Gender, Social Networks and Performance

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Abstract

This paper documents gender differences in social ties and develops a theory that links them to disparities in men's and women's labor market performance. Men's networks lead to better access to information, women's to higher peer pressure. Both affect effort in a model of teams, each beneficial in different environments. We find that information is particularly valuable under high uncertainty, whereas peer pressure is more valuable in the opposite case. We therefore expect men to outperform women in jobs that are characterized by high earnings uncertainty, such as the financial sector or film industry – in line with the evidence.

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 and sectors 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?

We offer a novel answer to this question, which is based on social network heterogeneity between men and women. In the labor market, social networks have been shown to play a crucial role in shaping workers' incentives and performance within a firm.[7] This paper takes these insights a step further and proposes that the *structure* of social ties matters for labor market outcomes on the job. We argue that men's network structures allow

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

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

[3]See BLS-Reports (2013), http://www.bls.gov/cps/cpswom2012.pdf, and also Goldin and Katz (2011) and Goldin (2014).

[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) and also Albanesi and Olivetti (2008), Albanesi and Olivetti (2009) on the empirical relevance of performance pay for the wage gap.

[6]See Dohmen and Falk (2011).

[7]See, for instance, Bandiera et al. (2009), Bandiera et al. (2010), Rotemberg (1994) or Podolny and Baron (1997). We do not aim to address the question of how social ties matter for job *search*, as analyzed, for example, in Arrow and Borzekowski (2004), Calvo-Armengol and Jackson (2004), Calvó-Armengol and Jackson (2007), but we are interested in how the structure of informal networks matters on the job.

them to perform better in uncertain environments with potentially high but risky returns compared to women and our model clarifies why this is the case. This theory is motivated by our 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 friends are more likely to be friends among each other, implying a higher *clustering coefficient*. Thus, women have smaller but tighter networks, whereas men have larger but looser ego networks. Supported by studies on the stability of individuals' network structures across different environments, we assume that network patterns among friends carry over to informal network structures at the workplace.[8]

We argue that there is an important trade-off between tight and loose networks as they provide different types of social capital: a tight network fosters trust or peer pressure among agents, which reduces their incentive to shirk. This is because they fear repercussions not only from the individual they affect directly with their behavior but also from other members of their tight 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 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 develop a theory where networks provide both access to information as well as peer pressure and analzye this trade-off. 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.

In our model, workers are repeatedly selected into partnerships to complete projects of uncertain output value. Project success positively depends on the partners' efforts, where effort is unobservable. 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, inducing inefficiently low effort.[12] We will show

[8]This assumption is in line with Burt (2011) and supported by case studies (Brands and Kilduff (2013)).
[9]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]See Holmstrom (1982) for moral hazard problems in teams.

how networks can attenuate this moral hazard 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. Each worker receives a signal about the true value, and can observe the signals of their friends in the network. The more signals and thus information a worker has, the more precise is his belief about the state of the world and the better is his judgment as the optimal effort is state dependent. Second, effort positively depends on the amount of *peer pressure* individuals face.

The amount of information and peer pressure of a worker depends on his network structure. Workers with a higher degree receive more signals and therefore hold more information. In turn, workers with higher clustering face more peer pressure through the following mechanism: A failed project leads to frictions not only between project partners but also between them and their common friends, that is their disagreement spreads through the entire group – an idea based on the *structural balance theory*.[13] Since an intact friendship is necessary for a successful project, repercussions of a failure are especially bad for a worker with high clustering. Therefore, higher clustering leads to higher effort in order to be on good terms with future potential project partners. We analyze under which circumstances a network with higher clustering (and thus more peer pressure) is more beneficial for job performance and ultimately wages and when a network with a higher degree (i.e. more information) is 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 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 states. In these cases, uncertainty about the state of the world and associated rewards is large and the benefits of purely information-based, loose networks outweigh the benefits of closed networks that lead 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

[13] 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.

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, workers facing high peer pressure exert extra effort even if the expected project reward is 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. 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.

Our empirical finding on gender differences in social networks coupled with the model described above leads to predictions that are consistent with well-known stylized facts: (1) Wage gaps within occupations are large and especially within those occupations that characterized by earnings uncertainty, such as the financial sector or the film industry.[14] (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 rewards whereas men are more selective in their effort choice. (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.

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

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 Our paper complements three strands of literatures. First, we contribute to the work on the gender gap in labor market performance and wages.[15] Common explanations for this gap are discrimination (Black and Strahan (2001), Goldin and Rouse (2000), Wenneras and Wold (1997)), differences in abilities and preferences which result in occupational self-selection (Polachek (1981)), differences in the number and length of career interruptions (Bertrand et al. (2010)) or differences in hours worked at home, translating into lower female effort at work (Albanesi and Olivetti (2009)). Differences between men and women have also been found in their competitiveness (Gneezy et al. (2003), Gneezy and Rustichini (2004), Niederle and Vesterlund (2007)), in their preferences for team-based over individual pay schemes (Kuhn and Villeval (2013)), risk aversion (for a summary, see Eckel and Grossman (2008)), in their ability to bargain (Babcock and Laschever (2003), Card et al. (2013)), and in terms of future fertility concerns (Adda et al. (2011)). Similar to us, some papers argue that the wage gap is more severe in high-powered jobs, especially in the financial and corporate world. Albanesi and Olivetti (2009) attribute this to women's higher cost of managerial effort due to more working hours at home. Goldin and Katz (2011) and Goldin (2014) argue that in these occupations the penalty for reduced and flexible work hours are particularly high. Our paper, which is complementary to this literature, suggests a new disparity between men and women, their network structure, as a source of the performance and ultimately wage gap.

Second, we add to the literature of how social ties impact job performance (e.g. Rotemberg (1994), Podolny and Baron (1997), Bandiera et al. (2009), Bandiera et al. (2010)) and, relatedly, how peer pressure can alleviate free-riding in the workplace (e.g. Kandel and Lazear (1992), Mas and Moretti (2009), Jackson and Schneider (2011)). Contrary to these papers, we highlight the role of the network *structure* for performance and link male and female network structures to the gender gap in labor market outcomes. The idea that

[15] Reviews of gender wage differences and possible explanations can be found in Blau and Kahn (2000) and Bertrand (2011).

gender differences in social networks matter for job performance and earnings has long been discussed in sociology (e.g. Burt (1992), Ibarra (1993), Ibarra (1997)); our contribution relative to this literature is to document differences in network structures in a large dataset and to develop a theory of how these differences can matter for job outcomes.

Finally, we contribute to the relatively small network literature on the trade-off between network density and network span. This trade-off is analyzed in Karlan et al. (2009) where individuals use their network to borrow goods. Dixit (2003) discusses the trade-off between sparse and closed networks in a trade setting. Different from these papers, our model focusses on the implications of this trade-off for job performance, where network sparsity translates into information and network density into peer pressure.

The paper proceeds as follows: In Section 2, we document empirically how men's and women's networks differ. In Section 3, we develop a stylized model, which we then solve for the static case in Section 4 and for the dynamic case in Section 5. Section 6 relates our model predictions to a variety of empirical facts. Section 7 concludes.

2 Gender Differences in Networks

A main assumption underlying our analysis is that women have a higher clustering coefficient than men, but that men have a higher degree than women. This is based on our findings from the AddHealth data set.

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. This sample contains information on 90,118 students. The AddHealth website describes surveys and data in detail.[16]

Friendship Network The friendship network constructed from the AddHealth data is a directed network, based on friendship nominations.[17] For this network, we compute both directed and undirected clustering coefficients as well as in-, out- and overall degree.[18]

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

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

[18]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.

The clustering coefficient is computed as the ratio of the actual 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 the two.

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. The Appendix contains the results for the entire sample including robustness checks.[19] We do a t-test of the standardized variables and consider the differences between boys and girls. The results are given in Table 2, in the Appendix. 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.

Why Do We Choose AddHealth? We use data on friendship networks of teenagers, not of men and women who are already employed, because we are interested in *informal* as opposed to formal networks. To the best of our knowledge, there does not exist a sufficiently large data set with information on informal networks at work. In addition, we argue that a dataset of *students* is more suitable to establish an individual's *network type* than a dataset of employees at work. Below we list several advantages of using our friendship data compared to data of employees in the workplace.

First, a person's environment and activities influence the formation of his social network. If we were using data on employees instead of students, a significant concern would be that their networks are shaped by their work environment. For instance, if men and women have a preference for same-gender friends, women would have smaller networks in many male-dominated work environments that characterized by exclusive old-boy networks. Moreover, if we were using data from particular firms or occupations we would be concerned that individuals sort into those firms and occupations for which their personal network type is most beneficial. However, at the school level there is no such selection bias based on network types nor constrained availability of same-sex in-

[19] A potential concern of the AddHealth Data set is that only up to 10 friends can be named. This is not an issue here for two reasons: first, this constraint binds only in a negligible number of cases. Second, we use different measures of degree, such as in-degree, which is not subject to this constraint and we find the same results.

dividuals, since schools have roughly equal shares of boys and girls. We can therefore estimate male and female network structures more accurately with this data set.[20]

Second, individuals are more likely to name others as their friends if these have a higher social status, (Marsden (2005)). At the workplace social status is connected to a higher position in the hierarchy and therefore to formal power. However, here we focus on informal links between individuals, i.e. on friendships. As higher status is connected to formal power, it would be 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 be named more often. But we believe that employees have more incentives to be strategic about their friendship nominations than students. 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 have no access to the nomination data.

Notice that a potential concern with our data could be that social ties of teenagers may be different from those of adults at the workplace. We argue that this is not the case based on a study by Burt (2011). He provides compelling evidence for the existence of different *network types* from a multi-role game in a virtual world:[21] People 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.[22] This evidence suggests that boys' and girls' networks at school reflect their network type (comparable to ability or skill types commonly used in the literature), and closely resemble the ones they will form as adults both in their private and work life in terms of *closure*.[23]

[20]To make sure our finding is not due to the fact that there are more 18 year old boys than girls in the sample, we conduct a robustness check where we restrict the sample to schools where the gender ratio for 18 year olds is balanced. We still find that older boys have a higher degree while girls have a higher clustering coefficient, see Appendix.

[21]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 other roles, having friends who are not connected is more beneficial. In other words, high clustering can be good or bad.

[22]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.

[23]Unfortunately, there does not exist much further evidence on the persistence of network types or, in general, on the persistence of differences between girls and boys over time. 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.

Male and Female Networks Beyond AddHealth To the best of our knowledge, gender differences in degree *and* clustering coefficient have not been documented in the literature with two exceptions. First, building on our work, Ductor and Goyal (2014) (unpublished) study gender differences in scientific collaboration in Economics. They look at articles published between 1970 and 2011 in journals listed in EconLit, a bibliography of journals in economics compiled by the American Economic Association. They find that men have a higher degree (i.e. more co-authors), whereas women have a higher clustering coefficient (i.e. it is more likely that two co-authors of a woman are co-authors themselves), providing strong support for our findings and showing that these network differences carry over to the workplace.

Second, Brands and Kilduff (2013) analyze a sample of 33 employees (16 men, 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)) and therefore closely related to the clustering coefficient. They find that men have a significantly lower constraint and higher out-degree – in line with our findings.

Finally, Fischer and Oliker (1983) look at the number of friends of employed people (but not at clustering). They show that women have a lower number of friends than men, in particular at the workplace, and this pattern is stable across age. Therefore, our finding that older girls have a lower degree than older boys does not suddenly reverse, but is also documented for men and women at the workplace across all age groups.

Several studies in sociology also find network differences across gender. Both Eder and Hallinan (1978) and Belle (1989) document that girls and boys have different types of networks. The emphasis in this literature is on dyadic and triadic relationships, whereas we focus on the entire network. Regarding adults, gender differences in networks are documented by Marsden (1987), Tattersall and Keogh (2006) and Kürtösi (2008). These studies stress the content of relationships but do not contain details on gender differences in network structure. Nevertheless, they also show that women form closed groups and emotional ties, whereas men build sparse networks and instrumental ties.

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. 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, $t \in \{1, 2\}$, but the analysis readily extends to a longer horizon. Once two workers are selected they have to complete a project. Whether they are successful depends on their exerted effort, which in turn depends on 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, any two workers are drawn with the same probability 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. 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 joint probability of being selected for a project and being partnered with a directly connected worker is given by (see Appendix for details)

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

This probability is proportional to the degree of an individual. This implies workers with

[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.

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 is high or low

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

and iid. 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 about the state (with a signal value of one (zero) indicating the high (low) state) but he can also observe the signals of workers he is directly or indirectly connected to. We assume signals are informative.

Since we focus on 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 from external sources including indirect connections, $n_{ext,i}$. This enables us to vary the baseline amount of information below. We denote by $n_i = n_{int,i} + n_{ext,i}$ the overall number of signals of worker i. Based on his observed signals, a worker then computes 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 two project partners hold the same information.

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 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, $e_i \geq 0$, $\forall i$

[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.

[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.

to exert on the project. This effort is costly with all workers facing the same cost function $c(e)$, which we assume quadratic for simplicity, i.e. $c(e) = e^2/2$. 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 if effort choices are e_i and e_j is given by $f(e_i, e_j) \in [0, 1)$. To ensure that $f(e_i, e_j)$ is strictly smaller than one, we assume that effort is bounded.[27] This implies that success cannot be guaranteed. Further, we make some natural assumptions on the success function f, namely that it is twice continuously differentiable, increasing and concave in each argument, that it has constant returns to scale and is symmetric in both arguments. Moreover, we assume that f is strictly super-modular, $f_{12}(e_i, e_j) = f_{21}(e_i, e_j) > 0$, implying that effort levels of the workers are strategic 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. Finally, if one team member chooses zero effort, the project fails for sure. After effort has been chosen, the project outcome – success or failure – is realized. A worker's payoff is his share of the project value minus cost of effort.

These three stages – worker selection, information acquisition, and effort choice – 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 here outline this peer pressure channel informally.

We assume that a project failure leads to discord among project partners, negatively affecting their friendship. We further argue that this discord between partners also spreads to common friends. This idea is based on the well-established *structural balance 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 three relationships are intact. Then, i and j work on a project together that fails, affecting not only their link but rendering the entire triad unstable. This instability is resolved by the workers taking sides. To simplify our

[27] That is $e_i \in [0, e_{max}]$ where $f(e_{max}, e_{max}) < 1$. By choosing an appropriate bound on v_h, we can guarantee an interior solution $e \leq e_{max}$.

analysis, we assume that *all* relationships in a triad will turn bad after a project failure.[28] This is why project failures affect workers with high clustering more than those with low clustering: they are deprived of more future project opportunities.

In sum, each project failure negatively affects 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 bad or good. A relationship between i and j turns bad after a project failure if in the previous period either (1) i and j were teamed up or (2) i or j were teamed with a common friend.

In each period, a strategy of an agent maps his signals y and the state γ into an effort level, where we focus on pure strategies. Given that both the relationship-status and signals are observable for both team partners, our equilibrium notion is public perfect equilibrium (PPE). This is a strategy profile that satisfies the usual requirement of being mutually best responses (NE) and sequentially rational. See the Appendix for the formal definition of strategies and 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 main 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.

4 The Static Game

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

$$\max_{e_i} f(e_i, e_j)\pi(y) - c(e_i). \tag{2}$$

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 and c, the first order condition of (2) is both necessary and sufficient for a maximum. The same holds true for worker j. Based on the first order approach, we

[28] Our assumption is a simplification of the following idea: When a project fails, 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.

can determine the pure strategy public perfect equilibria of the game where, to simplify notation, we denote $e(y)$ the optimal strategy based on y.

Proposition 1 (Static Game)**.** .

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

$$\begin{aligned} &\text{(a) Zero effort:} && e(y) = 0 \\ &\text{(b) Strictly positive effort:} && e(y) = f_1(1,1)\pi(y) \end{aligned} \tag{3}$$

. All proofs are in the Appendix. Given the symmetry in our setting, in particular, the symmetry of success function f, identical cost functions c and equal split of the payoff, both workers will always exert the same effort in equilibrium. Moreover, there exist two pure strategy PPE. There always exists an equilibrium where both project partners exert zero effort independently of signal realizations. It is a best response to choose zero effort given the partner chooses zero effort as, by assumption, $f(e_i, 0) = f(0, e_j) = 0$. But there also exists a PPE with strictly positive efforts. The uniqueness of the positive effort equilibrium follows from super-modularity and the constant returns to scale of f, as well as the convexity of the cost function.

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. The following result is based on equation (3).

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.*

Information impacts effort through the belief about the project value: A high signal leads to a more optimistic belief and therefore to higher effort.

Since signals are informative, the expected project value, $E[\pi(y)]$, increases in the number of signals given the realized state of the world is high and decreases in the number of signals given the state of the world is low. Therefore, the more signals are available the more accurate is the worker's posterior belief 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.

Notice that the effect of additional information on expected effort is reinforced when the uncertainty of the underlying environment is considerable and dies out when uncertainty is small. The reason behind this result is that the expected project value becomes independent of the number of overall signals as uncertainty vanishes, where throughout we refer to *vanishing uncertainty* as any of the following four cases: (i) There is no difference between high and low project values. (ii) The signals are completely informative. (iii) A worker's prior reflects complete certainty about the state of the world. (iv) Overall information becomes abundant. The last case occurs when the number of external signals, n_{ext}, becomes large, so that 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. For a more formal argument, see Lemma 1 in the Appendix.

5 The Dynamic Game

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: We focus on a strategy profile where, for any realization of signals, a worker puts positive effort if the relationship to the project partner is good, and zero effort if it is bad.[29] Although clearly, there are other equilibria in this model, in the Appendix (see *Equilibrium Selection*), we make a case why this equilibrium is a reasonable one to focus on.

We know from the static game that zero effort constitutes a PPE in every period, regardless of the signals. 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.

A team partner's optimization problem is dynamic since today's effort choice does not only impact the current project payoff but also matters for tomorrow's through its

[29] Again, see the Appendix for the formal definition of these strategies.

impact on relationships. Thus, the second period expected payoff of workers i and j, who are teamed up in period one, depends not only on second period effort but also on

(i) the probability of first period project success, $f(e_i, e_j)$, or failure, $1 - f(e_i, e_j)$,

(ii) the probability of being selected next period, s_i and s_j, defined in (1), as well as

(iii) the probability of team partners having a bad relationship after a first period failure, r_{ij} and r_{ji}, with $r_{ij} = r_{ji} \equiv \frac{C_{ij}}{d_i}$ where C_{ij} is a proxy for their common friends.[30]

We can then write the dynamic maximization problem of team partner i as

$$\max_{e_i, e_i'} \quad -c(e_i) + f(e_i, e_j)\left(\pi(y) + \beta s_i E\left[f(e_i', e_k')\pi(y') - c(e_i')\right]\right) \\ + (1 - f(e_i, e_j))\left(0 + \beta s_i (1 - r_{ij}) E\left[f(e_i', e_k')\pi(y') - c(e_i')\right]\right) \quad (4)$$

where the expectation is taken with respect to the distribution of the number of high signals in period two and where we index second period variables by *prime*.

We solve problem (4) by backward induction, starting in the second period. Clearly, the second period problem is identical to the static problem.[31] Recall that the high effort level in the static case solves $\max_{e_i'} f(e_i', e_j')\pi(y') - c(e_i')$ (see equation (3) for the solution to this problem). We denote by $V_i^*(y')$ the maximized second period payoff when the state is $\gamma' = \gamma_b$ (indicating a good relationship) and the number of high signals is y'. Using this notation along with (4), the maximization problem of agent i in the first period reads

$$\max_{e_i} \quad f(e_i, e_j)\pi(y) - c(e_i) + \beta s_i (f(e_i, e_j) + (1 - r_{ij})(1 - f(e_i, e_j))) E V_i^*(y'). \quad (5)$$

Similar to the static problem, we show that there exists a unique PPE in which both team partners exert positive effort. With some abuse of notation, we call the optimal effort levels in period one and two $e(y)$ and $e(y')$, and omit the relationship-state γ as an argument, because effort is only positive in case of a good relationship.

Proposition 3 (Dynamic Game)**.** .

1. *Every PPE is symmetric:* $e_i(y) = e_j(y) = e(y)\ \forall y$ *and* $e_i'(y') = e_j'(y') = e'(y')\ \forall y'$.
2. *In both periods, there exists a unique PPE with strictly positive effort levels,* $\forall y, y'$

[30] Formally, $C_{ij} = 1 + \sum_{k, k \neq i, k \neq j} g_{ik} g_{jk}$ where $\sum_{k, k \neq i, k \neq j} g_{ik} g_{jk}$ gives the number of common friends of i and j. So, r_{ij} is the probability that in the next period i is doing a project with someone who would be affected by today's project failure, *given* that i and j are chosen for a project.

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

$$
\begin{aligned}
e(y) &= f_1(1,1)(\pi(y) + \beta sr EV^*(y')) \\
e'(y') &= f_1(1,1)\pi(y').
\end{aligned} \tag{6}
$$

We already know from Proposition 1 that in the second period there exists a unique equilibrium 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 $\beta s_i r_{ij} EV_i^*(y') = \beta sr EV^*(y')$.[32] Notice how clustering comes into play in the dynamic game. For identical information $y = y'$, effort in the first period is higher than in the second one: 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 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.*

We first discuss the effect of *degree*, which impacts effort through the information channel and then turn to the effect of *clustering* through peer pressure.

According to (6), information impacts expected first period effort, $E[e(y)]$, through two channels, the expected first period project value, $E[\pi(y)]$, and second period value, $EV^*(y')$. Both higher $E[\pi(y)]$ and higher $EV^*(y')$ translate into higher effort on average. 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). Furthermore, we prove in Lemma 2 that $EV^*(y')$ is increasing in the number of signals: Having more signals yields a more precise belief about the state and therefore allows each team to better adjust their efforts. Generally, being able to adjust effort optimally leads to higher payoffs, and this

[32] 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.

is why more signals lead to a higher value of the problem.

In sum, a higher *degree* improves information about the state of the world and is particularly beneficial when the true state in the first period is high. In this case, additional signals induce the agents to put significantly more weight on the high state, translating into higher effort and project completion. (The same logic also applies to second period effort, see static case in Proposition 2.) The effect of information on effort dies out as the agents' uncertainty about the state vanishes.

In turn, the effect of peer pressure, sr, on first period expected effort (through clustering) is straightforward and unambiguously positive. 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 in 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. Their difference of efforts across states, $E[e(y)|\theta_h] - E[e(y)|\theta_l]$, is larger, which follows directly from (6).

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

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

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

$$w_i(\theta) \equiv E[f\left(e(y), e(y)\right) v|\theta] \tag{7}$$

$$w_i'(\theta, \theta') \equiv s_i Pr(\gamma_g'|\theta) E[f\left(e'(y'), e'(y')\right) v'|\theta'] \tag{8}$$

where $\theta, \theta' \in \{\theta_l, \theta_h\}$ are the realized first and second period states. We define these expected wages *given* that a certain state of the world has materialized. Wages reflect that agents obtain their share of output in case the project is successful. Recalling that q is the probability that the high state occurs, the expected wage across states can then be easily computed, e.g. $E[w_i] = qw_i(\theta_h) + (1 - q)w_i(\theta_l)$ for the first period.

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 joint probability of being selected and having a good friendship history with the project partner, given by $s_i Pr(\gamma_g'|\theta)$. Since friendship histories matter, the second period expected payoff not only depends 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: First, more information, i.e. a higher degree, unambiguously increases first and second period wages only if the state is high in both periods. The reason is that in this case, agents want to reap the benefits of a high project value and put high effort.[33] The effect of information on wages dies out as uncertainty vanishes.

Second, peer pressure, i.e. higher clustering, generates dynamic incentives, boosting the first period wage independently 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, it is important to note that 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 5 (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.
(ii) Comparative Advantage: If $E[\pi(y)|\theta_h]$ and $EV^*(y')$ are sufficiently concave in information, then C-Workers hold a comparative advantage in environments with less uncertainty.

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

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

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, $\frac{E[w^C]}{E[w^D]}$, increases when uncertainty diminishes, which happens when the amount of overall information, n, increases.[34] This result on the comparative advantage of C-workers also holds as signals become more informative (for p sufficiently large), or when the prior belief q becomes more correct.[35] This underlines one of our key 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.

We now use our model to predict in which environments men outperform women and show that these predictions are in line with the following empirical facts.

[34] 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 1 in the Appendix.

[35] In these cases, given that $E[\pi(y)|\theta_h]$ and $EV^*(y')$ are sufficiently concave in p or q, respectively.

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

There are several sectors and occupations in which gender wage and performance gaps are particularly pronounced.

First, the within-occupational wage gap is severe 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 only 74% of men's earnings. Similar findings hold for the UK. 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.[36]

A second 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 fast 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, a well-known area 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 stems from their underrepresentation in patent-intensive fields of study as well as patent-intensive job tasks like design and development. Patents can be interpreted as a measure of performance in the field of basic research.

All 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 network-based mechanism why men outperform women

[36]See the report by the Equality and H.R.Commission (2009), and also Albanesi and Olivetti (2009) for evidence on management occupations.

under uncertainty. This 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 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. (2006) 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 access 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, which is why they perform better. Along the same lines, our theory predicts that men perform better on high-risk projects. In fact, more men than women work on high-risk, "hot" projects, which are critical for career advancement (see recent Catalyst Report by Silva et al. (2012) as well as Silva and Ibarra (2012) for a discussion). We argue that men have a comparative advantage on these projects due to their information-based networks that proves particularly beneficial for projects with uncertain outcomes.

In contrast, in sectors characterized by stable earnings like health support or social services the wage gap is much smaller or even reversed in the case of some occupations like social counsellors or health support technicians.[37] It is not reversed in *all* occupations that lack performance pay because many factors – not just networks differences – fuel the wage gap. However, we argue that in these industries and occupations, the wage gap is smaller than it would be in the absence of women's network features. We show next that our theory also provides a rationale for gender differences in occupational choices.

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. Even though we do not model occupational choices explicitly, 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 high up in 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

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

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 in management, 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 rationalizes why the different types of social capital that emerge from tight versus 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 a small payoff, 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 future 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 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. (2010) 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 evidence for Germany documents an entry wage gap of already 25% (Kunze (2003)).

Our model predicts a strong impact of performance at the beginning of the career on future income trajectories 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. The effect is particularly important for women: Due to higher clustering, they would lose more second period project opportunities in case of first period failure even if first period performance is the same across gender. Moreover, a first period wage gap would persist even if there is no uncertainty in the second period (i.e. even if second period performance is the same across gender). 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 Conclusion

We identify a new dimension of heterogeneity between men and women in the data, namely differences in their social network structures, and develop a theory that connects 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 finding, we build a stylized 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 are advantageous, but in different environments. We find that, in environments where uncertainty is high, information is crucial and, therefore, men outperform women.

We connect our findings to several stylized facts on gender differences in labor market outcomes, such as wage and performance gaps in occupations and sectors characterized by considerable earnings instability. We provide a unified, network-based theory for these facts. We see this approach complementary to other explanations, such as differences in preferences, risk aversion and bargaining behavior, discrimination, or penalties for reduced and flexible work hours.

We believe it would be insightful to test our theory empirically in order to quantify the impact of network differences on performance and wages. We would need a dataset of informal networks *at* the workplace in environments where team and project work matter, along with performance measures. In particular, we need ways to measure informal networks and distinguish them from formal ones. In addition, we would need to control for the entry wage in order to distinguish our theory from a theory that men's networks are more effective for job search, and thereby leading to higher wages. This points also to the reason why we cannot use the most recent waves of AddHealth, that contain entry wages, to test our theory. We find that degree has a positive impact, but this might just mean that men are better at job search because of their network. We are aware of no dataset that fulfills all these requirements 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 these network structures could also emerge because boys and girls play different games. Whereas boys tend to play in big groups, girls are encouraged to socialize in a different manner already from an early age onwards. So, friendship formation could be influenced by both an innate trait and 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.

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[38] and can still be identified. The other friends cannot be identified and are dropped subsequently from the sample.[39]

Descriptive Statistics AddHealth

Table 1: 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. in Conti et al. (2013).[40] The purpose of this estimation is only to show that men's and

[38] 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.

[39] 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.

[40] 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

women's networks differ. Our results for the entire sample are given in Table 3. The results where we only consider students between ages 12 and 18 are given in Table 4.

Table 2: 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.

We find that girls have a significantly higher clustering coefficient, independently of how the clustering coefficient is measured. To be more precise, girls have a clustering coefficient that is between .068 and .110 standard deviations higher than that of boys. 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 care most about as we are interested in the network properties of men and women, girls have a lower in, out and overall degree.[41] This can be seen from Table 2.[42]

The interpretation of the estimates is that the clustering coefficient of boys is about

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.

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

[42] Note that our findings are in line with Burt (2011) who defines the network type in terms of clustering, but not degree.

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

	Cl. Coeff. (dir.)	Cl. Coeff. (dir.)	Cl. Coeff.	Cl. Coeff.	In Degree	In Degree	Out Degree	Out Degree	Degree	Degree
Female	0.110***	0.0800***	0.0922***	0.0680***	0.107***	0.164***	0.186***	0.209***	0.178***	0.226***
	(0.00565)	(0.0104)	(0.00563)	(0.0104)	(0.00683)	(0.0131)	(0.00609)	(0.0111)	(0.00634)	(0.0118)
Age-16	0.00440		0.00456		-0.0173***		-0.0500***		-0.0410***	
	(0.00249)		(0.00252)		(0.00271)		(0.00247)		(0.00255)	
Size/1000	0.0310	-2.199***	-0.0170	-2.734***	0.0420	1.545***	0.0339	0.0828	0.0457	0.963**
	(0.0634)	(0.395)	(0.0750)	(0.529)	(0.0571)	(0.307)	(0.0839)	(0.355)	(0.0714)	(0.329)
Age 16-17		0.00493		-0.00136		0.0472***		-0.0760***		-0.0189
		(0.00996)		(0.00989)		(0.0107)		(0.00993)		(0.0101)
Female*Age 16-17		0.0618***		0.0585***		-0.133***		-0.0732***		-0.123***
		(0.0133)		(0.0132)		(0.0144)		(0.0131)		(0.0135)
Age 18-19		-0.0295**		-0.0189		-0.105***		-1.031***		-0.696***
		(0.0107)		(0.0108)		(0.00947)		(0.00797)		(0.00833)
Female*Age 18-19		0.00313		0.0159		-0.164***		-0.236***		-0.242***
		(0.0158)		(0.0158)		(0.0130)		(0.0107)		(0.0113)
Female*Size/1000		0.00510		0.00137		0.00251		0.00887		0.00694
		(0.00873)		(0.00870)		(0.00833)		(0.00752)		(0.00771)
Constant	0.0767	0.0892	0.186	0.251	-0.242*	-0.453***	0.165	0.174	-0.0410	-0.161
	(0.127)	(0.133)	(0.151)	(0.178)	(0.114)	(0.0817)	(0.169)	(0.107)	(0.144)	(0.0944)
Additional Controls: School Fixed Effects										
Observations	84792	106982	84792	106982	84792	106982	84792	106982	84792	106982
R^2	0.198	0.159	0.205	0.167	0.132	0.129	0.170	0.343	0.205	0.287

Standard errors in parentheses

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

Table 4: Differences in Degree and Clustering for Men and Women: Ages 12-18

	Cl. Coeff. (dir.)	Cl. Coeff. (dir.)	Cl. Coeff.	Cl. Coeff.	In Degree	In Degree	Out Degree	Out Degree	Degree	Degree
Female	0.110***	0.0728***	0.0930***	0.0606***	0.108***	0.149***	0.187***	0.201***	0.178***	0.212***
	(0.00568)	(0.0107)	(0.00566)	(0.0106)	(0.00689)	(0.0145)	(0.00613)	(0.0125)	(0.00639)	(0.0132)
Age-16	0.00743**		0.00699**		-0.0129***		-0.0477***		-0.0370***	
	(0.00263)		(0.00263)		(0.00286)		(0.00257)		(0.00266)	
Size/1000	0.0363	0.0293	-0.0121	-0.0171	0.0483	0.0383	0.0391	0.0292	0.0526	0.0406
	(0.0635)	(0.0633)	(0.0750)	(0.0750)	(0.0570)	(0.0578)	(0.0839)	(0.0829)	(0.0714)	(0.0705)
Age 16-17		0.00505		0.00113		0.0491***		-0.0454***		0.00110
		(0.0103)		(0.0102)		(0.0110)		(0.0102)		(0.0103)
Female*Age 16-17		0.0591***		0.0557***		-0.137***		-0.0753***		-0.127***
		(0.0135)		(0.0133)		(0.0145)		(0.0132)		(0.0136)
Age 18-19		-0.0423*		-0.0297		-0.00676		-0.193***		-0.123***
		(0.0196)		(0.0205)		(0.0214)		(0.0203)		(0.0204)
Female*Age 18-19		0.0316		0.0419		-0.285***		-0.116***		-0.240***
		(0.0316)		(0.0325)		(0.0292)		(0.0294)		(0.0290)
Female*Size/1000		0.0115		0.00819		0.0171		0.0164		0.0202*
		(0.00927)		(0.00920)		(0.0101)		(0.00929)		(0.00951)
Constant	0.0768	0.0834	0.185	0.190	-0.241*	-0.232*	0.165	0.233	-0.0406	0.00640
	(0.127)	(0.126)	(0.151)	(0.151)	(0.114)	(0.116)	(0.169)	(0.167)	(0.144)	(0.142)
Additional Controls: School Fixed Effects										
Observations	83688	83688	83688	83688	83688	83688	83688	83688	83688	83688
R^2	0.199	0.200	0.206	0.207	0.132	0.134	0.170	0.170	0.205	0.207

Standard errors in parentheses

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

.06 standard deviations lower than that of girls but their degree is approximately .02 standard deviations higher.[43]

To address concerns that the higher degree for older male students is due to the fact that the number of 18 year old males is higher, we check robustness, restricting the sample to schools where the gender ratio for this age group is balanced. The results are give in Table 5. The pattern remains the same, that is boys still have a higher degree than girls.[44]

Table 5: Differences in Degree for Men and Women: Ages 12-18, Balanced Gender Ratio for Age 18

	In Degree	In Degree	Out Degree	Out Degree	Degree	Degree
Female	0.0728***	0.228***	0.197***	0.193***	0.164***	0.254***
	(0.0178)	(0.0542)	(0.0158)	(0.0464)	(0.0164)	(0.0491)
Age-16	-0.00299		-0.0388***		-0.0256***	
	(0.00697)		(0.00614)		(0.00640)	
Size/1000	-0.259***	-0.230***	-0.0413	-0.0587	-0.178***	-0.172***
	(0.0343)	(0.0391)	(0.0314)	(0.0357)	(0.0317)	(0.0363)
Age 16-17		0.0724*		-0.0288		0.0250
		(0.0281)		(0.0253)		(0.0259)
Female*Age 16-17		-0.152***		-0.0869**		-0.143***
		(0.0369)		(0.0329)		(0.0341)
Age 18-19		0.0673		-0.174***		-0.0675
		(0.0536)		(0.0484)		(0.0488)
Female*Age 18-19		-0.266***		-0.0709		-0.201**
		(0.0682)		(0.0638)		(0.0641)
Female*Size/1000		-0.0496		0.0343		-0.00814
		(0.0338)		(0.0306)		(0.0314)
Constant	0.405***	0.329***	0.325***	0.388***	0.439***	0.433***
	(0.0650)	(0.0710)	(0.0563)	(0.0619)	(0.0583)	(0.0641)
Additional Controls: School Fixed Effects						
Observations	12718	12718	12718	12718	12718	12718
R^2	0.081	0.084	0.099	0.101	0.126	0.129

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

[43] We believe our estimates are a lower bound, as high schools have a very balanced gender ratio. In contrast, many work environments have significantly higher shares of men, which would have an effect on these measures.

[44] We are omitting here the results on clustering coefficient, again the pattern remains unchanged.

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 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 $g_g(Sij) = g$.

Perfect Public Equilibrium

The relationship quality between two directly connected workers constitutes a state, $\gamma \in \Gamma = \{\gamma_g, \gamma_b\}$. Also, recall the publicly observed signals $y \in Y = \{0, 1, \ldots, n_{max}\}$ where $n_{max} = max_i n_i$. We can define a pure public strategy $\sigma : \Gamma \times Y \to E$, 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.*

We restrict attention to the strategies according to which agents exert high effort if the relationship to the project partner is good and zero effort otherwise. This implies for period one and period two strategies:

$$\text{Period 1:} \quad \forall\, y \quad \sigma(\gamma_g, y) > 0$$
$$\text{Period 2:} \quad \forall\, y' \quad \sigma'(\gamma_g', y') > 0 \qquad \text{and} \qquad \sigma'(\gamma_b', y') = 0.$$

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.[45] 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 conclusions of Section 6 unchanged.

In order to see this, we define the payoffs from choosing the static high effort PPE and

[45] 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.

from our proposed strategy, respectively:

$$W_i^{stat} = s_i(1+\beta)E\left[f(e'(y), e'(y))\pi(y) - c(e'(y))\right], \tag{9}$$

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

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

$$EV_1 - EV_2 > \beta r_i(1 - E[f(e(y), e(y))])EV_2 \tag{11}$$

So, if $EV_1 - EV_2 > 0$ and $E[f(e(y), e(y))]$ is sufficiently large, then welfare is higher under our strategy.[46] An example of parameter values for which equation (11) holds is given in Table 6. 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 6: 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

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

[46]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, 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.

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.

But the equilibrium that is payoff maximizing 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 mis-coordination it might be better to always choose zero effort. Whether the expected payoff maximizing equilibrium or the zero effort equilibrium (that even under mis-coordination yields no losses) will be selected depends on whether payoff or risk dominant strategies should 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 might risk to choose the high effort which can potentially result in a loss (namely 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.

Technical Appendix B: Proofs

Proof of Proposition 1: Static Decision Problem

Given the assumptions on $f(.,.)$, namely

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

1. *Symmetry: $f(e_i, e_j) = f(e_j, e_i)$.*
2. $f_1(e_i, e_j) > 0, f_2(e_j, e_i) > 0$.
3. $f_{11}(e_i, e_j) = f_{22}(e_j, e_i) < 0$.
4. *Strict Supermodularity: $f_{12}(e_i, e_j) = f_{21}(e_i, e_j) > 0$.*
5. $f(e_i, 0) = f(0, e_j) = 0$.
6. $f(\lambda e_i, \lambda e_j) = \lambda f(e_i, e_j)$, $\lambda e_i, \lambda e_j \leq e_{max}$.[47]

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 $e_i = e_j > 0$.

[47] 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 $\lambda e_i \leq e_{max}$, $\forall i$.

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

$$\frac{f_1(e_i, e_j)}{f_2(e_i, e_j)} = \frac{c'(e_i)}{c'(e_j)} \tag{12}$$

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 (12) 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.

$$f_1(e, e)\pi(y) = c'(e) \tag{13}$$

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.

Lemma 1

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) $n_{ext} \to \infty$.

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

$$\begin{aligned} Pr(\theta_h|y) &= \frac{Pr(y|\theta_h)Pr(\theta_h)}{Pr(\theta_h)Pr(y|\theta_h) + Pr(\theta_l)Pr(y|\theta_l)} = \frac{qp^y(1-p)^{n-y}}{qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y} \\ &= \frac{1}{1 + \frac{1-q}{q}\left(\frac{1-p}{p}\right)^{2y-n}} \end{aligned} \tag{14}$$

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

$$E\left[\pi(y_{n+1})|\theta_h\right] > E\left[\pi(y_n)|\theta_h\right] \tag{15}$$

$$E\left[\pi(y_{n+1})|\theta_l\right] < E\left[\pi(y_n)|\theta_l\right] \tag{16}$$

We will show that equation (15) holds and leave the proof of equation (16) to the reader. We can rewrite equation (15) 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 $y \sim \text{Binomial}(np, np(1-p))$ if $\theta = \theta_h$ and $y \sim \text{Binomial}(n(1-p), np(1-p))$ 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 $\lim_{n\to\infty} E\left[\pi(y)|\theta_l\right] = v_l$.

Lemma 2:

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).

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) $n_{ext} \to \infty$.

Proof of Lemma 2:

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

$$V^*(y') \equiv g(\pi(y')) \tag{17}$$

As $\pi(y')$ is a martingale, 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

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

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

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

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

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

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 (3)). 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 $n-2y < 0$, $\lim_{p\to1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = \lim_{p\to1} qp^y(1-p)^{n-y}$. Then we know that

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

If $n - 2y > 0$, $\lim_{p\to1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = \lim_{p\to1}(1-q)p^{n-y}(1-p)^y$. It follows that

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

Last, if $n - 2y = 0$, $\lim_{p\to1}(qp^y(1-p)^{n-y} + (1-q)p^{n-y}(1-p)^y) = \lim_{p\to1} p^y(1-p)^{n-y} = 0$, 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 2:

The proof follows from Lemmas 1 (Appendix) and equation (3).

Proof of Proposition 4:

The proof follows immediately from Lemmas 1 and 2 (Appendix) and equation (6).

Proof of Proposition 5: 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 (8), 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 $Pr(\gamma'_g|\theta) \equiv E[f\,(e(y), e(y)) + (1-r)(1-f\,(e(y), e(y)))|\theta] = E[e(y)|\theta]rf(1,1)+1-r$. 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 $v_l = 0$,

$$\frac{E[w^C]}{E[w^D]} = \frac{qw^C(\theta_h)}{qw^D(\theta_h)} = \frac{(E[\pi(y)|\theta_h])^C + \beta(sr)^C(EV^*(y'))^C}{(E[\pi(y)|\theta_h])^D + \beta(sr)^D(EV^*(y'))^D} \tag{18}$$

where we used the definition of wages and the expression for equilibrium effort (6). We want to show that (18) 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

$$(E[\pi(y)|\theta_h])^C = E[\pi(y_n)|\theta_h]$$
$$(E[\pi(y)|\theta_h])^D = E[\pi(y_{n+1})|\theta_h]$$
$$(EV^*(y'))^C = EV^*(y'_n)$$
$$(EV^*(y'))^D = EV^*(y'_{n+1})$$
$$(sr)^C = \overline{sr}$$
$$(sr)^D = \underline{sr}$$

We will show that (18) is increasing in n, that is,

$$\frac{E[\pi(y_n)|\theta_h] + \beta\overline{sr}EV^*(y'_n)}{E[\pi(y_{n+1})|\theta_h] + \beta\underline{sr}EV^*(y'_{n+1})} > \frac{E[\pi(y_{n-1})|\theta_h] + \beta\overline{sr}EV^*(y'_{n-1})}{E[\pi(y_n)|\theta_h] + \beta\underline{sr}EV^*(y'_n)} \tag{19}$$

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

$$EV^*(y'_n)^2 > EV^*(y'_{n-1})EV^*(y'_{n+1}) \tag{20}$$

$$E[\pi(y_n)|\theta_h]^2 > E[\pi(y_{n+1}|\theta_h)]E[\pi(y_{n-1})|\theta_h] \tag{21}$$

$$\frac{EV^*(y'_n)}{EV^*(y'_{n-1})}\frac{E[\pi(y_n)|\theta_h]}{E[\pi(y_{n+1})|\theta_h]} > \frac{\overline{sr}}{\underline{sr}} > \frac{EV^*(y'_{n+1})}{EV^*(y'_n)}\frac{E[\pi(y_{n-1})|\theta_h]}{E[\pi(y_n)|\theta_h]}. \tag{22}$$

To show this, rearrange (19) to get:

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

This expression is positive if (20)-(22) hold. To see that (20)-(22) are implied by sufficiently strong concavity note the following. A function $f(n)$ is *log-concave* if:

$$f(n+1)f(n-1) < f(n)^2 \tag{23}$$

Hence, for (20)-(22) 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

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

Then (24) implies (23) 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 (24). 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 (20)-(22) hold.

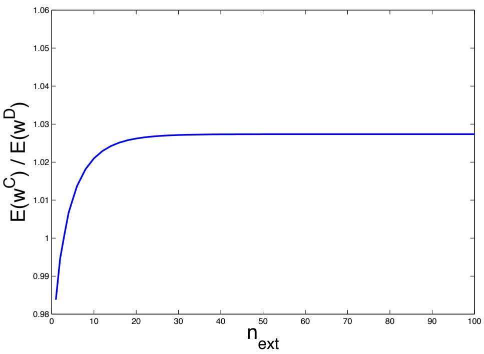
The arguments that (18) is increasing in p (for $p > p^*$) and q are analogous and slightly simpler because $E[\pi(y)|\theta_h]$ and $EV^*(y')$ are continuously differentiable in p and q. We omit them for brevity and instead highlight some of our simulation results.

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 7).

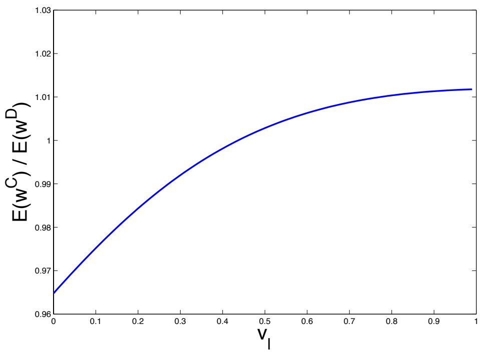
Table 7: Baseline Parameters

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

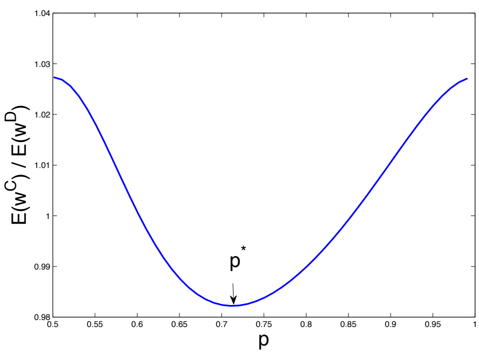
Figure 1: Expected Wage of Agent with Higher Clustering Relative to Agent with More Information



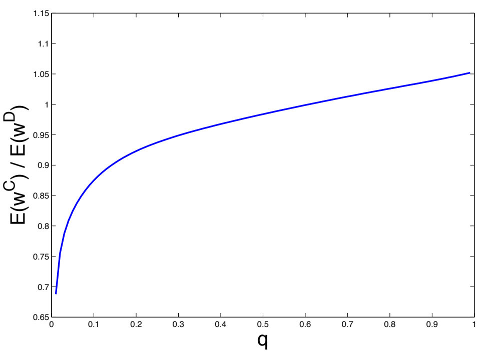
(a) As a Function of External Info



(b) As a Function of Low Value



(c) As a Function of Signal Precision



(d) As a Function of Prior Belief

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