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# The Role of the Social Environment

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# Self-Assessment: The Role of the Social Environment*

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**Abstract**

This study presents descriptive and causal evidence on the role of the social environment in shaping the accuracy of self-assessment. We introduce a novel incentivized measurement tool to measure the accuracy of self-assessment among children and use this tool to show that children from high socioeconomic status (SES) families are more accurate in their self-assessment, compared to children from low SES families. To move beyond correlational evidence, we then exploit the exogenous variation of participation in a mentoring program designed to enrich the social environment of children. We document that the mentoring program has a causal positive effect on the accuracy of children's self-assessment. Finally, we show that the mentoring program is most effective for children whose parents provide few social and interactive activities for their children.

*Keywords*: Self-Assessment, Beliefs, Experiments, Randomized Intervention, Children.

*JEL-Codes*: D03, C21, C91, I24

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# 1 Introduction

Many decisions of economic relevance entail an element of self-assessment of one's abilities. Should I go to college or pursue an apprenticeship? Should I choose a more or less challenging career path? Should I open a restaurant or not? All these decisions require prior reflection of own abilities, strengths, and weaknesses, and more accurate self-assessments will, on average, yield better decisions. Intuitively, achieving an accurate self-assessment can be challenging. The development of a sense of one's strengths and weaknesses naturally depends on the feedback one obtains. Learning opportunities may be scarce and their frequency likely depends on the social environment in which people grow up and live in. To fix ideas, think of two otherwise identical individuals, Marta and Jessica. While Marta grew up in an environment where abundant feedback was provided, Jessica grew up in an environment where feedback was rare. It is conceivable that Marta developed a clearer sense of herself and a greater ability to judge her own skills, strengths, and weaknesses, compared to Jessica. Despite their intuitive importance, little is known about the social determinants of accurate self-assessments.

In this paper, we seek to elucidate the role of the social environment for the development of accurate self-assessments. Making progress on this question is challenging for two reasons. First, to establish causality in the relationship between social environment and self-assessment, one would ideally like to observe exogenous changes in the social environment. However, such changes are rare in naturally occurring data. Second, measuring the accuracy of self-assessment is difficult, because many aspects of people's decision problems are unknown to the researcher. We circumvent these challenges by making use of a combination of field and lab-in-the-field experimental evidence.

We focus on children in elementary school, arguably an important time of development where many skills and abilities are formed (see, e.g., Roberts and DelVecchio, 2000; Cunha and Heckman, 2007; Falk et al., forthcoming). It is also a critical time for the development of metacognitive capacities (see, e.g., Veenman, Van Hout-Wolters, and Afflerbach, 2006; Veenman and Spaans, 2005; Perry, Lundie, and Golder, 2019). Hence, the feedback provided from the social environment during that period might be a crucial input into the development of self-assessment abilities. In the first step, we exploit naturally occurring variation in children's social environments as captured by the socioeconomic status (SES) of their parents. SES reflects the "social standing" of individuals or families in society and can be summarized as the level of economic, educational, and time resources available at the household level. It is conceivable that high-SES parents can provide their children with a richer social environment, consisting of more frequent and more diverse opportunities to obtain feedback and learn about their skills and abilities. In the second step, we then seek to establish causality in the role of the social environment. For that purpose, we exploit an exogenous enhancement of the social environment for a randomly determined subgroup of low-SES children via an existing social program in Germany (see Kosse et al. (2020)). In the program, children are provided with a mentor for around one year to enrich their social environment. The mentors introduce the children to new activities and generate new experiences and feedback for them.

After the completion of the mentoring program, we conducted controlled experiments and interviews with the children and parents of the treated and non-treated low SES groups, as well as the high-SES group. Our main goal was to obtain a measure of the accuracy of children's self-assessment. This was challenging for two reasons: the measure should (i) reflect the accuracy of self-assessment in an incentivized way, and (ii) be intuitive and easy to comprehend for children that age. We developed a tailored experimental game that, as we argue, meets both criteria. The experimental task was to hit a small hole with a marble and, after experiencing the basic task in a practice round, the key decision problem was to select a level of difficulty (the size of the hole). The trade-off we implemented is that higher difficulty levels yielded a higher reward, but at the same time came with a greater risk of not mastering the task, in which case the reward was zero. The key idea underlying the design of the game is that ceteris paribus, more accurate judgments of own skill levels allow children to achieve higher earnings in expectation, through the choice of more appropriate difficulty levels. Hence, controlling for other factors, rewards in the task serve as a measure of the accuracy of self-assessment. At the same time, the game is simple to understand and intuitive for children at that age.

Our first result is that children from families with high SES demonstrated more accurate self-assessments (as measured by higher earnings in the self-assessment game) compared to children from families with low SES. We then establish causality in the relationship between social environment and accurate self-assessments by exploiting the random variation in whether low-SES children participated in the mentoring program. Our second and main result is that the enhanced social environment substantially and significantly improves the accuracy of self-assessment. Both results are robust to using different empirical specifications and controlling for selective attrition, ability, as well as risk preferences. Taken together, these findings highlight the importance of the social environment as a causal determinant of accurate self-assessment.

We proceed by delving into the underlying mechanisms of our key result. Specifically, we seek to understand which environmental factors are missing in low-SES families that affect accurate self-assessments. Intuitively, feedback and experiences are prime candidates. This intuition is bolstered by the literature on the development of metacognition, which emphasizes that feedback and learning opportunities are crucial inputs for the development of metacognition (Flavell, 1979). To make progress, we look at self-reports obtained from parents about the nature of the social environment they provide to their children. We proxy the opportunities to learn about oneself provided by the social environment by looking at the number of highly interactive activities undertaken by the children. We find that these activities are correlated with the accuracy of self-assessment as measured by our paradigm and we find that the effect of participation in the mentoring program is more pronounced for children whose parents provided few highly interactive activities. These results suggest that highly interactive activities and the associated richness of feedback are a key aspect of the social environment that determines accurate self-assessment. It also appears to be an aspect that is missing in low-SES environments. Crucially, the mentoring program appears to fill this gap and thereby improves the belief accuracy of low-SES children.

It is well-documented that children from families with high and low SES differ in important life outcomes, such as educational attainment and labor market success (e.g. Bradley and Corwyn, 2002; Duncan, Morris, and Rodrigues, 2011; Heckman, Stixrud, and Urzua, 2006). Prevalent explanations for differences in educational or labor market attainment largely focus on differences in children's cognitive and non-cognitive skills, such as IQ, persistence, and patience (see e.g. Duckworth et al., 2007; Golsteyn, Grönqvist, and Lindahl, 2014; Hanushek and Woessmann, 2008; Heckman and Vytlacil, 2001; Schmidt and Hunter, 2004). Our paper relates to this literature and reveals that SES predicts the ability to assess one's strengths and weaknesses, arguably a key determinant of the quality of economic decision-making.

More specifically, the findings from this paper relate to an active literature that analyzes the causal effect of the social environment on skills and preferences (e.g. Alan, Boneva, and Ertac, 2019; Cappelen et al., forthcoming; Kosse et al., 2020). Our paper contributes to this literature by focusing on the self-assessment of skills. In other words, while existing work has highlighted the crucial role of a broad set of social and environmental factors for the development of both cognitive and noncognitive skills, our work sheds light on the role of the social environment for the ability to self-assess these skills.[1]

In the next section, we present details about the study design and our main outcome variables. Section 3 summarizes our findings and Section 4 concludes.

# 2 Study Design and Data

## 2.1 Recruitment and Randomization

Figure A1 in Appendix A presents a flow chart of the timing, sampling, and procedural details of the study (see also Kosse et al. (2020) for further details). Recruitment started in the summer of 2011. We used official registry data to obtain the addresses of families (with children aged from seven to nine) living in the German cities of Bonn and Cologne. Families were contacted via postal mail and informed about the possibility to take part in the mentoring program and the interviews. We informed parents that participation in the mentoring program was not guaranteed due to limited capacity. The interested families were asked to fill out and return a short questionnaire concerning the socioeconomic characteristics of the household and to sign a non-binding letter of intent to take part in the interviews and the mentoring program. We received 1,626 complete responses and, based on the questionnaire, we categorized respondents as either high or low-SES households.[2]

All low-SES families that expressed interest were invited to take part in the study. To take part, families had to participate in a baseline wave of interviews (fall 2011) and provide written consent to allow the transmission of their addresses to the mentoring program. Importantly, the mentoring program could only accommodate

[1]As such, our findings also relate to the literature that studies beliefs about own skills and abilities in the lab (e.g. Eil and Rao, 2011; Möbius et al., 2013; Zimmermann, 2020) and in the field (e.g. Malmendier and Tate, 2005, 2008; Huffman, Raymond, and Shvets, 2019). A common finding in this literature is that people on average tend to be overconfident, although people sometimes also appear underconfident. Moore and Healy (2008) provide evidence that the incidence of over- and underconfidence crucially depends on task difficulty. Importantly, thus far this literature has not considered the long-run effects of the social environment on the development of beliefs about own skills and abilities. The developmental psychology literature has focused on notions of self-esteem and self-confidence and their development in children and adolescents (e.g. Twenge and Campell, 2001; Wigfield et al., 1991). Apart from the focus on different outcome measures, this literature does not study the causal role of the social environment on these outcomes.

[2]SES reflects the level of resources available at the household level, i.e., material, educational, and time resources. Accordingly, a household was classified as low SES if at least one of the three following criteria was met (see Kosse et al. (2020) for further details): (i) *Low income*: Equivalence income of the household is lower than 1,065 Euro. This corresponds to the 30% quantile of the German income distribution. (ii) *Low education*: Neither the mother nor the father of the child has a school-leaving degree qualifying for university studies. (iii) *Single-parent status*: A parent is classified as a single parent if he/she is not living together with a partner.

212 families; hence, out of 590 low-SES families who participated in the baseline wave and gave consent, 212 were *randomly* selected and constitute our treatment group (Treatment Low SES). The remaining 378 families form the control group (Control Low SES).[3]

Notice that the actual assignment of mentors to children in Treatment Low SES was conducted by the mentoring program. Each child in the treatment group could potentially be matched, but not all selected children were matched in the end. A mentor-mentee match was successfully implemented for 74% of the 212 children. For the remaining 26%, matches could not be realized due to a local shortage of mentors, mentor refusals, or coordination problems between mentors and families (e.g., pregnancy of the mentor or moving of mentor or family). In the analysis, we hence focus on intent-to-treat effects (ITT) between Treatment and Control Low SES.

We also invited 150 randomly-chosen high-SES families to take part in the study (not the mentoring program). 122 took part in the baseline wave of interviews and serve as an additional benchmark group (Control High SES).

After the one-year mentoring program, all families that participated in the baseline wave (Treatment Low SES, Control Low SES, and Control High SES) were invited to take part in the post-treatment interviews and experiments (post-treatment wave) in which all of our main outcome variables were elicited.[4]

## 2.2 The Mentoring Program

We exogenously enhanced the social environment of the treated low-SES families with the help of an existing and well-established non-profit mentoring program in Germany, "Balu und Du".[5] In this program, elementary school children are provided with a mentor for up to one year. The mentors are predominantly university students (aged from 18 to 30) who volunteer to serve as a mentor for a child.

The mentoring program is not targeted toward specific learning goals (such as improved school grades), but rather to enriching children's everyday lives. A key component of the program is to introduce children to new activities, enable new experiences, and provide feedback; possibly exactly the inputs that are needed for

[3]Randomization was stratified by city (Cologne or Bonn) and SES criteria, for a total of 14 strata. Given the larger relative supply of mentors in Bonn, we assigned a higher share of children in Bonn to the treatment group. Thus, the assignment into treatment was random conditional on location. Therefore, we condition on location for the analyses.

[4]85.3% of the families took part in this second wave of interviews and experiments. See section 3.4 for a discussion of sample balance and attrition.

[5]More details about the mentoring program can be found on www.balu-und-du.de.

them to develop an accurate sense of their abilities and that might be missing in low-SES families. In practical terms, a mentor typically spends one afternoon per week in one-to-one interactions with his/her mentee. During this time, they engage in joint activities such as cooking, sports, handicraft work, or visiting a zoo, museum, or playground.

To date, "Balu und Du" has arranged and supervised around 10,000 mentor-child relationships in more than 50 different locations in Germany. The mentoring program is embedded in a tightly organized structure. Every week, mentors complete an online report in which they document their activities and potential problems that came up in their relationship with the child. Program coordinators offer support whenever necessary and provide coaching and advice to mentors. They also organize bi-weekly monitoring meetings in which mentors receive suggestions for new activities and can discuss potential problems.

The mentoring program is designed to last up to 12 months. In our sample, the average duration of mentor-mentee relationships was 9.3 months. Variation in duration is mainly due to unforeseeable events such as moving decisions of parents or mentors due to a job change. On average, treated children met their mentor 22.8 times (std. dev. 11.9), typically for an entire afternoon (amounting to an average total of around 92 hours).

## 2.3 Setting of Experiments and Procedures

In both waves of the experiment, the child was accompanied by one parent. In 95% of the cases, the interviewed parent was the biological mother. Therefore, for convenience, we use the term "mother" for the adult who was interviewed. The interviews took place at central locations in Bonn and Cologne. The interviews and experiments were conducted according to a detailed protocol. The interviews lasted about one hour and, for participation in the interview, mothers received 35 Euros at baseline and 45 Euros in the post-treatment wave.

The children participated in several experiments and intelligence tests and answered a brief questionnaire. The experiments were incentivized using toys. We introduced an experimental currency called "stars". At the end of the interview, children could exchange their stars for toys. Toys were arranged in four categories that increased in objective value and subjective attractiveness to children. Children were told that more stars would result in the option of choosing toys from a higher category.[6]

[6] We ensured that each additional star that would not result in a higher category was nevertheless valuable: these stars were exchanged into "Lego" bricks.

We took great care to create a pleasant interview situation. The mother and the child were seated in the same room but were not allowed to communicate. To avoid interaction between the two, a standardized seating plan was used so that the mother and child could not directly see each other. One experimenter ran experiments with only one child at a time. During the experiments, mothers completed a comprehensive survey covering topics such as basic information about the child, assessments of personality and attitudes of the child, the socioeconomic background of the family, details on how the parent(s) spend time with the child including joint activities, as well as economic preferences, personality, and attitudes of the mother.

Several measures were implemented to mitigate potential concerns related to biased reporting and experimenter demand effects (DeQuidt, Haushofer, and Roth (2018)): (i) mentors received no information about the elicited measures, to avoid any form of "training to the test"; (ii) interviewers were not informed about the purpose of the study or the treatment assignment of the participating families; (iii) the intervention was not mentioned during the data collection phase, and (iv) the research team never interacted directly with the children or their parents.

## 2.4 Main Variables

In the following, we summarize the key outcome measures used for this study.[7]

**Accuracy of Self-Assessments:** We designed an experimental paradigm with two main goals in mind. The paradigm should (i) provide a measure that reflects the accuracy of self-assessments and (ii) be intuitive and easy to comprehend for children of age eight or nine. The latter goal, in particular, posed a challenge. Arguably, the abstract state of the art belief elicitation paradigms that pervade modern experimental economics are unsuitable for children of that age. Hence, we opted for the following more intuitive paradigm.

The basic experimental task was to hit a small hole with a marble (see figure A2 in Appendix A). The children could first experience the task in a practice round (10 trials). This allowed them to become acquainted with the task. In addition, it served as an individual-level "marble lane ability" measure which we use as a control variable in the analysis.

After, the practice round, the key decision problem we implemented was that children had to select a level of difficulty (the size of the hole). The basic trade-off

[7]Kosse et al. (2020) summarize additional measures unrelated to this paper, such as measures of pro-sociality.

we implemented was that higher difficulty levels yielded a higher reward, but at the same time came with a greater risk of not mastering the task, in which case the reward was zero. Specifically, the difficulty levels were varied via the size of the hole (21, 18, 15, 12, 9, 6, or 3 cm diameter) that needed to be hit with the marble to score. Hitting fewer than five times in ten attempts resulted in zero earnings. Scoring at least five times in ten attempts on the chosen marble lane resulted in positive earnings, and earnings linearly increased with the difficulty of the chosen lane. For scoring at least five times on the easiest marble lane, a child earned one unit of the experimental currency; for scoring at least five times on the most difficult marble lane, a child earned seven units of the experimental currency. The key idea underlying the design of the game was that, ceteris paribus, more accurate self-assessment of skill levels allow children to obtain higher rewards, in expectation, due to more appropriate lane choices. At the same time, the game is simple to understand and intuitive for children at that age. Hence, controlling for other factors, the rewards in the task serve as a measure of the accuracy of self-assessment.

The downside of implementing our more intuitive paradigm is that other factors, namely ability in the marble game as well as risk preferences, potentially might play a role and, jointly with the accuracy of self-assessments, determine rewards in the task. Therefore, we make extensive use of our ability measure and our measure of risk preferences (see below) to account for their potential roles in various specifications. Section 3.4 summarizes how ability and risk preferences could affect earnings in the task and how we address this empirically.

The measure was elicited in the post-treatment wave. Before the start of the game, the experimenter asked several control questions to carefully check the child's understanding of the game and, if necessary, explained the rules again.[8] Appendix B contains a translated version of the exact wording of the instructions given to experimenters and children.

**Risk preferences:** Similar to our belief measure, measuring risk preferences among children poses a challenge. While one would ideally want to implement standard price lists or BDM mechanisms, one needs to ensure that children intuitively understand the risk-return trade-off. With this in mind, we implemented the following risk elicitation task (see Falk et al. (forthcoming)). We measured children's risk attitudes in the post-treatment wave by presenting two coins to children (situation

[8]We excluded 11 observations from the analysis (about 2% of observations for each of the three groups, Control High SES, Control Low SES, Treatment Low SES) because these children did not completely understand the rules of the game even after three repeated explanations by the interviewer.

A): one with three stars printed on each side, the other with seven stars on one side and zero on the other. The children had to choose which coin would be tossed. The safe value of three was also "determined" by a coin toss to ensure that children do not prefer the risky option for its higher entertainment value. After children made their decision, but before actually tossing the chosen coin, the experimenter presented two additional coins in another color (situation B): one with four stars on each side, the other, as before, with seven stars on one side and zero on the other. Again, children had to choose which coin would be tossed and the interviewer then tossed the two chosen coins. The order in which the two variations of the game (situation A and situation B) were played was randomized. In the analyses, we use the number of risky choices to control for risk preferences.

**Social interaction patterns:** The main goal here was to understand which aspects that are being offered by the mentoring program might be missing in low-SES environments. The literature suggests that feedback and learning opportunities are important inputs for the development of metacognitive capacities (Flavell, 1979).

To make progress, we asked mothers in structured interviews at baseline how they spend time with their child. We focused on activities that might be missing in low-SES families and that typically entail learning opportunities and feedback. We also focused on activities that we knew are typically part of the mentoring program. Such activities include having a conversation, playing board or card games, having a snack together, playing music together, or going to music lessons. For each activity, the precise wording of the question was: "How many times during the last 14 days have you or the main caregiver done the following activities together with your child?". We created a variable for "intensity of social interactions" as the average share of highly interactive activities.[9]

# 3 Results

## 3.1 Preliminaries and Data Description

Recall that after the one-year treatment period, all families who had participated at baseline were invited to take part in the post-treatment wave. 85.3% (607 out of 712) took part in this second wave of interviews. 596 answered the control questions correctly and constitute our core sample.

Our main treatment comparison is between Treatment Low SES and Control Low SES. Columns 1 and 2 in table 1 reveal no detectable sample imbalance between

[9]For further details on this measure, see also Kosse et al. (2020).

the two treatments, neither before (column 1) nor after the intervention (column 2). Columns 3 and 4 indicate no evidence for selective attrition. Attrition is not significantly related to treatment status, performance at baseline, the intensity of interaction at baseline, nor to the respective interactions. Nevertheless, we also include inverse probability weighting methods (IPW) to adapt for minor imbalances as a robustness check. We estimated the weights from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave), regressed on baseline measures of self-assessment, social interaction and ability, treatment and high-SES dummies, and the interaction of the baseline measures and the group dummies.

| Sample: Low SES T & C | Assigned to treatment | | Lost to follow-up | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Gained stars (baseline, standardized) | 0.008 | 0.003 | | -0.005 |
| | (0.020) | (0.022) | | (0.020) |
| Intense interaction (baseline, std.) | -0.000 | -0.006 | | -0.012 |
| | (0.020) | (0.022) | | (0.020) |
| Treatment dummy | | | -0.013 | -0.012 |
| | | | (0.033) | (0.033) |
| Gained stars x Treatment dummy | | | | 0.015 |
| | | | | (0.033) |
| Intense interaction x Treat. dummy | | | | 0.017 |
| | | | | (0.033) |
| Sample restriction | No | Wave 2 | No | No |
| Observations | 590 | 485 | 590 | 590 |
| $R^2$ | 0.000 | 0.000 | 0.000 | 0.001 |
| $p$-value F-test (all indep. vars. = 0) | 0.925 | 0.956 | 0.699 | 0.977 |

Table 1: Analyses of treatment assignment and attrition. Coefficients are OLS estimates, standard errors in brackets.***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Figure 1 displays histograms for chosen lane difficulty and earnings over all three groups of children (Control Low SES, Treatment Low SES, Control High SES). On average, children chose a lane difficulty of 4.74 (standard deviation: 1.22) and 24% of children failed the task for the chosen difficulty level. Average earnings from the self-assessment task were 3.30 (standard deviation: 2.08) units of the experimental currency ("stars"). For earnings, figure 1 reveals substantial left-censoring. Hence, we estimate a Tobit model (lower limit at zero). For robustness, we also provide OLS and Poisson (count data) estimates in Appendix A.

We focused on children in elementary school because the literature suggests that this might be the time in which abilities to accurately judge one's own strengths and weaknesses are formed. Table A1 in the Appendix corroborates this view and shows positive correlation between the accuracy of self-assessments and the age of the children. This pattern holds irrespective of controlling for ability and risk preferences.

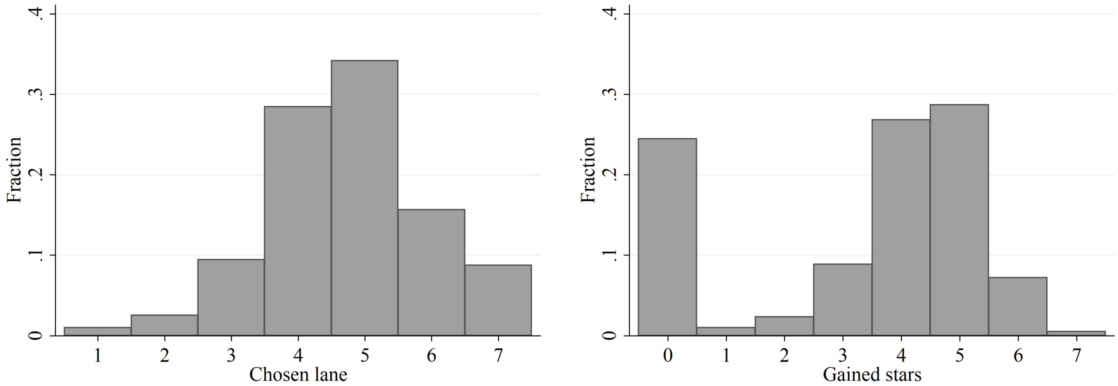


Figure 1: Histograms for chosen lane difficulty and earnings over all three treatment conditions.

## 3.2 Socioeconomic Status and Self-Assessment

We begin our analysis of the role of the social environment for the accuracy of self-assessments (measured post-treatment) by comparing children from a low-SES background to children with a high-SES background. While we do not claim causality for this comparison, we nevertheless view it as a useful benchmark exercise that allows us to document the extent to which the accuracy of self-assessment is associated with the social environment in which children grow up.

In all main regressions, we condition on ability fixed effects (FEs), interviewer FEs, location, gender, and age. As discussed above, given the nature of our data we report Tobit estimates. Table 2 displays the results of regressing earnings in the self-assessment game on an SES dummy (High SES versus Low SES Control). The results indicate that SES is significantly associated with earnings in the self-assessment game. In column 1, without using further controls, we show that children from high-SES families earn, on average, more than an additional half of a star. In columns 2 and 3 we check for robustness and show that the gap is largely unaffected by systematic attrition (column 2) and heterogeneities in risk preferences (column

3).[10] The gap is sizable and corresponds to about 25% to 30% of a standard deviation and to about 15% to 20% of average earnings.

| Sample: low & high SES Control | Gained stars (# 0-7) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Base: low SES Control | | | |
| High SES dummy | 0.612* | 0.624** | 0.511* |
| | (0.327) | (0.304) | (0.302) |
| Inverse probability weighting | no | yes | yes |
| Controlling for risk pref. | no | no | yes |
| Observations | 420 | 420 | 420 |

Table 2: Coefficients are Tobit estimates, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs and marble ability FEs. Marble ability is the performance in the trial round. Willingness to take risk is the number of risky choices (lottery over safe amount). IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

### 3.3 The Mentoring Program and Self-Assessment

We now move to our main analysis and shed some light on the *causal* role of the social environment. For this purpose, we exploit the randomization of low-SES children into the mentoring program. To do so, we follow the same estimation approach as before and regress earnings in the self-assessment game from the post-treatment wave on a treatment dummy (low-SES treatment versus low-SES control). In all main regressions, we again condition on ability FEs, interviewer FEs, location, gender, and age.

The results shown in table 3 (column 1) show a pronounced and significant positive causal effect of the enrichment of the social environment on the accuracy of self-assessment. The enrichment of the social environment through the mentoring program increased children's earnings in the self-assessment task by more than 0.5 stars. There is no evidence that the treatment effect is biased by selective attrition (column 2) or the effects of risk preferences (column 3). Relating these effects to the SES gap documented in table 2, it seems that the mentoring program has the

[10]The slight decrease in effect size in column 3 relates to a small high-to-low SES gap in risk preferences, see e.g. Falk et al. (forthcoming).

potential to close this gap.[11] These results are robust to various changes in the specification. In table A2, we show estimates of similar size and significance for estimations without control variables. In tables A3 and A4, we confirm these results by estimating Poisson and OLS regressions.

| Sample: Low SES T & C | Gained stars (# 0-7) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Base: Low SES Control | | | |
| Treatment dummy | 0.650** | 0.639** | 0.621** |
| | (0.283) | (0.284) | (0.279) |
| Inverse probability weighting | no | yes | yes |
| Controlling for risk pref. | no | no | yes |
| Observations | 485 | 485 | 485 |

Table 3: Coefficients are Tobit estimates, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs and marble ability FEs. Marble ability is the performance in the trial round. Willingness to take risk is the number of risky choices (lottery over save amount). IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

To shed light on the underlying choice pattern generated by the mentoring program, table 4 analyses children's lane choice and their failure rate. To this end, the table shows OLS coefficients of regressing the chosen difficulty level and the failure probability on high-SES and treatment dummies. Column (1) shows that untreated low-SES children selected more difficult lanes compared to treated-low SES children and high-SES children. Consequently, these children failed more frequently (see column (2) of table 4) which (as we saw in tables 2 and 3) leads to lower earnings on average.

[11] Using the full sample, including dummies for control high SES and treatment low SES (i.e., using control low SES as the base) and testing for equality of the treatment and high-SES coefficients, yields p-values greater than 0.6 for all specifications.

| Sample: Low SES T & C | Chosen lane (# 1-7)<br>(1) | Failure (0/1)<br>(2) |
|---|---|---|
| Base: Low SES Control | | |
| Treatment dummy | -0.310*** | -0.121*** |
| | (0.113) | (0.042) |
| High SES dummy | -0.457*** | -0.111** |
| | (0.121) | (0.046) |
| Observations | 594 | 596 |

Table 4: Coefficients are inverse probability weighted (IPW) OLS estimates, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs, marble ability FEs and standardized willingness to take risk. IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. The are two missings in our dataset for the chosen lane difficulty, due to experimenter misreporting. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

### 3.4 Discussion: Ability and Risk Preferences

Next, we discuss the role of ability and risk preferences in more detail. As emphasized earlier, both ability and risk preferences potentially affect our outcome measure. The main concern with ability is that it obviously relates to rewards in the game and that it might also be affected by the intervention. To address this concern, table A5 in the Appendix verifies that we do not detect any differences in marble ability between low-SES treatment and low-SES control. Moreover, Tables 3, A2, A3, and A4 indicate that our results are robust to including ability FEs in various specifications.

The concern with risk preferences might be less obvious, but risk preferences can affect lane choice because children may opt for a "safer" lane and thereby be willing to forego expected earnings. In addition, risk preferences might also be affected by the treatment. To address the role of risk preferences, similar to ability, table A5 in the Appendix verifies that we do not detect any differences in risk preferences between low-SES treatment and low-SES control. Furthermore, Tables 3, A3, and A4 show robustness when we include controls for risk preferences. Table A6 estimates the treatment effect separately for different risk groups (no risky choices versus at least one risky choice). We obtain similar and statistically significant treatment effects for both subsamples.

Taken together, we find no evidence that ability or risk preferences drive our results or change the interpretation of our findings in any meaningful way.

### 3.5 Heterogeneous treatment effects

We proceed by delving into the underlying mechanisms of our treatment effect. Specifically, we seek to shed light on the environmental factors that appear to be missing in low-SES families that influence accurate self-assessment. We take our measure of social interaction patterns as a proxy for the opportunities to learn about oneself that the social environment provides.

Following the estimation approach as before, column 1 of table 5 reveals that for control low SES children, there is a pronounced positive relationship between the self-reported intensity of social interactions and the accuracy of self-assessment. Crucially, if the intensity of social interactions is a critical element in the relationship between social environment and the accuracy of self-assessment, and if this is the input that the mentoring program delivers, then we should see that the effect of the mentoring program is more pronounced for families with fewer intense social interactions. Table 5 column 2 shows this to be the case for our sample. We regress earnings in the self-assessment game on our measure of the intensity of social interactions (measured at baseline), a treatment dummy, and an interaction term of treatment status and intensity of social interactions. The results indicate a significant negative interaction effect, which means that the mentoring program is less effective for children that already experience relatively more intense interaction in their families and is pronounced for children that experience fewer intense interactions in their families. The same pattern is found when we look at the effects of lane choice and the probability of failure, see table A7. This suggests that the mentoring program provides resources that are scarce in low-SES family environments, namely intense social interactions that allow children to have new experiences and obtain feedback that sharpens their sense of their strengths and weaknesses.

| | Gained stars (# 0-7) | |
|---|---|---|
| | (1) | (2) |
| Intense interaction (baseline, std.) | 0.417** | 0.378** |
| | (0.161) | (0.154) |
| Treatment dummy | | 0.613** |
| | | (0.280) |
| Treatment x intense interaction | | -0.460** |
| | | (0.227) |
| Sample: | Control low SES | T & C low SES |
| Observations | 309 | 485 |

Table 5: Coefficients are inverse probability weighted (IPW) Tobit estimates, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs, marble ability FEs and standardized willingness to take risk. IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

# 4 Concluding remarks

In this paper, we introduced a novel tool to measure the accuracy of self-assessment among children. We employed this tool to study the role of the social environment in shaping the accuracy of self-assessment. We showed that: (i) children from high-SES families are more accurate in their self-assessments compared to children from low-SES families; (ii) an exogenous enrichment of the social environment via a mentoring program has a causal positive effect on low-SES children's self-assessments; (iii) the mentoring program is most effective for children whose parents provide fewer social and interactive activities for their children.

The skill to accurately assess one's strengths and weaknesses is arguably a key determinant of good decision-making in many contexts of economic relevance, e.g., educational or career choices. The literature on the development of metacognition posits that metacognition and related skills are malleable and shaped by feedback and experiences. Our results bolster this view and provide causal evidence for the importance of feedback and experiences for the development of an accurate sense of self.

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# Appendix

## A Additional Tables and Figures

| Sample: all children | Gained stars (# 0-7) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Age (in years) | 0.532** | 0.497** | 0.410* |
| | (0.232) | (0.232) | (0.227) |
| Controlling for ability | no | yes | yes |
| Controlling for risk pref. | no | no | yes |
| Observations | 596 | 596 | 596 |

Table A1: Coefficients are inverse probability weighted (IPW) Tobit estimates, standard errors in brackets. All regressions also include a constant, gender, location fixed effects (see sampling) and interviewer FEs. Marble ability is the performance in the trial round. Willingness to take risk is the number of risky choices (lottery over safe amount). ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

| Sample: Low SES T & C | Gained stars (# 0-7) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Base: Low SES Control | | | | |
| Treatment dummy | 0.557** | 0.611** | 0.518* | 0.629** |
| | (0.279) | (0.278) | (0.276) | (0.285) |
| Marble ability FEs | no | yes | no | no |
| Age & gender | no | no | yes | no |
| Interviewer FEs | no | no | no | yes |
| Observations | 485 | 485 | 485 | 485 |

Table A2: Coefficients are inverse probability weighted (IPW) Tobit estimates, standard errors in brackets. All regressions also include a constant and location fixed effects as treatment probabilities differ by location (see sampling). IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

| **Poisson regressions** | Gained stars (# 0-7) | | |
|---|---|---|---|
| Sample: Low SES T & C | (1) | (2) | (3) |
| Base: Low SES Control | | | |
| Treatment dummy | 0.440** | 0.436** | 0.413* |
| | (0.192) | (0.213) | (0.211) |
| Inverse probability weighting | no | yes | yes |
| Willingness to take risk | no | no | yes |
| Observations | 485 | 485 | 485 |

Table A3: Coefficients are average marginal effects after Poisson regressions, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs and marble ability FEs. Marble ability is the performance in the trial round. Willingness to take risk is the number of risky choices (lottery over safe amount). IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

| **OLS regressions** | Gained stars (# 0-7) | | |
|---|---|---|---|
| Sample: Low SES T & C | (1) | (2) | (3) |
| Base: Low SES Control | | | |
| Treatment dummy | 0.435** | 0.429** | 0.419* |
| | (0.219) | (0.217) | (0.214) |
| Inverse probability weighting | no | yes | yes |
| Willingness to take risk | no | no | yes |
| Observations | 485 | 485 | 485 |

Table A4: Coefficients are OLS estimates, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs and marble ability FEs. Marble ability is the performance in the trial round. Willingness to take risk is the number of risky choices (lottery over safe amount). IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

| Sample: Low SES T & C | Marble ability (standardized) (1) | Willingness to take risk (standardized) (2) |
|---|---|---|
| Treatment dummy | 0.016 | -0.024 |
| | (0.099) | (0.102) |
| Observations | 485 | 485 |

Table A5: No treatment effects on marble ability and risk preferences. Coefficients are inverse probability weighted (IPW) OLS estimates, standard errors in brackets. Marble ability is the number of scores in the trial round. Willingness to take risk is the number of risky choices (lottery over safe amount). All regressions also include a constant, location and interviewer fixed effects. IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

| Sample: Low SES T & C | Gained stars (# 0-7) (1) | (2) |
|---|---|---|
| Base: Low SES Control | | |
| Treatment dummy | 0.713* | 0.743* |
| | (0.369) | (0.390) |
| Regarded sub-sample: | Zero risky choice | At least one risky choice |
| Observations | 156 | 329 |

Table A6: Coefficients are inverse probability weighted (IPW) Tobit estimates, standard errors in brackets. Column 1 regards the sub-sample of children who did not make any risky choice in the coin toss experiment. Column 2 regards the sub-sample of children who did make at least one risky choice in the coin toss experiment. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs and marble ability FEs. Marble ability is the performance in the trial round. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

| | Chosen lane (# 1-7) | | Failure (0/1) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Intense interaction | -0.067 | -0.045 | -0.057** | -0.054** |
| (baseline, std.) | (0.064) | (0.062) | (0.024) | (0.024) |
| Treatment dummy | | -0.316*** | | -0.122*** |
| | | (0.115) | | (0.043) |
| Treatment x intense interaction | | 0.191* | | 0.082** |
| | | (0.113) | | (0.034) |
| Sample: | Control low SES | T & C low SES | Control low SES | T & C low SES |
| Observations | 307 | 483 | 309 | 485 |

Table A7: Coefficients are inverse probability weighted (IPW) OLS estimates, standard errors in brackets. All regressions also include a constant, age, gender, location fixed effects (see sampling), interviewer FEs, marble ability FEs and standardized willingness to take risk. IPWs account for potential selective attrition and are estimated from a linear probability model of a binary selection indicator (indicating whether the self-assessment measure is available for the post-treatment wave) regressed on baseline measures of self-assessment, social interaction and ability, treatment and high SES dummies and the interaction of baseline measures and the group dummies. In columns 1 and 2 two observations are missing due to experimenter misreporting. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

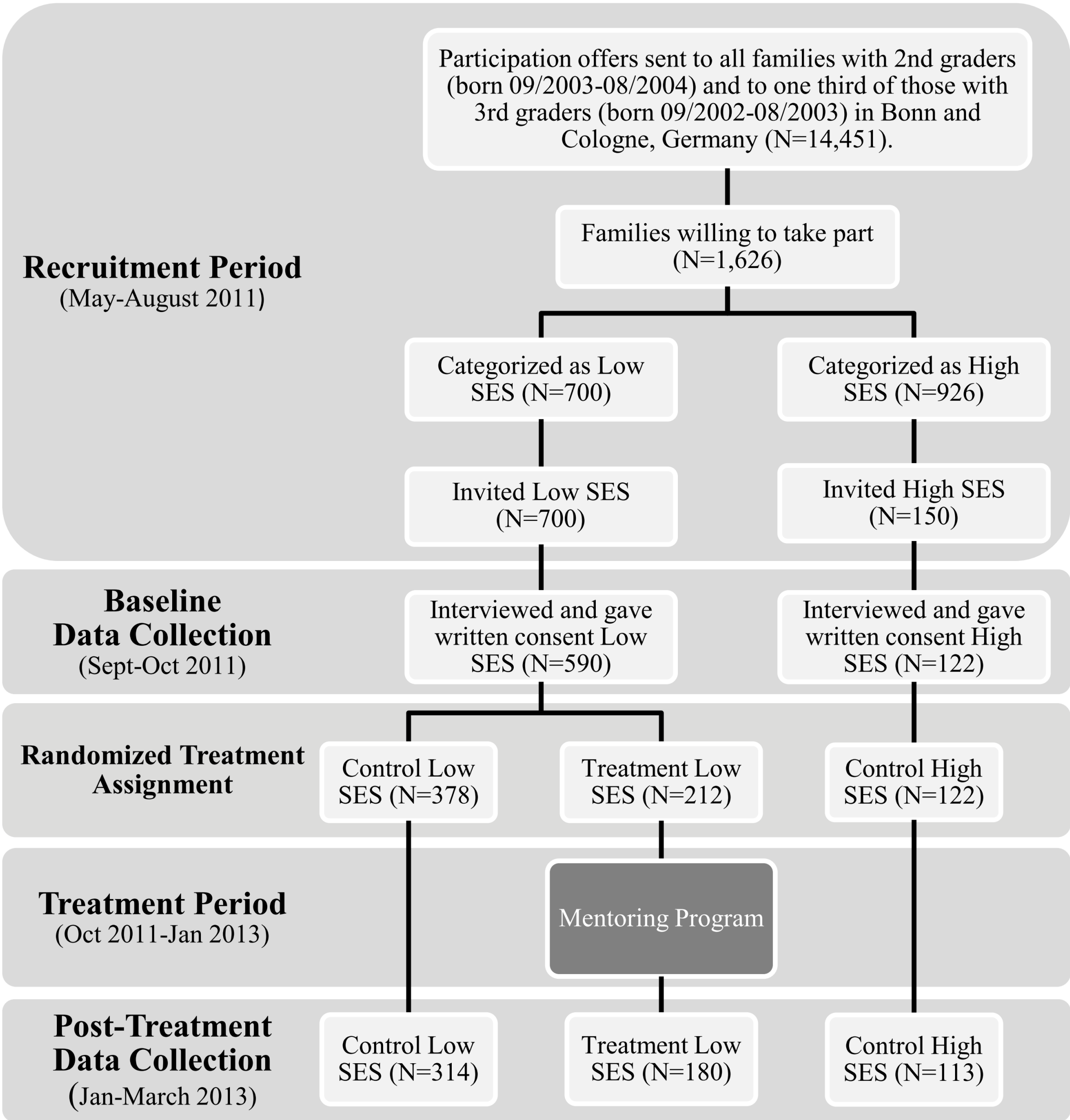


Figure A1: Flow chart of sampling and procedural details.

Figure A2: The marble lanes

# B Translated Version of Instructions

**1st round**

**Rules of the game**

*"Look, here I have a marble lane. At the end there is a squared hole. That is where you are supposed to get the marble in. You have to stay here at this end of the lane and are not allowed to touch the lane while rolling your marble. If the marble does not stay in the hole, we cannot count it as a success. You can now try ten times. Just see how often you can hit the hole out of these ten times."*

**Results**

The child scored _ times (0-10).

**2nd round**

*"That worked out fine. Please come over here. Here are seven more marble lanes with round holes which have different sizes.*

*You can now win stars with your marbles. However, you can only win stars if at least five of your ten marbles drop into the hole. So, only if you either score 5, 6, 7, 8, 9 or 10 times. If you score less than five times (which means 4, 3, 2 or 1 time or never), you won't get any stars.*

*All marble lanes have different levels of difficulty. That is why you can win different amounts of stars playing on them. On the easiest lane with the biggest hole you can win one star; on the hardest lane with the smallest hole you can win seven stars. How many stars you can win on each lane is written on the lanes themselves. On this lane one star, here two, here three, here four, here five, here six and here seven."*

→ Point to the lanes while stating the amounts of stars.

*"But remember: You will only win stars at all if you score at least five out of ten times!*

*You can now pick one of the seven lanes on which you would like to play. Think carefully about your choice. Okay, now we try to recapitulate the rules together."*

**Testing how well the rules were understood**

→ Pick the two-stars lane!

*"Please tell me, if three of your marbles drop into this lane's hole, how many stars will you get?"*

Correct answer: 0

Answer to "Three-marbles question" correct ☐

Answer to “Three-marbles question” false ☐

*“And if eight of your marbles drop into this lane’s hole, how many stars will you get?”*
Correct answer: 2
Answer to “Eight-marbles question” correct ☐
Answer to “Eight-marbles question” false ☐

→ Pick the five-stars lane!
*“Please tell me, if four of your marbles drop into this lane’s hole, how many stars will you get?”*
Correct answer: 0
Answer to “Four-marbles question” correct ☐
Answer to “Four-marbles question” false ☐

*“And if six of your marbles drop into this lane’s hole, how many stars will you get?”*
Correct answer: 5
Answer to “Six-marbles question” correct ☐
Answer to “Six-marbles question” false ☐

→ If the child does not understand the rules of the game, thus if it doesn’t answer the control questions correctly, please briefly repeat the rules and pose a new control question. If the answer is wrong again, repeat again. Repeat the rules at most three times. If the child does not grasp the rules at all, play the game anyhow to avoid disappointing the child, except for the case that the child is so frustrated that it does not want to play the game.

The child has understood the rules of the game at once. ☐
The child has understood the rules of the game after _ (1, 2 or 3) repetitions. ☐
The child has not understood the rules after three repetitions. ☐

*“Well done, you have understood the game very well. So please decide now on which marble lane you would like to play.”*

**Results**
Time until the decision was made: _ seconds [Start measuring time at the end of the phrase.]

The child has decided to play on lane _ (1-7).
The child scored _ times (0-10). [In any case let the child play all ten rounds.]

→ If the child **scored at least 5 times:**
Hand out the stars; put them into a NEW bag labeled with the child's name and put the bag next to the table close to the child.
*"That was great. You have scored [#score] times at the [ ]-stars lane, therefore you get [ ] stars."*
→ If the child **scored less than 5 times:**
*"Unfortunately, less than five of your marbles have dropped into the hole, hence you won't get any stars. But never mind, later on you can win more stars."*

**Remarks:**

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