\beta^2([EV^*(y'_n)]^2 - EV^*(y'_{n+1})EV^*(y'_{n-1})) +$$
$$\beta\overline{sr}E(\pi(y_n)|\theta_h)EV^*(y'_n) - \beta\underline{sr}E(\pi(y_{n-1})|\theta_h)EV^*(y'_{n+1}) +$$
$$\beta\underline{sr}E(\pi(y_n)|\theta_h)EV^*(y'_n) - \beta\overline{sr}E(\pi(y_{n+1})|\theta_h)EV^*(y'_{n-1}) > 0$$

This expression is positive if (21)-(23) hold. To see that (21)-(23) are implied by sufficiently strong concavity note the following. A function $f(n)$ is *log-concave* if:

$$f(n+1)f(n-1) < f(n)^2 \tag{24}$$

Hence, for (21)-(23) to hold, $E(\pi(y)|\theta_h)$ and $EV^*(y')$ must be sufficiently log-concave. But concavity implies log-concavity: Concavity of an increasing discrete function means

$$\frac{1}{2}(f(n+1) + f(n-1)) < f(n) \tag{25}$$

Then (25) implies (24) since

$$\frac{1}{2}(f(n+1) + f(n-1)) > (f(n+1)f(n-1))^{0.5}.$$

Last, we established before that $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are increasing in n and converge. Consequently, for all $n > n^*$, $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are concave as defined in (25). We focus on the part of the parameter space where $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are sufficiently concave, i.e. where conditions (21)-(23) hold.

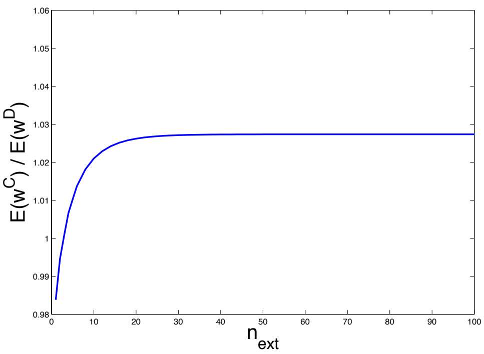
The arguments that (19) is increasing in p (for $p > p^*$) and q are analogous and slightly simpler because $E(\pi(y)|\theta_h)$ and $EV^*(y')$ are continuously differentiable in p and q. We omit them for brevity and instead highlight some of our simulation results.

To graphically illustrate the comparative advantage results, we compute a parametric example of this model and provide some simulations. Effort and cost functions are respectively given by $f(e_i, e_j) = \sqrt{e_i, e_j}$ and $c(e_i) = \frac{1}{2}e_i^2$. We set the parameters s.t. $e < e_{max}$ always holds (see Table 6).

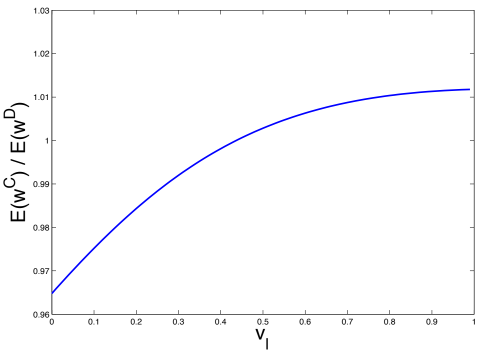
Table 6: Baseline Parameters

v_l	v_h	p	q	β	d^W	d^M	C^W	C^M	N
0	1	0.75	0.5	0.9	2	3	2	1	10

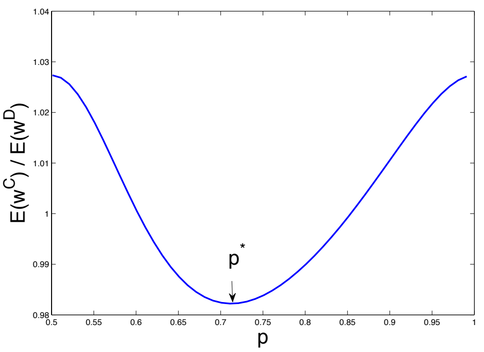
Figure 2: Expected Wage of Agent with Higher Clustering Relative to Agent with More Information



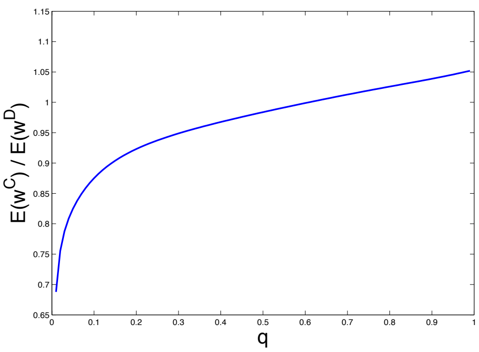
(a) As a Function of External Info



(b) As a Function of Low Value



(c) As a Function of Signal Precision



(d) As a Function of Prior Belief