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Abstract

I model research quality as the outcome of a CES production technology that uses human capital measured by publication records as inputs. Investigating a sample of scientific publications with two co-authors I show that the CES-complementarity parameter is a function of the age difference of the authors. Complementarity is maximized if the age difference between the authors is about 10 years. Two theories are presented which may explain my findings. According to these models, older and younger researchers differ not only in their skill levels but also in the types of their skills and their interpersonal relationships.

Keywords: Academic Collaboration, CES Technology, Team Production, Human Capital.

JEL Classification Numbers: A14, D24, I23, J24.

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1 Introduction

This paper examines the technology of scientific collaboration. It addresses the question under which circumstances co-authorship is most productive in ways that go beyond the co-authors' human capital endowments. A vast existing literature on co-authorship has compared single-authored articles with co-authored articles and articles with fewer authors with articles with more authors. In this paper, in contrast, I use a sample of articles written by two people, thus keeping the number of authors per article constant. The idea is that when two people work together, the quality of what they produce depends not only on person A and person B, but also on the quality of their relationship. The relationship represents a third entity, which economics has paid little attention to in the past. My analysis shows that age composition of the collaborating authors is highly correlated with their relationship. A measure of the relationship's quality is maximized if one author is ten years older than the other. The average age difference in my sample of roughly nine years is very close to this optimum, which suggests a selection problem. I explore different explanations for the observed phenomenon but one should keep in mind that factors that are not accounted for in this study may drive both, age composition and productivity.

The paper is part of an emerging literature on academic team work. Researchers' increasing tendency to collaborate has shifted not only economists' interest towards co-authorship. Wuchty, Jones, and Uzzi (2007) describe how the focus in the history and sociology of science has moved from the individual genius to teams. De Solla Price and Beaver (1966) regard the global research community as forming a network referred to as the 'invisible college' in which geographic boundaries and proximity have become less important (cf., Kim, Morse, and Zingales, 2009). Formal co-authorship, which I study in this paper, is the most important type of scientific collaboration. Collaboration occurs in all fields of economic activity. In the academic setting, however, one aspect of individual output, i.e. research, is observable, which has given rise to the field of bibliometrics. Using data on scientific output, Hamermesh and Oster (2002) and Kim, Morse, and Zingales (2009), for instance, investigate how easier communication, in particular via the internet, has affected productivity. Oster and Hamermesh (1998) and Rauber and Ursprung (2008) analyze how individual productivity evolves over the life cycle.

A number of studies have dealt with co-authored articles. Laband and Tollison

(2000) report a steady increase in both, incidence of co-authorship, i.e. the fraction of co-authored papers, as well as in the number of authors per co-authored paper over the last decades: the incidence of co-authorship increased from under 10 percent in the 1950s to more than 67 percent in the year 2000, whereas the number of authors per co-authored paper increased only rather slightly from 2.0 to 2.2. More recent research by Wuchty, Jones, and Uzzi (2007) shows that teams have become increasingly important in all scientific disciplines. Barnett, Ault, and Kaserman (1988) investigated whether there were any gains from this trend towards more co-authorship. They obtained strong evidence that increasing opportunities for specialization and division of labor have made teamwork more beneficial and that co-authorship reduces publication uncertainty through diversification. Laband (1987) and Ursprung and Zimmer (2007) find that co-authorship leads to a higher quality of articles as measured by acceptance rates or citations. The evidence on peer effects in academic networks is mixed. Using the dismissals of Jewish scientists from Nazi Germany as an instrument for the number and quality of the faculty at German universities in the 1930s, Waldinger (2012) finds no evidence for local peer effects. Kim, Morse, and Zingales (2009), in contrast, who focus on economics departments, observe that such local peer effects existed in the 1970s but vanished afterwards. Azoulay, Graff Zivin, and Wang (2010) document a drop of 5 to 10 percent in the publication rates of the collaborators of 161 'superstar' life scientists following their premature deaths.

On the other hand, team work is also associated with coordination costs. Starting with Alchian and Demsetz (1972), economists have become interested in designing incentive structures to render team work more efficient. Prat (2002) investigates the optimal composition of teams given the degree of complementarity of the team members' tasks. He finds that the more complementary the inputs of its members, the more homogeneous a team should be.

This paper uses publication data for all current faculty members of departments of economics and business administration at German, Austrian and Swiss universities. Table 1 documents that the findings discussed above also hold for the data and output measure used in this paper: article quality as measured by Combes and Linnemer (2010)'s journal quality weighting scheme CLm is closely related to the number of authors in my sample. CLm assigns positive weights to all journals listed by *EconLit* with a maximum of 100 attained by the *Quarterly Journal of Economics*.

The number of co-authors has a significant positive effect on output across all specifications. Specification (2) confirms that the effect is lower if a linear time trend is included because both, co-authorship and German economists' tendency to publish in international journals, have increased over time. In specification (3), I introduce a squared term for the number of authors. Quality is highest when an article has 4.6 authors.

The fact that co-authored articles are of higher quality is intuitive. When two scholars work together, each of them can specialize on the task that corresponds to his or her comparative advantage. Indeed, when two researchers work together, they often perform tasks in which they even have an absolute advantage. This study is related to a literature in psychology which emphasizes the importance of the social environment and relationships for human creativity.[1] This literature confirms the view that a team is more than the sum of its members. The relationship between collaborating individuals represents a third entity, which determines their joint productivity.

The objective of this paper is to examine this third entity. It identifies age as one determinant of the extent of complementarity of the team members' inputs. The identification strategy uses the variation in a set of articles with exactly two co-authors rather than by comparing co-authored with single-authored articles. The employed method, a two-step technique, is novel in the literature and leads to new insights. The structure of the paper is as follows. Section 2 outlines the first step, in which a CES production function serves to measure complementarity in a specific collaboration when article output and human capital of the two authors are given. This strategy allows me to measure the quality of the pairs controlling for individual abilities. Section 3 describes the data. In the second step, the revealed, team-specific complementarity parameter is regressed on the average age of the authors and on their age difference. The results are presented in Section 4. The main finding is that pairs of co-authors are most productive when the age difference between the authors is about ten years. In Section 5 I develop theoretical explanations of the complementarity parameter. Section 6 presents survey-based tests of these theories. Section 7 concludes.

[1] For an overview, see e.g. Cacioppo and Berntson (2005) and Cacioppo, Visser, and Pickett (2006).

2 Identifying Variation in Complementarity

Scientific collaboration is teamwork. Therefore it might seem straightforward to think that research output is the outcome of a corresponding teamwork production function. Productivity therefore might be harmed by shirking (see Alchian and Demsetz, 1972). Collaborating scientists, however, can usually observe each other's inputs pretty well and have the opportunity to retaliate, if necessary. Hence, their collaboration is not likely to represent a non-cooperative Nash-equilibrium. In the framework I will present, each individual has a given amount of human capital. Since there are no costs associated with the input of human capital, human capital is always fully employed. When two scholars collaborate, variation in the final output does not arise according to how much of their human capital is used but according to how it is used.

My unit of analysis is published articles that have exactly two authors. Assume that the quality y_i of publication i is produced by a constant elasticity of substitution (CES) production function (Arrow, Chenery, Minhas, and Solow, 1961)

$$y_i = A\left[\alpha h_{i1}^{\rho_i} + \beta h_{i2}^{\rho_i}\right]^{\frac{1}{\rho_i}}, \tag{1}$$

where h_{i1} and h_{i2} are human capital measures of the two co-authors. For CES functions, the exponent ρ may assume values smaller than 1. We have three special cases. For $\rho_i \longrightarrow -\infty$ output will be equal to $A\min\{h_{i1}, h_{i2}\}$, for $\rho_i \longrightarrow 0$ output will be $Ah_{i1}^{\frac{\alpha}{\alpha+\beta}} h_{i2}^{\frac{\beta}{\alpha+\beta}}$ and for $\rho_i = 1$ we have $y_i = A\left[\alpha h_{i1} + \beta h_{i2}\right]$. If h_{i1}, h_{i2} and y_i are given, ρ_i can be obtained through approximation if that $\alpha+\beta > 1$. This assumption is crucial. Only if $\alpha + \beta > 1$ a lower ρ implies a higher degree of complementarity, i.e. more output for given human capital endowments. Note that, other than in a Cobb-Douglas framework, $\alpha+\beta > 1$ does not imply increasing returns to scale (only a Cobb-Douglas production function with constant returns to scale is a special case of the CES production function). The upper panel of Figure 1 shows how output varies with ρ for given levels of human capital endowment for the case $\alpha + \beta > 1$. The lower panel shows input combinations required to produce a given output level $\bar{y}$ for different values of ρ.

If the two inputs are complementary, the cross-derivative of the production function will be positive, $\frac{\partial^2 y_i}{\partial h_{i1}\partial h_{i2}} > 0$, in the case of substitutes the cross-derivative will be zero (or negative), $\frac{\partial^2 y_i}{\partial h_{i1}\partial h_{i2}} \leq 0$. My objective is to distinguish between author combinations that are more or less complementary. For each article i, I will compute a ρ_i in the range between 0 and 1 through approximation, indicating varying degrees of complementarity. The closer ρ_i will be to 1, the less complementary the human capital inputs of the two co-authors. To obtain $\rho_i \in (0,1]$, y_i must be larger or equal to $A\left[h_{i1}+h_{i2}\right]$ for all observations i. I obtain this by setting $A=\min\{\frac{y_i}{h_{i1}+h_{i2}}\}$. The elasticity of substitution $\sigma = 1/(1-\rho)$ will, therefore, only assume values larger than unity. Note that this is not restrictive because no interpretation is given to absolute values of ρ and σ. All that is needed is relative variation.

In my model, human capital is the only input. Human capital thus measures time spent working on a research project in efficiency units. Time itself can, of course, not be measured. Many scholars have their best ideas during what is officially their spare time. Questions and problems keep spinning in their minds. Most researchers do not even know themselves, how much time they spent on a project. Individual heterogeneity with respect to human capital endowments is reflected by publication records. The human capital input provided by person j in the production of article i measures that person's ability and willingness to publish in academic journals as demonstrated in the past until the year t in which project i is published. As the baseline version of this measure, I will thus use

$$h_{ij} = \sum_{k=1}^{t-1}(1-\delta)^{t-k-1}y_{jk}, \tag{2}$$

where $y_{jk} = \sum_{h=1}^{\infty} y_{hjk}$ is researcher j's output in year k,[2] δ is a discount factor, and $k=1$ is the year of researcher j's first publication. Based on citation vintage, e.g. McDowell (1982) estimates that human capital of academic economists depreciates at rate 13.18. The approach is in line with the evidence that creative output typically rises toward middle age and falls thereafter (see e.g. Galenson and Weinberg, 2000; Jones, 2010a). Note that this is a somewhat broader concept than what we classically understand under human capital. It captures not only skills acquired e.g. in grad school, but also other factors such as cognitive ability and incentives that vary with age, too.

A drawback of the above specification of human capital is that this measure is inverse U-shaped. It tends to increase with age with a maximum late in the researchers' careers. This feature penalizes younger researchers. Assume, for instance, that two talented, young scholars with short publication records and hence low h_{ij}'s write a paper i that appears in a highly ranked journal. ρ_i has to be very low in

[2] I account linearly for co-authorship, i.e. $y_{ij} = y_i/n_i$, where n_i is the number of authors of article i.

that case to produce high output, indicating a high degree of complementarity. If ability were constant over life, then ρ might be downward-biased simply because the authors have not had careers long enough to publish many articles in the past. Using h_{ij} will also lead to imbalances in the human capital inputs of the two authors when the age difference is large. A number of studies suggest that input ratios should be balanced when inputs are complementary.[3] In the context of this analysis, a higher degree of complementarity would be required to produce the same output if one author has a larger share of the combined human capital than if the shares are equal. Such imbalances are most likely when the age difference is large.

The following specification of human capital accommodates a possible downward bias of ρ_i when at least one author is young,

$$l_{ij} = \sum_{i' \neq i} \frac{y_{i'j}}{2011 - t_{1j}}, \tag{3}$$

which is a scholar's average yearly career output excluding the publication of interest i (t_{1j} denotes the first year of j's career).

In Section 5 I shall present a model in which a scholar who searches for a collaborator uses the potential collaborators' age as a proxy for quality. Note that the relationship between age and human capital does not need to be taken into consideration at this stage, because human capital, as I define it, is assumed to be fully observable. This assumption appears to be reasonable since publication records of virtually all academic economists are available online.

3 Data

The employed publication data were collected from *EconLit* by the *Committee for Research Monitoring* (CRM) of the *German Economic Association*. This database contains all journal articles authored or co-authored by all economists (including business researchers) affiliated with German, Austrian and Swiss universities.[4] German economists working abroad had to register themselves to be included. All individual researchers were granted access to their entries so that they could, if necessary, correct and complete their publication records. The data set, retrieved

[3]See Prat (2002) for the composition of teams. Griliches (1969) made a related argument for physical and human capital.

[4]To be precise, only the universities in German-speaking Switzerland are covered.

in May 2010, provides not only article characteristics, but also comprehensive and accurate background information on the authors.

In line with the production function outlined in Section 2, I used all articles with exactly two authors with active accounts in the database. This also excludes retired faculty. Articles that were published before 1969 were not included because *EconLit*, which is the major source of my data, started listing articles only in 1969. This restriction is not likely to bias my results since people who are still active in research in 2010 are not likely to have published much before 1969. Articles written by authors whose birth dates were unavailable, were dropped. Note that to estimate the CES production function (1) it is necessary that both authors have non-zero human capital as measured by Equation (2). Hence, I only use articles whose authors have had positive output prior to publication. A larger sample is obtained when I use average yearly output over researchers' careers as human capital measure because, in that case, I do not need positive output in preceding years. The data set contains current affiliations but it does not list complete employment histories. I am, therefore, not able to investigate whether distant co-authorship affects complementarity in a different manner than close-by co-authorship.[5]

Article quality is measured by the CLm indicator (cf. Combes and Linnemer, 2010). CLm is based on a bibliometric two-step procedure. In a first step all 304 *EconLit* journals which are also covered by the SSCI database were ranked using the indirect method.[6] In a second step, Combes and Linnemer imputed quality indices for the remaining journals using the research performance of these journals' authors according to the SSCI journal publications and Google Scholar citations. This procedure results in a cardinal journal-quality index for all 1168 journals indexed by *EconLit*.

CLm can, therefore be thought of as a more comprehensive alternative to impact factors, which are available only for a small share of the set of *EconLit*-indexed journals. The CLm index is not time-varying, i.e. it does not reflect changes of a journal's quality over time. CLm shares this shortcoming with most other common measures of journal quality. However, Combes and Linnemer's journal-quality weighting scheme is unique in the field of economics due to its comprehensiveness and its cardinal nature. Citation counts, which would allow to account for quality

[5]The survey-based empirical analysis in Section 6 includes a measure of distance for a subsample of this data set.

[6]See, for instance, Palacios-Huerta and Volij (2004).

differences between articles that appeared in the same journal are not available in my data base. However, e.g. Azoulay, Graff Zivin, and Wang (2010) find effects of about the same magnitude independent of whether impact factors or citations are used to measure article quality.[7]

Table 2 provides descriptive statistics for the two benchmark data sets. The employed weighting scheme is CLm, for the value of δ I use two alternatives: (1) no human capital depreciation, i.e. $\delta = 0$, and (2) $\delta = 0.15$. I have 1470 observations, the respective articles were written by 825 different authors. The complementarity measures ρ_i were computed by numerical methods (approximation) because Equation (1) cannot be solved explicitly for ρ. The mean of ρ is 0.2072 for $\delta = 0.15$ and 0.1631 for $\delta = 0$. The variance is also higher when $\delta = 0.15$. Figure 2 shows the corresponding distributions of ρ. At a first glance, it may be surprising that, on average, ρ is lower when human capital does not depreciate. After all, article output y is the same in both cases, but h_1 and h_2 are higher when $\delta = 0$. Hence, imputed complementarity of the inputs is smaller without human capital depreciation. The explanation is that the technology parameter A is different in the two cases. As explained before, ρ is normalized by adjusting A such that there is one observation which corresponds to perfect substitution, while for all others we have varying degrees of complementarity.

The average age of the author pairs ranges from 29.5 to 65 years with a mean of 41.6 years. The younger co-authors are between 23 and 64 years old, the older co-authors between 31 and 70. Figure 3 displays a bar chart in the upper panel and a three-dimensional kernel density estimate in the lower panel. Collaborations between scholars of the same age, which are located on the diagonal, are quite frequent. Indeed, the share of co-productions of authors of the same age appears to be even higher internationally according to earlier findings by Laband and Piette (1995). In my sample 41.7% of all co-authorships involved scholars whose age difference was 5 years or less, in the sample examined in Laband and Piette (1995) it was more than 50%. 62.7% of the articles were co-authored by authors whose age difference was 9 years or less; the respective share amounted to almost 75% in Laband and Piette (1995). These observations together with the large share of articles in my sample that involves younger co-authors in their late 20s or early 30s indicate that mentor-protégé collaborations between doctoral students and supervisors are somewhat more

[7]See Online Appendix V of their paper.

common among German economists than internationally. On average, the authors are around 8.7 years of age apart, the highest difference being slightly above 38 years. Note that the sample contains exact dates of birth rather than simply years of birth. Despite some measurement error, these exact birth dates were used to compute age differences.

1.6% of all articles were written by two women, in 11.8% of the cases one author was female, the other male. Exactly ten percent of all articles were written by authors who both identified themselves as business administration researchers. Business administration, or "Betriebswirtschaftslehre", as it is called in German, comprises classical business fields such as finance and marketing as well as some microeconomic subjects like organizational theory. 7.6 % of the papers in the sample have mixed pairs of authors, one being an economist, the other one a business researcher. I have also computed the number of preceding collaborations. This variable measures how many articles have been co-authored by the two authors of paper i up to the year before paper i was published, the value ranges from 0 to 17 with a mean of 1.1.

Combes and Linnemer (2010) have also provided the journal-quality scheme CLh which maintains the ordering of CLm but which is more convex, i.e. the quality weights of top journals compared to lower-ranked journals are higher in CLh than in CLm. I will use CLh for a robustness check. Other robustness checks will be performed using average yearly output l_{ij} as human capital measure and different rates of human capital depreciation.

4 Empirical Analysis

Before imposing the assumptions from Section 2 about the functional form, Table 3 presents a first, non-structural look at how age affects complementarity in my sample. The dependent variable in these regressions is CLm multiplied by 1000, human capital is computed as in Equation 2 where the depreciation rate equals zero. Given the standard definition, the coefficient on the product of the human capital inputs captures complementarity. I interact this product with indicators for whether the age difference of the two authors is less than seven years or more than thirteen years to examine whether complementarity differs between groups of author pairs. It turns out that inputs of authors that are farther apart in terms of age are less complementary, whereas no significant difference is observed between pairs less than seven years apart and pairs with an age difference between seven and thirteen years. Note that the younger collaborator's prior publication record (h_2) is more correlated with the quality of the journal, in which the article appears than the older author's publication record h_1. Also, the small negative coefficient on $h_1 * h_2$ suggests that there is no evidence for complementarities in the human capital of the two researchers in the raw data if age composition is not taken into account. The structural analysis that follows will lead to deeper insights.

To structurally estimate the determinants of complementarity in scientific collaboration, I will use a linear regression equation,

$$\rho_i = c + \lambda m_i + \chi m_i^2 + \kappa d_i + \eta d_i^2 + \psi' w_i + \varepsilon_i, \tag{4}$$

where m_i is the average age of the co-authors of paper i, d_i is their age difference, w_i is a vector of covariates and ε_i is an error term. The dependent variable is ρ_i from Equation (1) and was obtained by numerical approximation.

Table 4 shows the regression results for human capital depreciation rates of 15% and 0% per year. In both cases, the coefficients are pretty robust across specifications. In Specifications (1) to (4), the dependent variable is computed using $\rho = 0.15$. The coefficients of interest are average age, age difference and squared terms for average age and age difference. All these variables significantly affect the complementarity parameter ρ, the squared average age is significant only at the 10 percent level, all others at the 1 percent level. I also include dummies for gender and for the sub-disciplines in which the authors are active. Unreported results show that the coefficients that measure the impact of age composition hardly change if these controls are dropped. Specification (2) also controls for the years in which the articles were published. The coefficients on age difference and the squared term increase slightly in absolute value and become more significant. Specification (3) adds controls for the number of preceding collaborations. Again, inclusion of year dummies only slightly affects the coefficients of interest.

The age difference has a significantly negative effect on ρ, i.e. the larger the difference, the more complementary are the two authors' inputs. However, due to the positive coefficient on the squared term, this effect is reversed once a certain difference is reached. Based on specification (4) which includes the full set of regressors, ρ is minimized, i.e. complementarity is maximized, if the age difference between the two authors is 10.39 years. Up to 65 years, a higher average age of the two co-authors means that their human capital inputs will be less complementary.

This is plausible given the fact that, up to a certain age, older authors tend to have higher human capital endowments.

The coefficient of the gender dummies indicates that complementarity is increased if both co-authors are female. For mixed pairs, the effect is insignificant in most specifications and disappears once the number of preceding collaborations is controlled for. This confirms earlier findings by McDowell, Singell, and Stater (2006) who report significant gender differences in publication behavior. Although, in a given year, female economists are less likely to publish, conditional on publishing they are not less likely to have a co-author.[8] And, even more importantly, women are not less likely than male economists to publish in the leading journals in economics. This is true in my sample as well. Articles that were authored by two women on average are of higher quality than articles written by two male authors. Human capital, on the other hand, is lower if both authors are female.[9] Since men's human capital proxy is higher, less of their output will have to be explained by complementarity.

The coefficient on business co-authors is stronger and more significant than the coefficient of both authors being female. Surprisingly, average article quality is lower if the business administration dummy equals one. This suggests a positive coefficient because less complementarity is required. This effect, however, is reversed by the fact that the human capital of business researchers in my sample is far lower than the human capital of economists. Team work is often associated with increasing specialization. As knowledge accumulates, it becomes harder to attain the research frontier. As a consequence, scientists can either choose to learn more or to specialize on more narrow subjects (see Jones, 2009). Ductor (2011) uses JEL codes to model co-authorship formation. For scientific collaboration, it is important whether the collaborators have similar backgrounds and employ similar techniques or whether one is, for example, a theorist and the other one is an econometrician. Economics and business administration are fairly different subjects and this intellectual distance is

[8] Boschini and Sjögren (2007), in contrast, find that women are more likely to work alone. They also observe that women's propensity to collaborate with other women increases more strongly than men's in the share of female researchers that are active in their subfield suggesting that co-authorship formation is not gender-neutral.

[9] The gender differences in human capital are significant at a 5% level of significance, those on article output y at the 10 % level of significance. Average output of the 1273 articles authored by two men is 10.1798 with a standard deviation of 9.7706, for the 24 articles authored by two women, the mean is 13.6980 with a standard deviation of 11.9885. This yields a t-test statistic for the gender difference of the averages of 1.74.

confirmed by the highly significant dummies which indicate that publication behavior is indeed different across these two groups. The fact that the coefficients of interest remain unaffected suggests that intellectual distance is unrelated to the link between age and complementarity.

For the number of preceding collaborations, I obtain a positive coefficient. The more often people have worked together in the past, the less complementary future collaborations will be. This may seem surprising, since one would expect coordination costs to be higher for pairs that collaborate for the first time. The preceding collaborations variable may however also pick up how much people like each other. At least, it can be assumed that if people keep working together they do not dislike each other. This coefficient can therefore be interpreted as indication for a trade-off between consumption benefits and productivity, which will be discussed in more detail in Section 5.2.

Specifications (5) to (8) repeat the analysis for $\delta = 0$. Given that the McDowell (1982) estimate of $\delta = 13.18\%$ appears to be rather high, it makes sense to compare estimates for different rates of human capital depreciation. The coefficients of average age and average age squared become insignificant. All other coefficients of interest remain virtually unchanged in terms of signs, magnitudes and levels of significance. Complementarity is now highest if the age difference is 9.46 years when the full set of regressors is included. One thing, however, changes substantially. With $\delta = 0$, the R^2 is higher across all specifications. When I control for the full set of regressors, it increases from 0.2624 with $\delta = 0.15$ in specification (4) to 0.4067 with $\delta = 0$ in specification (8).

Table 5 provides further robustness checks. In all specifications, I control for all available characteristics of articles and authors. If human capital is measured as in Equation (3), i.e. by average output over the entire career, the sample size increases by 365 observations because output in previous years does not necessarily have to be positive. Average age now has a significantly negative effect on complementarity. This makes sense given that the human capital measure l_j is not increasing with age.[10] The coefficients on age difference and the control variables hardly change at all.

Columns (2) to (4) of Table 5 vary the rates of human capital depreciation. All

[10] Division by a linear term in years since the first article ignores the insight from Oster and Hamermesh (1998) and Rauber and Ursprung (2008) that age-productivity profiles are quadratic.

that changes is the R^2 which increases as delta becomes lower. A rate of depreciation of human capital of academic economists equal to 15% may thus be too high. The relationship between age and complementarity is practically unaffected by the way human capital is measured. In columns (5) to (8), different measures not only for human capital but also for article quality are used. Columns (5) and (7) show results if output is measured by the more convex scheme CLh for the baseline rates of human capital depreciation of 0% and 15%. In columns (6) and (8), article output is measured by the product of CLm and article length in pages. The sample size is reduced when pages are taken into account because number of pages was not available for 130 publications, in particular for articles that were in press when the data were retrieved. Again, the results are highly robust. All coefficients of interest have the same signs as before. Although they become somewhat smaller in absolute value, most of them remain significant at a 1% level of significance. In columns (6) and (8), the coefficients on age difference and the squared term are significant only at the 5% and 10% levels, respectively.

5 A Theory of Complementarity

This section presents two explanations for the link between age and complementarity. Specialization and learning are not taken into account. I do not focus on specialization since Ductor (2011) has already shown that the authors' fields of specialization (as measured by JEL codes in their other work) matter for co-authorship formation. My results, however, suggest that specialization proxied by business administration and economics is unrelated to how age affects complementarity. Learning does not appear to be an issue either. If, over the course of their careers, authors were to observe that they are most productive when working with collaborators who are ten years younger or older, one would expect age difference of their co-authors to converge to ten years as scholars get older. Unreported results show that it does not: controlling for individual fixed effects, authors tend to collaborate with scholars that are farther away in terms of age as they get older. Age difference is not only increasing with the authors' age, it also diverges away from the optimal level of ten years.

5.1 Age-Specific Skill Heterogeneity

The decision to collaborate is often made jointly. However, I will illustrate my interpretation of ρ by providing an example in which one economist searches for a collaborator. This conceptual scholar has an idea, say a concept for a new model. He knows that he needs a collaborator to solve the model. I will refer to this collaborator as the technical scholar. He meets a colleague, say at a conference, and they agree to collaborate. The conceptual scholar does not know with certainty whether his and the collaborator's skills match and their joint project will be successful. But in the following I will argue that he can use the collaborator's age or the difference between his own and the collaborator's age as an indicator for skill match. The probability of a skill match s can be thought of as being equal to $1 - \rho$, where ρ is a function of age difference and average age as in Equation (4).

Cognitive skills may be one channel through which age affects human capital complementarity. To establish this link formally, one may assume that the complementarity parameter ρ is a function of skills that are not reflected by our human capital measures. These can be thought of as different methods and approaches to do research. Anecdotal evidence suggests that when two researchers of different age collaborate, the younger scholar usually performs the technical tasks such as detailed computations and programming, whereas the older scholar is responsible for the overall concept. I use this as a starting point and assume that each individual has technical skills $T(a)$ which decrease with age a and conceptual skills $C(a)$ which increase over the life cycle. Technical skills capture an individual's ability to handle complicated theoretical setups and complex econometric techniques, in particular tools and techniques that were not known to previous generations. Conceptual skills comprise everything that is related to the accumulation of knowledge. Acquisition of experience implies increased conceptual skills.

This framework is related to the concept of fluid and crystallized intelligence suggested by the noted psychologist Raymond Cattell and to David Galenson's theory of old masters and young geniuses. Cattell[11] distinguishes between fluid intelligence which is hereditary and crystallized intelligence which captures all skills that are due to an individual's education and experience. Just as Cattell's two factors, Galenson's technical and conceptual skills have different life-cycle patterns. An individual's ability to acquire knowledge, i.e. fluid intelligence, is highest when someone is young,

[11] See e.g. Cattell (1963) and Horn and Cattell (1966).

whereas knowledge itself, i.e. crystallized intelligence, increases over time. The two factors are, of course, related to each other: someone with a high capacity to learn learns more and learns faster. This may also apply to technical and conceptual skills, the best technicians may turn into the best conceptualists.

Galenson[12] divides artists (painters, novelists, movie directors) into two categories. Artists belonging to category one, which he labels conceptual, attain their greatest achievements at a relatively young age.[13] Picasso belongs to this group. Galenson describes the working style of conceptual artists as being characterized by long periods of advance planning. The actual working process in which a painting comes to existence, however, is rather short. Experimental artists like Cézanne, on the other hand, are most productive at a relatively older age. According to Galenson, experimental painters rarely have elaborate plans in mind when they start painting. Work on a particular painting may take an experimental painter many years. Galenson emphasizes how difficult the decision to stop working often is for an experimental painter.

A similar approach can be found in Jones (2010a) who observes that, at the beginning of the twentieth century, Nobel Laureates and great inventors were between five and eight years younger at the time of their scientific achievements, than hundred years later. He introduces early life cycle effects and late life cycle effects. Early life cycle effects depend on the point in time at which researchers complete formal education and determine the increase in productivity early in their careers. Late life effects capture that part of an individual's innovation potential which is not related to education. Jones finds empirical support for the assumption that people's ability to produce scientific breakthroughs is declining as they get older implying a negative slope for late life effects. While the late life effects have remained stable over the course of the twentieth century, due to an accumulation of knowledge, it has taken scholars longer to obtain their highest degrees and, hence, to achieve the research frontier. According to Jones, the fact that researchers have to learn longer during the period in which their raw ability to innovate is highest has reduced scientific output.

I put Galenson's labeling on its head by referring to the skill that increases over life as conceptual. Galenson's analysis only considers some of the most outstanding

[12]See Galenson (2006), Galenson and Weinberg (2000) and Galenson and Weinberg (2001).
[13]The quality of artists' works is measured by auction prices.

geniuses in the history of art, whereas my data set includes the works of all academic economists working in Germany, Austria and Switzerland as well as some German-speaking scholars working abroad. At most a handful of the individuals in my sample fit into Galenson's genius category. The conceptual ability includes not only having good ideas but also knowledge of the research process which requires some experience. Although Galenson discusses the possibility that painters may change during their careers from being conceptual artists to experimental artists who make important contributions in both approaches, he mostly treats the two types as mutually exclusive. Here I assume that all researchers have both skills, however they evolve differently over their life cycles.

My formalization of this idea closely follows Jones (2010a). Abilities are logistic functions of a scholar's age a. Conceptual skills follow a strictly increasing S-shaped pattern,

$$C(a) = \frac{1}{1 + e^{-(a-\mu)/\omega}},$$

whereas technical skills are strictly decreasing in age,

$$T(a) = 1 - \frac{1}{1 + e^{-(a-\tau)/\theta}}.$$

I model the complementarity parameter ρ as a function of how abilities of the two collaborating researchers interact. Consider the following model, in which complementarity is simply the product of conceptual and technical skills of the two co-authors. Since ρ is decreasing in complementarity, I write

$$\begin{aligned} \rho &= 1 - C(a_1) \cdot C(a_2) \cdot T(a_1) \cdot T(a_2) && (5) \\ \rho(d) &= 1 - C(a_1) \cdot C(a_1 - d) \cdot T(a_1) \cdot T(a_1 - d), && (6) \end{aligned}$$

where the sub-index $j = 1$ indicates the older of the two researchers and $j = 2$ is his younger colleague. The conceptual scholar's problem is then to minimize $\rho(a_2)$ over a_2 as in Equation (5) for given a_1. The objective will thus be to compute the optimal age of the younger co-author a_2^*. It can be shown that $\rho(a_2)$ in Equation (5) has a unique and global minimum in a_2. Equivalently, one can derive the optimal age difference d^* from Equation (6).

5.2 Interpersonal Relationships

Another channel through which the age pattern may drive complementarity is the relationship between the two co-authors. This idea was first introduced in Hamermesh and Oster (2002). In their model productivity is not the sole purpose of collaboration. People may also work together because they enjoy interacting with each other. Research may then create two streams of benefits: research output and consumption benefits realized during the production process. Hence, scholars seek to maximize a utility function $U(y_j, c_j)$, where j is a potential co-author, y is the research output and c is the consumption stream.

Hamermesh and Oster (2002) investigated how the decline in communication costs experienced over the last decades of the 20th century affected research behavior and productivity. Distant co-authorship generates additional costs compared to other forms of research. If scholars were only interested in producing superior research, one would expect distant co-authored research to be more productive than other types of research. This conjecture turns out not to find support in their data. The consumption benefits model, in contrast, can explain the observed patterns. Answers to a survey conducted by Hamermesh and Oster suggest that distant co-authorship is positively correlated with friendship. There may be reasons to believe that friendship is related to age. As suggested by Hamermesh and Oster (2002), many lasting friendships between fellow economists develop in graduate school and involve peers of the same age group. If personal interactions between friends take away time from research production, this implies that the time input of a pair of co-authors becomes more complementary with increasing age difference.

A second effect, which works in the same direction, relates to competition. Especially in early phases of their careers, researchers from the same age group are likely to be competitors on the job market. Competition is, of course, not restricted to the job market. Science is, after all, an inherently competitive game. True scientists seek challenges and are inspired and motivated by competition. And when it comes to choosing their peer group, scientists are likely to consider their relative positions within their age category. Competition may even harm collaboration between scientists. The above framework with one conceptual and one technical scholar implies a hierarchical team structure. The conceptual scholar maintains control over the project and guide the technical scholar towards the tasks to be performed. If the age difference between the two co-authors becomes smaller, the younger co-author may not accept this division of labor because the collaborator becomes a competitor and both co-authors may want to prove that they are smarter than the other one. Consumption benefits and competition can, again, be portrayed by a logistic function

$$B(d) = 1 - \frac{1}{1 + e^{-(d-\xi)/\gamma}}.$$

A "common paradigm effect" may countervail the positive relation between age difference and complementarity. Economics is a relatively new discipline which has, over time, undergone substantial transitions. Collaborating scholars need to share some common paradigm as a starting point for their communication, especially with respect to the method of investigation. This argument is less related to changes in topics that are considered en vogue within the profession - researchers with different interests rarely collaborate anyway (see Fafchamps, Goyal, and van der Leij, 2010) - than to changes in the techniques that are employed. The common paradigm effects may be formalized with the help of the following function

$$P(d) = \frac{1}{1 + e^{-(d-\pi)/\varpi}}.$$

I assume that ρ is a function of d which has the following form

$$\rho(d) = 1 - P(d) \cdot B(d),$$

which gives rise to a unique d^* which globally minimizes ρ. This framework, therefore, justifies the regression Equation (4), too.

6 Survey-Based Analysis

In summer 2011, I administered a survey with the objective to discriminate between the two potential explanations of scientific collaboration presented in the previous section. I drew a random sample from the 1470 articles in my data set and asked the authors of these articles about their experiences in collaborating with their co-authors. Each author was asked only about one publication and the questionnaire was always sent to both authors of an article.[14] Details about the administration of the survey with additional descriptive statistics can be found in Appendix A.

To quantify their conceptual and technical skills, I asked the authors how much they contributed to the research concept, how much of the technical tasks they

[14] While the survey was being conducted, it turned out that it could not be sent to authors affiliated with institutions outside Germany Austria or Switzerland. Hence, if one of the respondents living in one of the three countries had a co-author outside these three countries, only he was asked about the paper.

performed, and about their share in writing up the article. To test the explanation based on interpersonal relationships, I asked the authors whether they were already friends with their co-authors when they started working on the project, whether they became friends during that process or whether their relationship was purely professional. I also asked the two co-authors whether they ever applied for the same jobs. The answer to this question serves as a proxy for competition between the two collaborators. Note that the age difference is now defined as the age of the respondent minus the age of the co-author. It can, therefore, assume negative values.

Table 6 compares the arithmetic means of the responses of the two collaborators. The difference is most pronounced for the share that the authors claim to have had in the technical execution of the project. Figure 4 visualizes these differences. Note the spike at 50%, which can also be observed in the distributions of the conception and writing shares.

I also calculated a measure of the shares in the three tasks relative to the average contribution. For this measure, I first computed the arithmetic mean of the three shares for every respondent and then divided each share by this arithmetic mean. This measure accounts for the fact that an author may have had a higher or lower overall share in the realization of an article. In other words, even if an author said that 30% of the idea of a project were his, this may be high relative to his overall contribution if he says he performed only 10% of the technical tasks and of writing up the result.

Table 7 shows tests of the skill heterogeneity theory presented in Section 5.1. The upper panel includes all respondents, whereas the middle panel only considers the older co-authors, and the lower panel only considers younger co-authors. An author's share of the concept does not increase with the age difference. However, relative to the overall contribution, older scholars have contributed more conceptually, because older authors tend to contribute less overall relative to their younger collaborators. The correlation between an author's share of the technical execution and the difference between his and his co-author's age is highly negative. The same applies to the share of writing the report. These findings provide some support for skill heterogeneity, but they do not exactly confirm it. In Section 5.1 it was argued that conceptual skills were increasing with an author's age, whereas technical skills were decreasing with age. However, most coefficients of the age variable are insignificant.[15]

Table 8 shows tests of the theory of personal relationships. In column (1), a dummy indicating whether the respondent said that he and his co-author were friends when they started working on the project is regressed on the respondent's age, the difference between his and his co-author's age, and various covariates. The coefficient on own age is significantly negative and the coefficient on age difference is significantly positive when the whole sample is used. More informative are the middle and lower panels, which divide the sample into older and younger authors. For older authors, age difference is positive, for younger authors, it is negative. In both subsamples, the coefficients on age difference are significantly different from zero. When older authors are taken into consideration, the coefficient is negative, for younger authors it is positive. Even though the coefficients have different signs, the picture is the same: the smaller the age difference, the more likely the two authors were friends before they started their collaboration. In column (2), the dependent variable is equal to 1 if the authors were either friends before they started working on their joint project or if they became friends in the process. The coefficients are smaller in absolute value for older authors and larger in absolute value for younger authors than in column (1). This finding indicates that younger authors are more likely to say they became friends while they collaborated with their colleagues than older authors if they were not already friends in the first place.

Columns (3) and (4) repeat this analysis for indicators for whether the respondent and his co-author have ever applied for the same job or whether the respondent could not to exclude the possibility that they had ever applied for the same job.[16] Again, I find that the smaller the age difference, the more likely it is that the two authors have ever competed on the job market. The survey, therefore, provides strong support for the hypothesis that personal relations matter for collaboration. Common paradigms were not examined.

Table 11 in Appendix B shows the coefficients on the covariates from the regressions of the shares in the three tasks when the entire sample was used (upper panel of columns (1), (3) and (5) in Table 7) and the dummies indicating whether the

[15] Unreported results show that the coefficients on own age are different from zero at the 5% level of significance with the expected positive sign in column (2) and negative signs in columns (3) and (4) if the age difference is not controlled for.

[16] In column (4) the dependent variable is equal to 1 if the respondent either checked that he and the co-author have ever applied for the same job or if he checked that he did not know.

authors had already been friends before their collaboration when the entire sample was used (upper panel of columns (1) and (3) in Table 8). One notable and intuitive result is that mentor-protégé relationships tend to reduce the probability that the two collaborators were friends before they started working together.

7 Conclusion

Jones (2010b) identifies two major trends in science: important innovations are made increasingly later in a scientist's life and by teams rather than solo researchers. Age and team work are, therefore, of prime interest in the economics of science and this study demonstrates that the two must not be analyzed in isolation. It investigates the relation between age composition of collaborators and the complementarity of their inputs. It suggests an optimal age difference between co-authors of about ten years. This result is highly significant and robust to the way research output and human capital are measured.

To be sure, the assumptions underlying the analysis in this study are rather restrictive. The production function is not estimated, it is simply assumed that it is of a CES type. Neither do I estimate the complementarity parameter ρ. Based on my assumptions concerning production of knowledge, I obtain it by solving a simple production equation. Furthermore, my sample only includes collaborations that actually lead to published results. Although most researchers submit their working papers until they eventually find an outlet, some papers actually end up in the waste bin. It is, however, not clear whether and how such failure might be correlated with the age structure of the team. Such a correlation would induce an estimation bias. Collaboration between exactly two researchers is only a subset of all teamwork in economics, although by far the most frequent one. But age difference has a different meaning when more than two researchers collaborate. The exclusion of researchers whose birthdates were not available is another potential source of bias, but it is not clear in which direction this bias would go. Finally, given the institutional setting in the German-speaking area, I might get different results if I looked at researchers from other countries.

Despite all these caveats, the findings presented in this paper may have implications for the way we think about collaboration in outside the science system. I advance two theoretical approaches which may explain my findings. The first is based on a framework with two complementary skills, the second uses the theory of consumption benefits as a starting point and addresses interpersonal relationships. Survey-based analysis shows that scientific production and personal relations are both related to the age difference between collaborators.

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A The Survey

The survey used in Section 6 was conducted via mail in June 2011. I sent the questionnaire to 579 economists and business researchers. Among these scientists, 434 were affiliated with German, 72 with Austrian and 73 with Swiss institutions. I picked a random sample of pairs from the original sample. Each individual researcher was asked about one paper only. Initially, it was intended to ask researchers outside Germany, Austria and Switzerland, too. However, this idea had to be abandoned for organizational reasons, which is why not always both co-authors received the questionnaires.

The survey participants were not informed that the aim of the study was to relate their answers to the age structure of the collaborating pair. People may have suspected that the survey would be used to investigate plagiarism, e.g. professors letting their students do all the work and then publishing under their own name, which might have reduced the response rate. In order to avoid this, the survey informed all scholars that their co-authors were asked the same questions.

Each letter contained one sheet of paper with a cover letter on the front and the questionnaire on the back and a stamped and self-addressed envelope for the reply. The survey was administered in Germany via the University of Konstanz, in Switzerland via the Thurgauer Wirtschaftsinstitut (TWI), which is located in Kreuzlingen, Switzerland but part of the University of Konstanz and in Austria via the University of Vienna. The survey was sent out in early June 2011, responses were received until mid August 2011.

The cover letter read as follows:

```
Dear [respondent],

My name is Matthias Krapf and I am a PhD Student at the University of Konstanz.
For an analysis of co-authorship, I would like to ask you eight questions regarding
the paper ‘‘[title]’’ with [co-author], which was published in the year [year]. Your
co-author is being asked the same questions. Answering my questions will not take
you longer than a couple of minutes. I respect your privacy and will not share your
personal information with others.
```

Please turn this page to answer the questionnaire. After that, please send it back using the enclosed envelope. If there are questions you do not want to answer, please leave the corresponding boxes empty.

Best regards,
Matthias Krapf

The questionnaire contained eight questions which could be answered by checking the corresponding boxes. To avoid going too much into the intimate details of their personal relations, people were only asked to distinguish between their relationship being purely professional or friendship.

1. The process of writing the article
1.1 When we were writing the paper...
 a) ...we were both at the same institution
 b) ...we were at different institutions but within 100km from each other
 c) ...we were at different institutions and more than 100km from each other
2. Individual Contributions
2.1 How much of the idea that lead to the article was yours or your co-author's?
2.2 How much of the technical tasks did you and your coauthor perform?
2.3 Who wrote the paper down?
 (for questions 2.1 to 2.3 eleven possible answers were given from 100 percent mine / 0 percent co-author's to 0 percent mine / 100 percent co-author's in steps of ten percentage points)
3.1 When have you first met your co-author?
 a) More than three years before we started working on the paper
 b) Up to three years before we started working on the paper
 c) The decision to collaborate was made when / before we first met
3.2 How did your collaboration begin?
 a) We were fellow students, e.g. in grad school, or colleagues at the same institution
 b) We were in a mentor-protégé relation
 c) We met at a conference
 d) One contacted the other exactly for the purpose of collaboration
3.3 How would you describe your relationship with your co-author
 a) We were friends when we started working on the paper
 b) We became friends while we were working on the paper
 c) Our relationship is purely professional
3.4 Have you and your co-author ever applied for the same jobs?
 a) yes

```
b) no
c) I do not know
```

Table 9 shows additional descriptive statistics beyond the ones already displayed in Section 6. It compares the data for respondents with those for the overall sample. 317 of the surveyed scholars responded, which corresponds to a response rate of 54.75%. No significant differences between the two groups can be observed. The sample of survey respondents is representative of the overall sample, non-response bias does not appear to matter.

Table 10 shows descriptive statistics for the 83 articles, for which responses by both authors were available. Although there is substantial variation, on average the shares of the three tasks that the two authors claimed for themselves, respectively, add up to about 100 percent. This provides further support for the assumption that the respondents answered the survey questions honestly.

B Supplementary Outputs

Table 11 repeats regressions from Tables 7 and 8, but also reports the coefficients for the additional controls. Only very few of these coefficients are significant. Only one distance measure ($<$ 100 km) is correlated with a scholar's share of the idea that lead to the article. The better a scholar's prior publication record, the less of the technical tasks he performed. The better the co-author's publication record, the smaller a scholar's share in writing down the results. If, on the other hand, the co-author is female, scholars tend to write more. Scholars affiliated with Swiss universities are more likely to have been friends when they started collaborating. If the authors knew each other for longer than three years, it is also more likely that they were friends before they started to work together. Mentor-protégé relationships tend to reduce the probability of having been friends before. That two co-authors have ever, i.e. before or after their collaboration, applied for the same jobs, is less likely the higher-ranked the journal in which the article they have written has appeared in. Competition on the job market is also less common among scholars affiliated with Austrian institutions.

Table 1: Article Quality Measured by CLm.

	(1)	(2)	(3)
constant	16.3231***	-142.2219***	-103.4477***
	(51.67)	(-3.85)	(-2.79)
number of authors	2.0389***	1.8849***	4.9070***
	(12.30)	(11.18)	(11.02)
co-authors squared			-0.5336***
			(-6.67)
year		0.0793***	0.0583***
		(4.30)	(3.14)
R^2	0.0087	0.0097	0.0149
observations	19606	19606	19606

Notes: OLS regression; robust standard errors; t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Descriptive Statistics.

	Mean	Std. Dev.	Min.	Max.
ρ with $\delta = 0$	0.1631	0.0595	0.0778	1
ρ with $\delta = 0.15$	0.2072	0.0869	0.0846	1
average age (years)	41.5878	5.6201	29.5	65
age difference (years)	8.6891	7.5636	0.0055	38.0575
both female	0.0163	0.1268	0	1
male/female	0.1177	0.3223	0	1
business administration	0.1000	0.3001	0	1
ba/econ	0.0762	0.2654	0	1
preceding cooperations	1.1000	2.1280	0	17

Notes: weighting scheme CLm; 1470 observations.

Table 3: A First Look

	(1)	(2)	(3)
constant	9155.157***	20389.84**	20490.33**
	(10.03)	(2.19)	(2.21)
h_1	1.6818**	4.1449***	3.9110***
	(2.32)	(6.36)	(5.85)
h_2	12.6248***	13.8173***	13.1215***
	(4.98)	(6.63)	(6.17)
$h_1 * h_2$	-0.00763**	0.0016	0.0021
	(-2.27)	(0.38)	(0.47)
average age		-432.6902***	-433.6862***
		(-7.89)	(-7.87)
$\mathbb{I}(d < 7)$		-21.4394	-59.2774
		(-0.03)	(-0.09)
$\mathbb{I}(d > 13)$		-803.3326	-611.7713
		(-0.99)	(-0.75)
$\mathbb{I}(d < 7) * h_1 * h_2$		-0.0036	-0.0035
		(-0.78)	(-0.77)
$\mathbb{I}(d > 13) * h_1 * h_2$		-0.0157***	-0.0159***
		(-3.47)	(-3.49)
both female			3821.4**
			(2.03)
male/female			-1120.956
			(-1.48)
business administration			-1792.617**
			(-2.17)
ba/econ			175.2619
			(0.19)
# collab's before			28.2587
			(0.23)
year dummies	yes	yes	yes
R^2	0.0677	0.1295	0.1363
observations	1470	1470	1470

Notes: dependent variable: CLm*1000; OLS regression; robust standard errors; $\delta = 0$; t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Regression Analysis of the Complementarity Parameter ρ.

	$\delta = 0.15$				$\delta = 0$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
constant	-0.1097	-0.1457*	-0.0595	-0.0905	0.0180	-0.0020	0.0502	0.0337
	(-1.48)	(-1.84)	(-0.80)	(-1.16)	(0.38)	(-0.04)	(1.07)	(0.69)
average age	0.0115***	0.0133***	0.0093**	0.0108***	0.0028	0.0024	0.0013	0.0021
	(3.18)	(3.48)	(2.55)	(2.84)	(1.21)	(1.57)	(0.59)	(0.90)
average squared	-0.0001*	-0.0001**	-0.0001	-0.0001*	0.0000	0.0000	0.0000	0.0000
	(-1.93)	(-2.21)	(-1.58)	(-1.82)	(0.77)	(0.43)	(1.13)	(0.86)
age difference	-0.0030***	-0.0036***	-0.0029***	-0.0034***	-0.0024***	-0.0027***	-0.0024***	-0.0026***
	(-2.92)	(-3.40)	(-3.03)	(-3.48)	(-3.27)	(-3.56)	(-3.43)	(-3.71)
difference squared	0.0001***	0.0002***	0.0001***	0.0002***	0.0001***	0.0001***	0.0001***	0.0001***
	(3.06)	(3.38)	(3.31)	(3.61)	(3.54)	(3.72)	(3.83)	(4.00)
both female	-0.0398***	-0.0382***	-0.0365***	-0.0352***	-0.0216***	-0.0208***	-0.0194***	-0.0188***
	(-5.85)	(-5.65)	(-5.11)	(-4.77)	(-4.72)	(-4.59)	(-4.18)	(-3.95)
male/female	-0.0104**	-0.0090*	-0.0043	-0.0025	-0.0043	0.0031	-0.0004	0.0011
	(-2.03)	(-1.71)	(-0.87)	(-0.49)	(-1.47)	(1.03)	(-0.13)	(0.36)
business administration	-0.0472***	-0.0481***	-0.0391***	-0.0396***	-0.0312***	-0.0313***	-0.0260***	-0.0258***
	(-11.08)	(-9.92)	(-10.05)	(-9.04)	(-10.74)	(-10.11)	(-9.67)	(-9.04)
ba/econ	-0.0138***	-0.0152***	-0.0067	-0.0081	-0.0061*	-0.0072**	-0.0016	-0.0026
	(-2.60)	(-2.69)	(-1.27)	(-1.45)	(-1.84)	(-2.03)	(-0.47)	(-0.73)
# collab's before			0.0122***	0.0121***			0.0079***	0.0078***
			(5.99)	(6.17)			(5.75)	(5.80)
year dummies	no	yes	no	yes	no	yes	no	yes
R^2	0.1555	0.1826	0.2397	0.2624	0.3180	0.3352	0.3921	0.4067
observations	1470	1470	1470	1470	1470	1470	1470	1470

Notes: OLS regression; robust standard errors; t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1; weighting scheme CLm.

Table 5: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					CLh	CLm pages	CLh	CLm pages
	l_j	δ=.05	δ=.1	δ=.2	$\delta = 0.15$	$\delta = 0.15$	$\delta = 0$	$\delta = 0$
constant	0.3592***	-0.0283	-0.0712	-0.0887	-0.1188**	0.0985	-0.0338	0.1148**
	(6.60)	(-0.48)	(-1.04)	(-1.07)	(-2.20)	(1.58)	(-0.74)	(2.15)
average age	-0.0057**	0.0060**	0.0089***	0.0115***	0.0090***	-0.0002	0.0040*	-0.0023
	(-2.23)	(2.10)	(2.69)	(2.88)	(3.50)	(-0.08)	(1.83)	(-0.91)
average squared	0.0001**	-0.0000	-0.0001	-0.0001**	-0.0001***	0.0000	-0.0000	0.0001*
	(2.06)	(-0.59)	(-1.43)	(-2.04)	(-2.80)	(0.78)	(-0.72)	(1.92)
age difference	-0.0028***	-0.0028***	-0.0031***	-0.0034***	-0.0021***	-0.0019**	-0.0019***	-0.0026*
	(-3.93)	(-3.63)	(-3.57)	(-3.44)	(-3.29)	(-2.22)	(-2.77)	(-1.69)
difference squared	0.0002***	0.0001***	0.0002***	0.0002***	0.0001***	0.0001**	0.0001***	0.0001*
	(5.05)	(3.85)	(3.73)	(3.55)	(3.23)	(1.98)	(2.78)	(1.66)
both female	-0.0340***	-0.0246***	-0.0302***	-0.0390***	-0.0176***	-0.0231***	-0.0127***	-0.0150***
	(-4.89)	(-4.32)	(-4.59)	(-5.01)	(-3.51)	(-5.15)	(-3.11)	(-4.26)
male/female	-0.0117***	-0.0001	-0.0013	-0.0039	0.0015	-0.0033	0.0034	-0.0009
	(-2.84)	(-0.04)	(-0.30)	(-0.72)	(0.35)	(-1.10)	(1.01)	(-0.40)
business administration	-0.0501***	-0.0309***	-0.0356***	-0.0415***	-0.0210***	-0.0135***	-0.0176***	-0.0099***
	(-14.19)	(-9.21)	(-9.19)	(-8.91)	(-6.67)	(-4.12)	(-7.33)	(-3.73)
ba/econ	-0.0156***	-0.0044	-0.0062	-0.0099*	-0.0016	-0.0023	-0.0003	-0.0000
	(-3.16)	(-1.03)	(-1.24)	(-1.67)	(-0.39)	(-0.60)	(-0.10)	(-0.01)
# collab's before	0.0083***	0.0093***	0.0108***	0.0124***	0.0051***	0.0059***	0.0046***	0.0047***
	(6.64)	(6.11)	(6.21)	(6.32)	(4.45)	(4.30)	(3.43)	(3.92)
year dummies	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.1896	0.3508	0.3017	0.2348	0.1513	0.1847	0.2155	0.2492
observations	1835	1470	1470	1470	1470	1340	1470	1340

Notes: OLS regression; robust standard errors; t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Survey Data: Descriptive Statistics.

	all respondents	older author	younger author
same institution	0.6613(313)	0.6582(158)	0.6645(155)
different institution (< 100 km)	0.0703(313)	0.0633(158)	0.0774(155)
different institution (> 100 km)	0.2684(313)	0.2785(158)	0.2581(155)
own share concept	50.75(308)	51.62(154)	49.87(154)
own share tech tasks	50.58(308)	44.74(154)	56.43(154)
own share writing	51.07(308)	48.90(154)	53.25(154)
idea rel. to av. contribution	1.0034(308)	1.0760(154)	0.9307(154)
tech rel. to av. contribution	0.9900(308)	0.9152(154)	1.0648(154)
writing rel. to av. contribution	1.0083(308)	1.0120(154)	1.0045(154)
met >3y before collaboration	0.6804(316)	0.7063(160)	0.6535(156)
met <3y before collaboration	0.3006(316)	0.2750(160)	0.3269(156)
not met before collaboration	0.0190(316)	0.0188(160)	0.0192(156)
colleagues / fellow students	0.4684(301)	0.5098(153)	0.4257(148)
mentor-protégé relation	0.3389(301)	0.3203(153)	0.3581(148)
met at a conference	0.1063(301)	0.0915(153)	0.1216(148)
contacted to collaborate	0.0864(301)	0.0784(153)	0.0946(148)
were friends before	0.6181(309)	0.6795(156)	0.5556(153)
became friends	0.1812(309)	0.1538(156)	0.2092(153)
purely professional	0.2006(309)	0.1667(156)	0.2353(153)
ever applied for same jobs	0.1529(314)	0.1635(159)	0.1419(155)
never applied for same jobs	0.7038(314)	0.6667(159)	0.7419(155)
do not know	0.1433(314)	0.1698(159)	0.1161(155)

Notes: Number of respondents in parentheses next to relative frequencies. 317 responses received in total (rate 54.75%).

Table 7: Concept, Technique, Writing and Age

	dependent variable	(1) share concept	(2) rel. concept	(3) share tech	(4) rel. tech	(5) share writing	(6) rel. writing
all respondents	own age	0.2920	-0.0009	0.2913	0.0019	0.1928	-0.0013
		(0.94)	(-0.19)	(1.00)	(0.37)	(0.74)	(-0.33)
	age difference	0.0438	0.0098**	-0.7437***	-0.0080*	-0.4666**	-0.0016
		(0.17)	(2.52)	(-3.29)	(-1.93)	(-2.09)	(-0.49)
	controls	yes	yes	yes	yes	yes	yes
	R^2	0.1224	0.2160	0.2484	0.2266	0.1959	0.1744
	observations	289	289	289	289	289	289
older authors	own age	-0.4298	-0.0175**	0.7226*	0.0128	0.4066	0.0046
		(-0.85)	(-1.99)	(1.69)	(1.35)	(1.12)	(0.89)
	age difference	1.0635*	0.0311***	-1.1071**	-0.0206*	-0.7521*	-0.0117*
		(1.88)	(3.26)	(-2.17)	(-1.88)	(-1.75)	(-1.88)
	controls	yes	yes	yes	yes	yes	yes
	R^2	0.3408	0.4461	0.4340	0.4545	0.3856	0.4125
	observations	144	144	144	144	144	144
younger authors	own age	0.6966	0.0075	0.1400	-0.0023	0.0141	-0.0052
		(1.38)	(1.09)	(0.30)	(-0.30)	(0.03)	(-0.69)
	age difference	-0.5643	-0.0044	0.0130	0.0100	-0.7591*	-0.0056
		(-0.96)	(-0.55)	(0.03)	(1.35)	(-1.88)	(-0.81)
	controls	yes	yes	yes	yes	yes	yes
	R^2	0.2855	0.3783	0.3294	0.3404	0.2912	0.3083
	observations	145	145	145	145	145	145

Notes: OLS regression; robust standard errors; t-statistics in parentheses; additional controls include indicators for respondent and co-author being female or economists, respectively, their human capital endowments, the article score CLm, indicators for distance during collaboration, how long the authors knew each other and how their collaboration started, as well as year and country dummies; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Job Market Competition, Friendship and Age

		(1)	(2)	(3)	(4)
	dependent variable	were friends	were/became	competed	cannot exclude
all respondents	own age	-0.0583***	-0.0655***	-0.0484**	-0.0464**
		(-3.37)	(-3.51)	(-2.31)	(-2.48)
	age difference	0.0482***	0.0468***	0.0299**	0.0295**
		(3.77)	(3.32)	(2.12)	(2.25)
	controls	yes	yes	yes	yes
	Pseudo-R^2	0.2204	0.2072	0.1179	0.1084
	observations	289	289	294	294
older authors	own age	0.0238	-0.0027	-0.0071	-0.0158
		(0.79)	(-0.09)	(-0.25)	(-0.58)
	age difference	-0.1156***	-0.0858**	-0.1290***	-0.0938***
		(-3.34)	(-2.35)	(-3.07)	(-2.82)
	controls	yes	yes	yes	yes
	Pseudo-R^2	0.3350	0.2931	0.2675	0.2389
	observations	145	145	148	148
younger authors	own age	-0.0301	-0.0708*	-0.0379	-0.0017
		(-1.59)	(-1.93)	(-1.10)	(-0.06)
	age difference	0.0922***	0.1143***	0.1142***	0.0945***
		(3.10)	(4.08)	(3.10)	(3.29)
	controls	yes	yes	yes	yes
	Pseudo-R^2	0.2773	0.3151	0.2166	0.2044
	observations	144	135	132	146

Notes: Probit estimates; robust standard errors; z-statistics in parentheses; additional controls include indicators for respondent and co-author being female or economists, respectively, their human capital endowments, the article score CLm, indicators for distance during collaboration, how long the authors knew each other and how their collaboration started, as well as country dummies; other than before, year of publication was accounted for linearly; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Survey Data: Additional Descriptive Statistics.

	all surveyed				respondents			
	mean	sd.	min.	max.	mean	sd.	min.	max.
own age	41.17	7.7992	27	70	41.27	7.9715	27	70
age co-aut	40.91	7.6854	27	70	40.93	7.3242	28	70
age diff	0.2683	11.09	-34.94	34.94	0.3486	10.79	-34.94	34.94
female	0.1209	0.3263	0	1	0.1009	0.3017	0	1
co-aut fem	0.1123	0.3160	0	1	0.1073	0.3099	0	1
econ	0.7703	0.4210	0	1	0.7791	0.4155	0	1
co-aut econ	0.7772	0.4165	0	1	0.7855	0.4111	0	1
CLm	9.4890	8.5082	2.49	49.21	9.0838	8.4052	2.61	49.21
own hc	138.06	241.87	1.10	3554	139.58	267.18	2.33	3554
co-aut hc	135.06	240.04	1.10	3554	141.96	271.98	1.82	3554
GER	0.7495	0.4337	0	1	0.7192	0.4501	0	1
AUT	0.1244	0.3303	0	1	0.1451	0.3528	0	1
CH	0.1261	0.3322	0	1	0.1356	0.3430	0	1
year	2004.47	5.5824	1981	2010	2003.86	6.0784	1981	2010
# obs.	579				317 (rate: 54.75%)			

Notes: Age is age in the year of publication. CLm and hc computed as in baseline case without human capital depreciation. Other than in the main part of the paper, age difference is not given in absolute values, i.e. it can become negative.

Table 10: Survey Data: Papers of Which Both Authors Responded.

	mean	sd.	min.	max.
sum concept	101.1957	19.2064	30	140
sum tech	98.1522	19.4388	40	160
sum writing	102.5000	18.3749	60	150

Note: Percentages; Sample size is 92.

Table 11: Coefficients on Control Variables

	(1)	(2)	(3)	(4)	(5)
dependent variable	share concept	share tech	share writ	were friends	competed
constant	31.9899**	51.1233***	62.3459***	54.7033*	-11.6831
	(2.16)	(3.66)	(4.85)	(1.80)	(-0.39)
own age	0.2920	0.2913	0.1928	-0.0582***	-0.0484**
	(0.94)	(1.00)	(0.74)	(-3.37)	(-2.31)
age difference	0.0438	-0.7437***	-0.4666**	0.0482***	0.0298**
	(0.17)	(-3.29)	(-2.09)	(3.77)	(2.12)
female	-2.6431	-0.9320	-2.6513	-0.1558	-0.3791
	(-0.51)	(-0.22)	(-0.70)	(-0.64)	(-1.07)
co-aut fem	2.9609	3.7378	10.3497***	0.2022	-0.0982
	(0.74)	(1.03)	(3.07)	(0.62)	(-0.31)
econ	-3.0832	-1.7375	-0.5864	-0.2163	0.2320
	(-0.88)	(-0.41)	(-0.13)	(-0.60)	(0.77)
co-aut econ	1.6294	-4.8936	-3.8408	-0.1648	-0.4595
	(0.49)	(-1.24)	(-0.90)	(-0.45)	(-1.51)
CLm	0.1715	0.0939	-0.2647*	0.0097	-0.0513***
	(0.92)	(0.58)	(-1.96)	(0.74)	(-3.04)
own hc	-0.0053	-0.0116**	0.0023	-0.0000	-0.0003
	(-1.16)	(-2.52)	(0.45)	(-0.11)	(-0.87)
co-aut hc	-0.0125	0.0095	-0.0113**	0.0007**	0.0001
	(-1.43)	(1.19)	(-2.39)	(2.02)	(0.44)
AUT	0.8188	4.0705	5.7496*	0.3739	-0.8877***
	(0.19)	(1.06)	(1.66)	(1.36)	(-2.64)
CH	4.9336	-4.8654	5.3199	0.6188**	-0.0768
	(1.48)	(-1.13)	(1.46)	(2.49)	(-0.24)
distance (>100km)	-1.3445	-1.1881	-2.7160	0.1631	-0.0974
	(-0.42)	(-0.36)	(-0.91)	(0.74)	(-0.41)
distance (<100km)	-11.6621*	-8.4060	-8.2957	-0.4971	0.0578
	(-1.73)	(-1.33)	(-1.60)	(-1.41)	(0.11)
met >3y before	3.5559	0.9695	-17.6318*	1.6758***	-0.0136
	(0.35)	(0.11)	(-1.95)	(2.65)	(-0.02)
met <3y before	-0.3913	-0.1285	-17.6902**	0.6127	-0.1234
	(-0.04)	(-0.01)	(-1.99)	(0.96)	(-0.16)
mentor-protégé	-2.6654	2.3489	4.6128*	-0.6786***	-0.3193
	(-0.81)	(0.72)	(1.73)	(-3.33)	(-1.39)
conference	1.0520	-3.3691	5.7260	-0.2590	-0.1873
	(0.19)	(-0.61)	(1.44)	(-0.83)	(-0.52)
contacted	1.4600	-3.3154	-6.2510	-0.5297*	0.0787
	(0.27)	(-0.70)	(-1.41)	(-1.71)	(0.22)
year	dummies	dummies	dummies	linear	linear
Method	OLS	OLS	OLS	Probit	Probit
(Pseudo-)R^2	0.1224	0.2484	0.1959	0.2204	0.1179
observations	289	289	289	289	294

Notes: OLS and Probit regression; robust standard errors; columns (1)-(3): t-statistics in parentheses; columns (4)-(5): z-statistics in parentheses additional controls include indicators for respondent and co-author being female or economists, respectively, their human capital endowments, the article score CLm, indicators for distance during collaboration, how long the authors knew each other and how their collaboration started, as well as year and country dummies; *** p<0.01, ** p<0.05, * p<0.1.

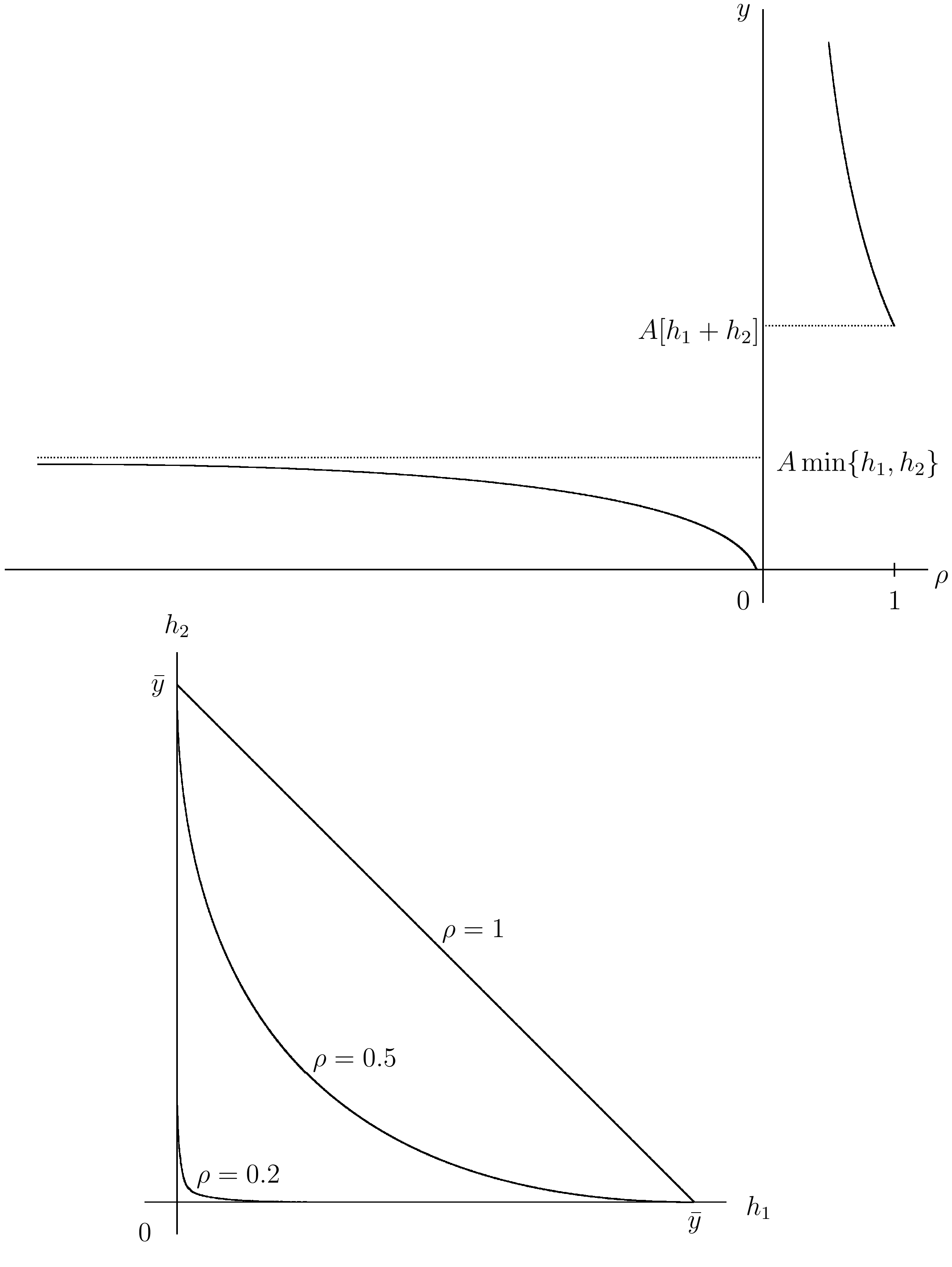

Figure 1: The CES Function for $\alpha + \beta > 1$.

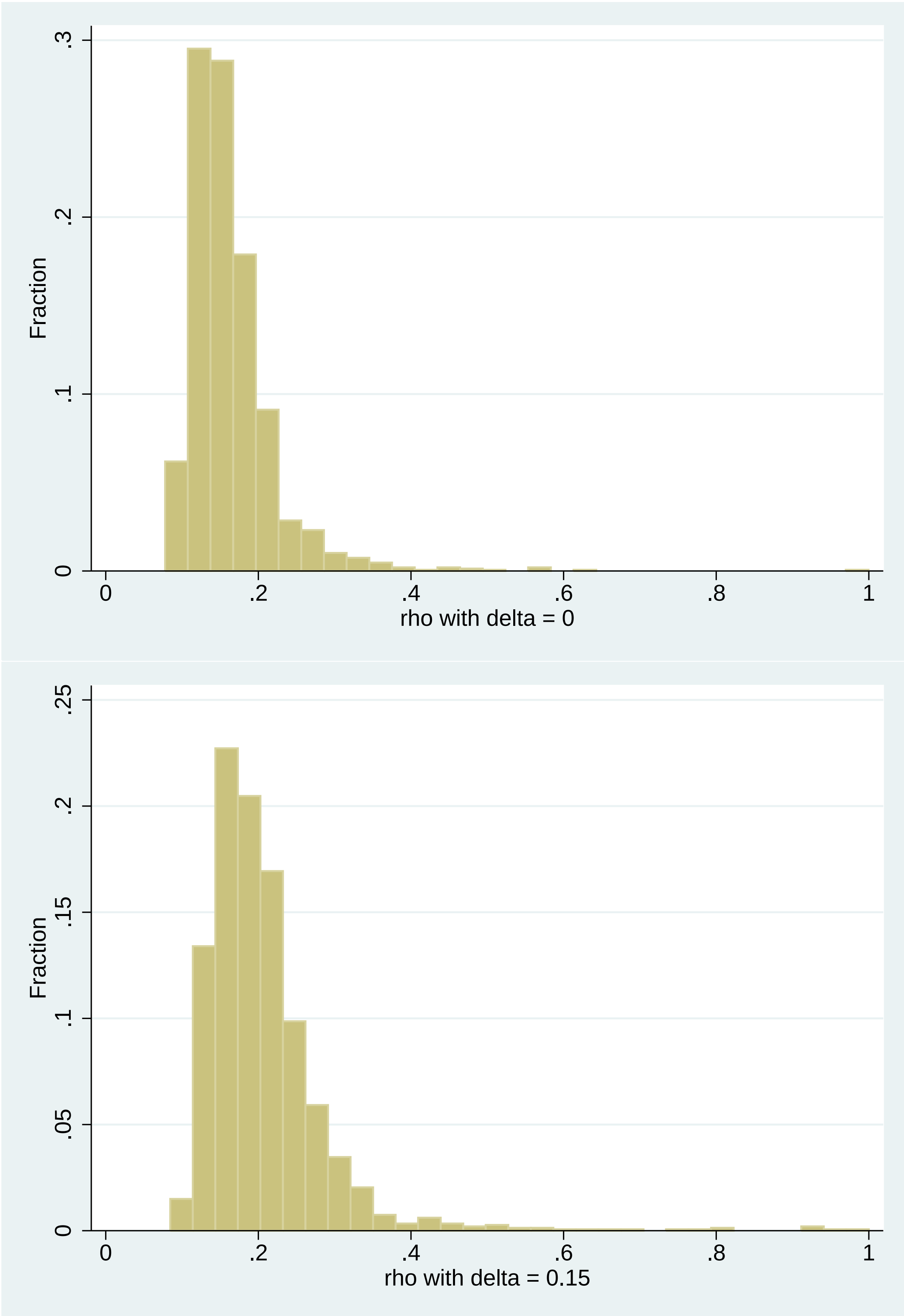

Figure 2: THE DISTRIBUTIONS OF THE COMPLEMENTARITY PARAMETER FOR DIFFERENT RATES OF DEPRECIATION.

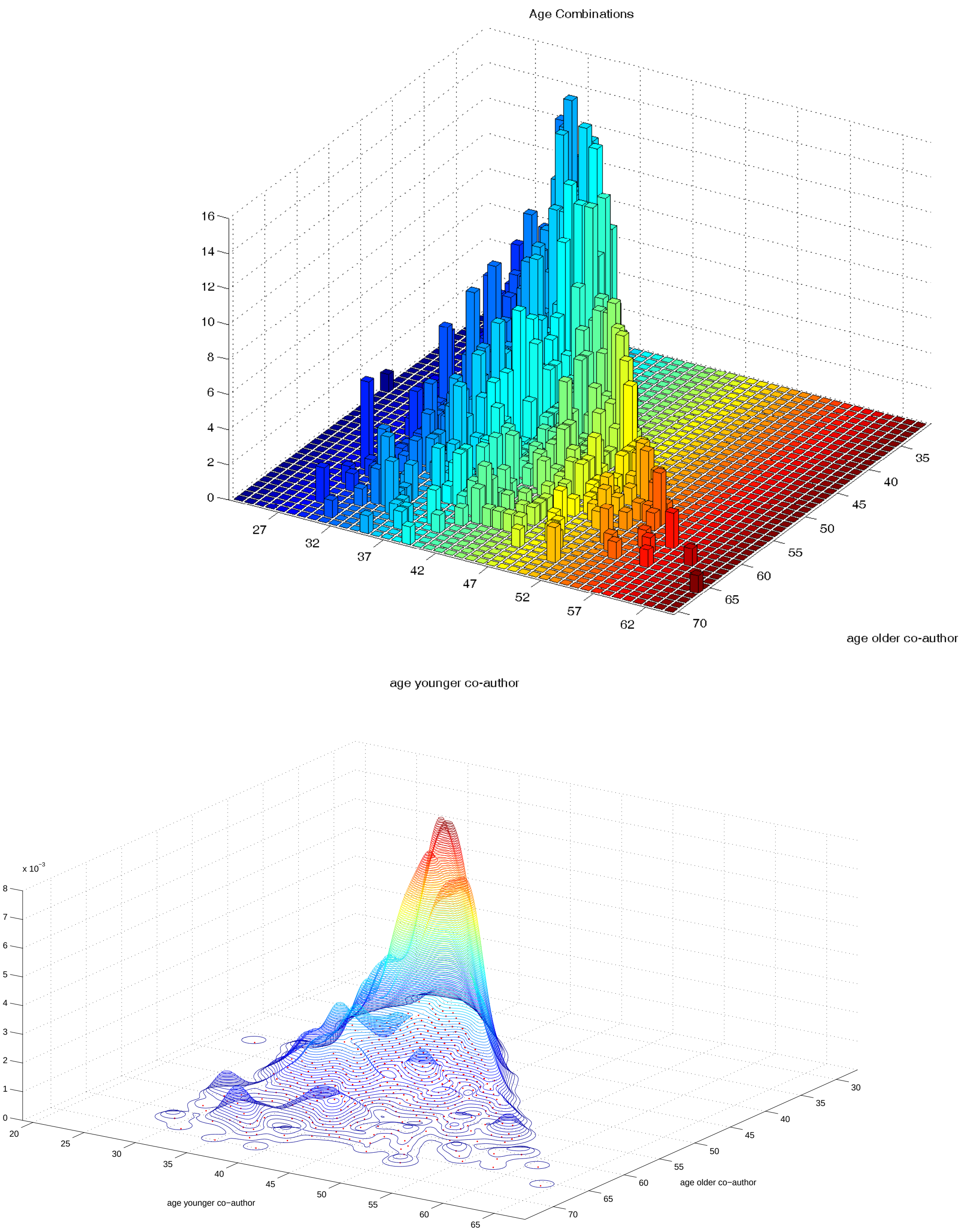

Figure 3: The distribution of author age combinations.

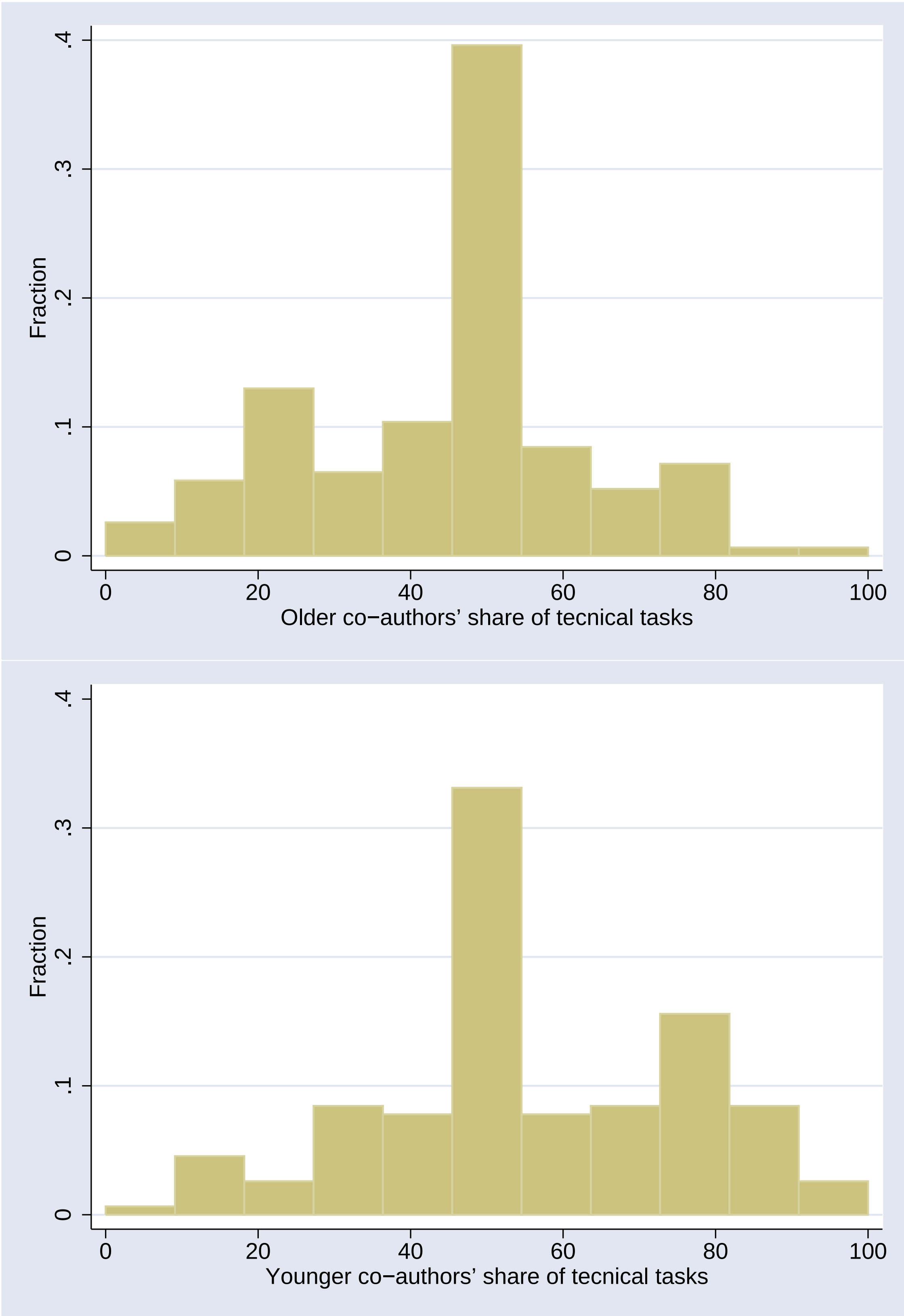

Figure 4: Older and younger co-authors' claimed shares of the technical tasks.