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Three Essays on Skills and Individual Decision-Making

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THREE ESSAYS ON SKILLS AND INDIVIDUAL DECISION-MAKING

A Dissertation
Presented to
The Academic Faculty

By

Olga Churkina

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
Georgia State University
and
Ivan Allen College of Liberal Arts
Georgia Institute of Technology

Georgia State University
Georgia Institute of Technology

December 2023

THREE ESSAYS ON SKILLS AND INDIVIDUAL DECISION-MAKING

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Date approved: November 28, 2023

ACKNOWLEDGMENTS

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SUMMARY

The dissertation examines the concept of skills, and and their impact on charitable giving behavior, labor market outcomes, and marital choices. The first essay conducts a controlled laboratory experiment, investigating the relationship between worker performance and their pro-social behavior in the context of charitable contributions. The second essay estimates the employment premium associated with online certificates in data science through a randomized field experiment. The third essay expands on a multi-period microeconomics model of educational and marital choices in developing countries. The outcomes of this study address questions that are shared concern for the academic community and policy-makers.

CHAPTER 1

INTRODUCTION

The relationship between skills, knowledge and education and their implications for social policy has been a topic of interest within the realms of economics and public policy. This dissertation comprises three essays and addresses the research questions on how skills affect individual decision-making across various domains.

The first dissertation chapter contributes to the literature on the pro-social incentives, specifically, charitable donations. The paper evaluates differences in response to monetary and pro-social stimuli between high- and low-performing individuals, measured by means of field functional competence tasks in a laboratory contest setting. Expectations are derived from theories of altruistic behavior, recognition, and skill bundles. The participants recognized as high-performers appeared to be more likely to proceed with the supererogatory task and received higher overall payoffs. Although, both groups were equally likely to contribute to charity, the overall fundraising potential expanded as a result of the contest. The study findings reveal policy implications for organizations and charities seeking to engage a broader audience and entice individual contributions through contest activities.

The second chapter evaluates the employment premium associated with online specialization certificates through the implementation of a randomized control trial. The project draws upon labor market discrimination literature and speaks to the widespread interest in data science online education. This paper contributes to the broader discourse on the intersection of education and employment outcomes, specifically focusing on the growing field of data science and online learning. The study design is a correspondence study which involves collecting data on callback rates for fictitious resumes that include or exclude online specialization certificates. The analysis of callback rates serves as an indicator of the perceived value of these certificates in the labor market for non-traditional work-

ing arrangements, while being a female increases a likelihood of a positive response for in-person occupations. The findings have implications for individuals seeking to enhance their employment prospects through online education, as well as for online learning platforms aiming to understand and communicate the value of their certifications.

The third dissertation chapter elaborates on the partial equilibrium model of marital choice conditional on the educational level. Throughout history, marriages at a younger age, usually arranged between families within close-knit communities, have been common in many cultures. The practice still persists in developing countries, although recent research indicates a decline in the prevalence of such marriages in the Middle East, East and Southeast Asia, and Africa. This study examines the hypothesis that a higher level of education is associated with a greater likelihood of entering a self-selected marriage at a later age or choosing to abstain from the marriage market altogether, as opposed to an arranged marriage at a younger age. The paper introduces a theoretical framework based on a non-cooperative static two-period game between parents and children, and employs an empirical regression model using data from the Chinese Household Income Project (CHIP) to investigate how education level obtained by the child with the support of their parents influences their marital outcomes. The policy implications of this research suggest the importance of investing beyond compulsory schooling until older ages to address early marriage practices during adolescence.

Overall, the dissertation features three separate studies that are connected through the concepts of knowledge, skills and education. The last chapter concludes the dissertation addressing policy implications for these projects.

CHAPTER 2

SKILLS AS MEDIATORS FOR PRO-SOCIAL BEHAVIOR

2.1 Introduction

Themes of monetary and pro-social incentives that motivate workers to exert more signif-
icant effort are extensively discussed in the research literature, and so is the literature on
worker performance and skill bundles. Using an experimental economics approach, this
paper mimics real-world scenarios and compares the effectiveness of monetary and pro-
social incentives. It analyzes whether a pro-social incentive (i.e., a donation to charity)
does better than financial stimuli in terms of encouraging potential donors to select into a
supererogatory intellectual task.

Anecdotal evidence suggests that individuals more proficient in particular areas of
knowledge are more willing to participate in extra activities involving their topic of ex-
pertise when rewarded with a charitable donation in their name rather than encouraged fi-
nancially. This study evaluates differences in response between high- and low-performing
individuals given monetary and pro-social stimuli based on theories of recognition and
altruistic behavior.

The findings of this study have major policy implications for charitable organizations
seeking to motivate individuals to participate in activities related to their areas of expertise
when coupled with charitable donations. The paper aspires to learn the relationship be-
tween the performance of high- and low-performing individuals and their tendency towards
pro-social behavior. The research questions posed in this study also relate to the possible
differences in charitable practices based on the recognition of donors. Suppose there is
indeed a positive relationship, and proving subjects with charitable giving options affects
how willing they are to share their expertise. In that case, charity organizations could con-

sider partnering with skill competitions or other types of similar events to build the contest structure around charitable donations as a way of rewarding the participants. If this intuition is correct, then the opportunity to do good socially would boost interest towards the competition and the overall potential results of the contestants. For instance, WorldSkills UK is a partnership between employers, education and governments that organizes national skill competitions such as contests in construction and infrastructure, engineering and technology, health and hospitality, and digital, business, and creative fields (WorldSkills, 2023). The annual New York Marathon run by the nonprofit New York Road Runners would be another good example of the type of partnership, when contest organizers team up with various charities to encourage the participation and boost the competitiveness among the contestants. Therefore, if high-performing participants are willing to continue taking part in the contest, then consequently, the major part of cumulative donations would most likely come from their contributions.

The present experimental design provides a controlled environment that further enables to disentangle the wealth effect and study charitable behavior under risk. The wealth effect represents the change in spending that accompanies a change in perceived wealth, by spotting possible changes in the contributing behavior among participants. The decisions under risk relate to the notion that, dependent on the treatment arm to which participants are assigned, subjects are not aware of their final payoff at the time they are allocating their charitable donation amounts. The possible differences in participant behavior would inform beneficiaries of the charitable donations about the optimal timing of charitable giving in order to structure pro-social incentives in the most effective way.

The following sections describe the experimental design and procedures as well as explicate the results of the study. The practical implications follows the study findings in the concluding section.

2.2 Theoretical framework

2.2.1 Altruism and pro-social behavior

A growing body of literature suggests that non-monetary incentives, such as pro-social stimuli, are essential for worker motivation and productivity. Providing workers with meaning to their efforts has a positive effect on their overall performance (Jeffrey, 2004; Sorauren, 2000). According to Harbaugh (1998), Fehr and Schmidt (2006), Evren and Minardi (2017), and the survey study by Meier (2007), other-regarding, or pro-social, the behavior itself gives individuals utility. In other words, individuals derive private value from the altruistic act apart from the overall outcome provided for others (Andreoni, 1989, 1990). Therefore, pro-social incentives may be particularly effective at motivating workers and improving their performance in certain situations. For example, Tonin and Vlassopoulos (2015) found that pro-social incentives induced a greater increase in productivity than offered financial incentives in an online experiment involving a bibliographic repository platform.

Most of the findings are based on the observations of the subjects participating in realistic activities as a form of effort provision, or so-called "real effort tasks" (Erkal et al., 2011). In a recent study, Cassar and Meier (2017) evaluate the effect of non-monetary and pro-social incentives on worker productivity as opposed to monetary ones and they find a positive effect of charitable giving on performance for workers independent of practicing Corporate Social Responsibility (CSR) instrumentally, in other words, taking steps towards preventing or alleviating social and environmental damages in their business operations. In their follow-up paper, Cassar and Meier (2018) also find that the possibility of altruistic giving increases workers' effort both in the lab setting and in the field.

The recent literature also provides more nuanced evidence of the effect of pro-social incentives, with some studies finding that they are effective at motivating workers while others have found less clear results. For example, Charness et al. (2016) conducted a study

in which participants were asked to complete a real effort task of entering data from a pen-and-paper experiment into an Excel file. They found that offering larger monetary rewards was associated with a relative decline in charitable giving, while the inverse relationship held when amounts were relatively low. Similarly, Imas (2014) shows that individuals work harder for charity than for themselves when the stakes are low. Gneezy et al. (2011), Erkal et al. (2017) and DellaVigna and Pope (2018) have also provided evidence from real-effort tournaments that, while monetary rewards can often promote desired behavior and effort provision among individuals, they might not always be sufficient to make a significant impact. Overall, these findings suggest that the effectiveness of pro-social incentives may depend on the specific context and amounts of alternative monetary stimuli.

Schwartz et al. (2021) add to the prior evidence and inform the present study by evaluating the effectiveness of both standard and pro-social incentives in motivating individuals to take on a real effort task in the first place and how much of their payoff to contribute to the charity organization. They found that the participants are more likely to continue with the experiment when offered monetary incentives rather than pro-social ones. The present study expands on these questions by exploring whether the differences between performance levels lead to the differences in participation and donation behavior. It also differs from a previous study by Crumpler and Grossman (2008) in that it asks participants to exert some effort in order to earn a payoff that can then be redistributed between themselves and a charity of their choice, rather than simply donating from the predetermined endowment provided by the experimenter in a double-anonymous, modified dictator game.

2.2.2 Recognition

The current research also acknowledges the role of recognition in worker motivation and pro-social behavior, by stratifying participants into low and high types based on their performance in a real effort task. Recognition, as an acknowledgment of employees for exemplary performance, can have a positive impact on worker motivation and can be effectively

implemented in both academic and business environments. The experimental study by Bradler et al. (2016) highlights a significant boost in subsequent performance after public recognition. At the same time, according to Ellingsen and Johannesson (2007), even private encouragement fosters feelings of competence, makes work more meaningful, and can be successfully implemented in both academic and business environments. Kosfeld and Neckermann (2011) also find that as little as a purely symbolic award such as a congratulatory card honoring the best performance has a positive impact on worker motivation, while negative feedback might have an opposite effect (Lee and Keil, 2018; Holderness JR et al., 2019). Hence, the recognition message is used in the current study mainly to communicate the status of the participant, however, might be as well a main driver of the differences in performance between participant types instead of their expert status.

2.2.3 Skills, competence and performance

Another distinctive research area concentrates on the returns to skills and the differences between domain-specific and functional competence. Domain-specific competence refers to knowledge of a specific subject area that does not transfer across disciplines and can be improved through exposure to the subject area. In contrast, functional competence refers to skills that transfer and are typically learned outside of formal instruction. These skills are often predictive of important life outcomes, such as college graduation, gainful employment, and civic engagement (Burkhardt, 2007).

For example, Schoenfeld (1992) emphasizes that quantitative literacy and numeracy are essential for everyday life activities and involve strategies and tactics for modeling with basic mathematical knowledge. Other researchers, such as Hanushek et al. (2015, 2016) and Niss and Højgaard (2019), have also examine performance on PISA and PIAAC tests traditionally used to evaluate the application of functional numerical thinking to domains of all sorts (Gal and Tout, 2014).

The current study draws upon this literature to construct the instruments for the real ef-

fort task that tests neither domain-specific knowledge nor general intelligence. Therefore, the constructed real-effort task questions avoid selecting subjects based on differences in general intelligence, which could introduce unobservable bias (Burkart et al., 2017). On the contrary, the task aims at constructing empirical distributions of functional mastery that more closely align with our a priori notions of expertise (Swan et al., 2020). Therefore, the real effort task questions follow the structure of PISA tests of numerical literacy and allow to evaluate the functional mathematical competence of the study participants. This approach aims to identify differences in individual functional competence rather than relying on measures of general intelligence or domain-specific knowledge.

2.3 Exploratory research questions

All the mentioned evidence on pro-social incentives, recognition and functional competence provides insights into how to identify high- and low-performing individuals and the appropriate magnitude of rewards to use in order to motivate them. The study draws from the "warm glow" model proposed by Andreoni (1989, 1990) and allows us to assess the differences in pro-social behavior between high- and low-performing subjects. To do this, the study uses real effort tasks in the form of a functional mathematical competence test to assign subjects into two groups. The subjects are then offered an extra, or supererogatory, task in order to elicit their preferences for continuing, exerting further effort, and donating to a cause. By using this approach, the study aims to understand how different incentives and performance levels may influence an individual's willingness to take on additional tasks and donate to charity. Specifically, the research questions on the behavior of the two types of subjects are the following:

- **Are high-performing individuals more willing to engage in the second task than others?**

    Namely, are high-performers more willing to complete the second task than low-performers as participation is less costly for them in terms of effort (i.e., opportunity

cost) or because of the received recognition?

- **What type of stimuli work better for high and low types of experimental subjects?**

  Are high- or low-performing participants more willing to complete the second task and donate to charities versus for a monetary reward?

- **Do high-performing individuals donate larger monetary amounts relative to low-performing individuals?**

  The underlying hypothesis would be similar to the first one: does willingness to donate higher amounts correlate with lower costs of performing the tasks?

- **Do subjects show more generosity before/after the supererogatory task?**

  In other words, are either or both high- and low-performing individuals more willing to allocate more to the charity upon completing the second task or in advance when they make the donation decision under risk?

2.4 Experimental design

The present experimental design consists of two stages: real effort and supererogatory tasks. The first real effort task administers a problem set to participants and rank-orders test scores to identify and privately recognize the high-performers among them. Participation in the other task is voluntary under the following conditions: either a pure monetary reward or allocating a part of participant payoffs to the charity of their choice. Thus, the present research design allows to study how the difference in subject expertise, measured as functional mathematical competence level, makes people more inclined to work for the sake of charitable giving.

Figure 2.1 provides a graphic illustration of the experimental design, which is discussed in detail in the following sections. One of the main strengths of this approach is that it allows researchers to control the focal experimental variables that cannot be directly
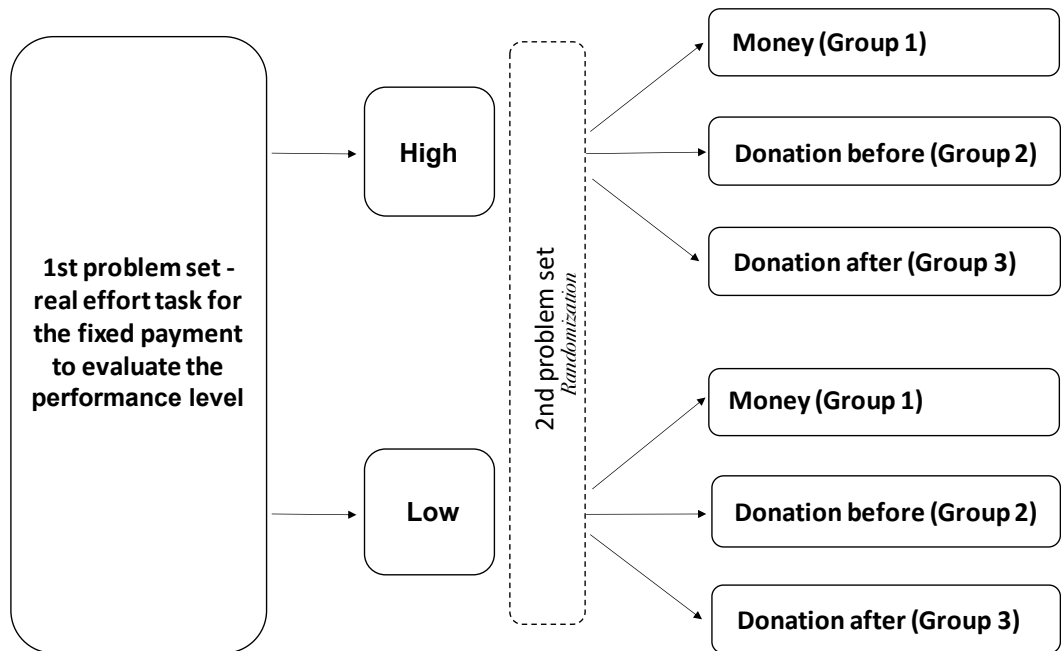
Figure 2.1: The experimental design.

observed in the field and to eliminate selection bias by randomly assigning participants to different treatment conditions. This design also has high levels of internal validity and replicability.

Besides that, random assignment of the treatment conditions eliminates the selection bias among participants: equal groups of randomly selected participants either allocate a portion of their payoff to charity before or after completing the supererogatory task. Thus, the experiment allows to learn how people select into a supererogatory task based on their attitudes towards risk, as participants might behave differently, when assigning a portion to the charity before learning about their payoff (Kahnemann, 1979; Holt and Laury, 2002; Cox and Harrison, 2008). The experimental design described allows to differentiate between the timing of the charitable donation and, therefore, study whether participants are

more interested in experiencing the satisfaction of doing a good deed immediately or after they have learned about their total payoff.

2.4.1 Ranking task

In the first stage of this experimental design, the goal is to identify high-performing participants among the study subjects. To do this, participants are presented with a problem set consisting of 10 exercises that tackle their functional mathematical competence. This real effort task is aimed at evaluating the performance of subjects as they have to solve as many problems as possible in a limited time period of 30 minutes (Bjork et al., 2015).

After completing the task or when the time runs out, the participants' scores are rank-ordered, with ties being broken by adding a small random number to all scores. The high-performers at the top half of the score distribution are assigned with the respective status and receive a congratulatory message. This badge serves as a reputation stimulus, according to the literature recognized in this study. Low-performing participants who were not classified as high-performers receive an opposite message, reinforcing the reputation effect for those who were selected as belonging to the high type.

2.4.2 Supererogatory task

In the second stage of the experiment, participants in each performance group are randomly allocated into one of the three treatments. The participants are given the option to skip the second problem set and go straight to the post-experiment questionnaire, which asks about their basic demographics and self-reported behavioral patterns. Otherwise, they would complete the demographic questionnaire after proceeding to and finishing the supererogatory task. The supererogatory task consists of questions that are similar to the ones from the first problem set.

Regardless of the choices made at the second stage, all participants collect $10 upon completing the post-experiment questionnaire. Hence, this fee is given to the subjects

independently of their abilities and solely on the basis of their participation in the first stage of the experiment.

Monetary treatment

In this treatment, the subjects receive a message with information about their performance in the first stage of the experiment. This message also includes an explanation of their potential prospective payoff if they choose to participate in a supererogatory task. The monetary reward assumes that subjects participate in solving five randomly chosen questions out of the pool of 10 questions from the second problem set and complete the post-experiment questionnaire. Thereforew, participants can earn money for each additional question that they solve, with a maximum payout of $10 upon completion of the task, provided that they choose to participate in the supererogatory task and are successful at solving the questions.

Charity treatments

This treatment is designed to test the hypothesis that individuals may engage in altruistic behavior for both pure altruistic reasons (i.e., they care about how much money they transfer to charity) and for the "warm glow" of feeling good about themselves for being charitable as proposed in the model by Andreoni (1989, 1990).

The participants who were not subjected to the monetary reward are randomly assigned into two groups that differ by the timing of when they are allowed to select the amount to donate. One group is asked to make their decision before attempting the questions on the second problem set, while the other group decides after attempting the questions. This allows the researchers to examine whether the timing of the selection affects the amount that participants choose to donate.

In the charity treatment, some of the participants are given the option to donate a portion of their potential earnings to a charity of their choice from a list of the widely recognized charities in the US. The research idea for distinguishing between the types is nested in

both: the definition of pure altruism by Becker (1974) so that donors care how much money they transfer to charity and "warm glow" model by Andreoni (1989, 1990) showing that individuals also derive private value from their altruistic behavior.

In this scenario, the participants who were not subjected to the monetary reward are randomly assigned into two groups that differ by the timing of when they are allowed to select the amount they want to donate:

- before attempting the questions on the second problem set;

- after attempting the questions on the second problem set.

This additional design feature adds another layer to the present research by examining whether the timing of the selection affects the amount that participants choose to donate. In particular, this design feature aims to assess whether individuals exhibit varying levels of willingness to contribute to charity based on what they know about their performance in the second stage of the experiment. The former scenario could be characterized as a decision under risk, as participants decide on donations without knowledge of their potential earnings but derive a sense of satisfaction from their generosity at the moment. On the contrary, in the latter case, participants are informed of their final score before deciding on their donation, potentially influencing their approach to the decision-making. In other words, their financial choices may be significantly dependent on circumstances before and after engaging in the second task, attempting the second task due to the risk involved (Kahnemann, 1979; Holt and Laury, 2002; Cox and Harrison, 2008). For example, Brock et al. (2013) study how risks affect pro-social behavior, regarding certain final payoffs versus arbitrary chances to earn some monetary amounts. In their turn, Fahle and Sautua (2021) show that pro-social dictators with higher degree of loss aversion increases are more likely to contribute to a recipient than the ones inclined to bear higher risks in a modified dictator game. Another possible confounder that might influence individuals' charitable giving behavior is the transaction costs associated with donating on their own versus specifying

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the charitable amount within an experimental setting. Upon learning about their payoffs, participants might be more inclined to donate than if they were to undertake the task of charitable giving on their own.

2.5 Results

2.5.1 Study implementation

The experiment took place at the GSU ExCEN lab from December 2021 - February 2022 using a *z-Tree* environment (Fischbacher, 2007; Downen, 2012). Overall, the subject pool comprised 180 undergraduate students, with 30 participants in each group (i.e., high- and low-performing subjects under three different compensation schemes). At the beginning of each session, the subjects were presented with a consent form and instructional materials. They then moved on to the first mandatory problem set, which tested their functional mathematical competence using questions constructed by the experimenter and based on the PISA tests (OECD, 2019). Each answer given by the subjects was documented by the experimental software as well as their overall scores and presented to the participants along with the correct answers later on a separate screen. According to the experimental design, the participant performances were rank-ordered upon completion of the first problem set. The subjects from the upper half of the score distribution received a congratulatory message praising their performance, while the other subjects were shown a message to the contrary on their screens. Any possible ties in the scores were broken by adding a small random number to all participant scores, which allowed the subjects to be sorted into the high- and low-performing groups as intended by the experimental design.

The information presented to subjects in the second – supererogatory – stage was dependent upon their type assigned upon completion of the first stage of the experiment, either high- or low-performing type. Each subject was allocated to one of three following treatments in the second stage, which required them to complete additional questions. They could have either received a monetary reward under the first treatment condition or
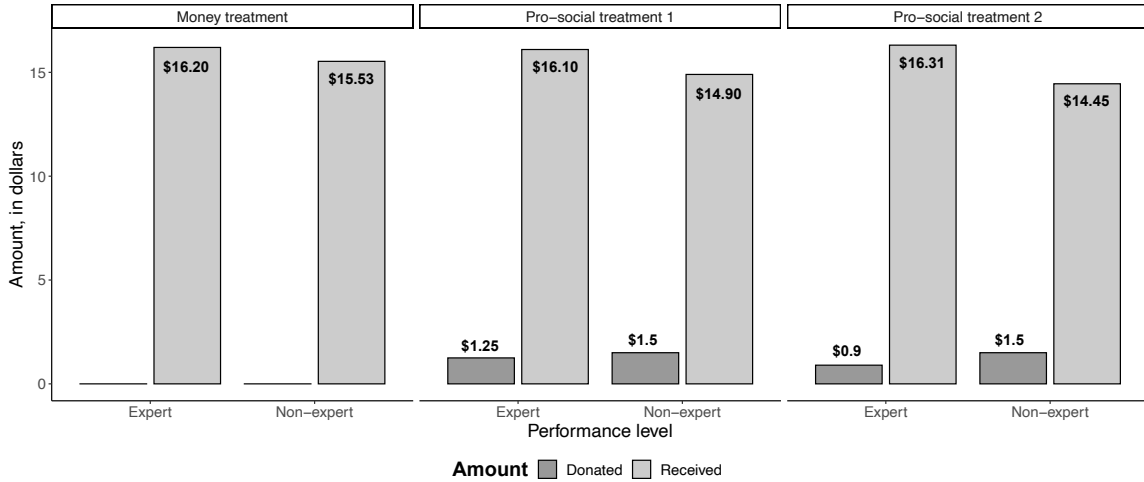
Figure 2.2: Received and donated amounts by treatment and performance level.

donated a part of the reward to some charity under the second and the third ones. If the subjects participated in the second or third treatments, they were presented with a choice of charities and donation amounts before or after the supererogatory task, depending on the treatment to which they were assigned. Hence, a separate pre-programmed path was constructed for each condition: monetary rewards of high and low-performers; charitable giving of either types assigned before or after undergoing the second stage of the experiment. Each treatment also included the option for the subjects to leave the experiment after the first stage and concluded with a screen reflecting the participant's score, final payoff, and amount donated to the charity of their choice (for the second and third treatment groups). Moreover, the second-stage questions were randomized, so the sequence and even the appearance of the questions were not predetermined. Each experimental session concluded with the demographic questionnaire that the subjects were required to complete at the end of the session. The subject characteristics obtained from the survey were later used for subsequent statistical analysis. Finally, the experiment was completed using a single-blind payoff protocol.

2.5.2   Analysis of subjects' behavior

The results of the experiment show that a high percentage of both the high- and low-performing subjects chose to participate in the supererogatory task. Specifically, 90% of the high-performing and 80% of the low-performing subjects participated in the second stage of the experiment, with more subjects staying for the monetary reward scheme (*p-value = 3.882e-08*). This evidence is consistent with the research articles by Lazear et al. (2012) and Schwartz et al. (2021), which showcase subject tendencies to opt out of the sharing environment, and exhibited in Table A1 in the Appendix A. One possible explanation for this result is that the average payout of $14-16 was considered a reasonable price for a 30-minute activity, given Georgia's state minimum wage rate of $7.25 per hour (DOL, 2022). The availability of outside options, such as the opportunity cost of half an hour of activity, may also have influenced the subjects' financial choices within the experimental setting, according to Eckartz (2014). In this case, it is likely that the opportunity costs of the subjects did not exceed the received payoffs. Therefore, pure monetary rewards are favored more among students due to the relatively high payment scheme, which also aligns with the study by Imas (2014).

Figure 2.2 further clarifies that that there is no statistical difference in the average payouts or donation amounts across the charity treatments, indicating that the subjects did not exhibit different behavior under risk, according to Student's t-tests as well as Kolmogorov–Smirnov tests. Additionally, there is no statistical difference between the time to completion and donated amounts coming from participants of different performance levels. However, when subjects do donate, they tend to prefer charities with goals related to improving health or eliminating poverty rather than environmental ones.

Figure 2.3 showcases the distributions of points for high and low-performing individuals: none of the participants answered all the questions incorrectly, and only three high-performing subjects were able to give all correct answers, which is about 3.3% of all high-performers and 1.7% of the whole subject pool. Figure 2.4 plots the time to completion for
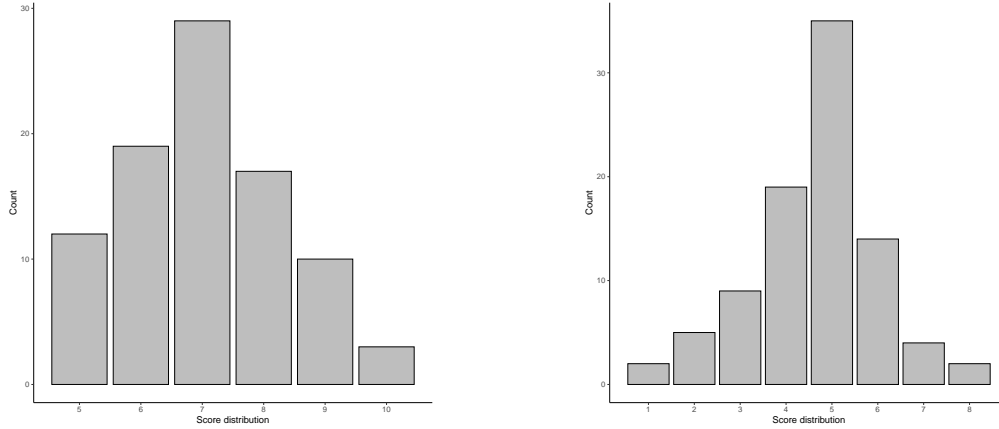
Figure 2.3: Score distribution of high and low-performing subjects for the real effort task.
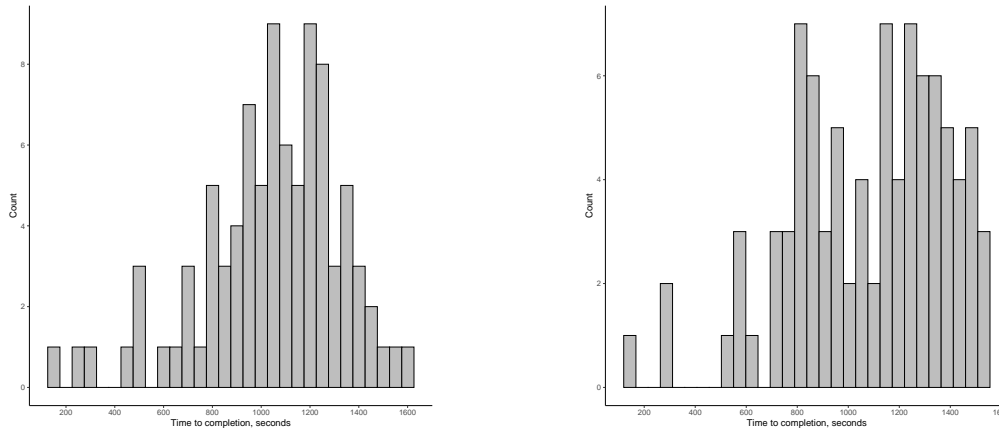
Figure 2.4: Time to completion of high and low-performing subjects for the real effort task.

high- and low-performing subjects and shows that the time to completion is not statistically different between the two groups and the subjects who dropped out of the study. Table A2 in the Appendix A provides demographic characteristics of the study participants.

Table 2.1 provides results of the regression analysis that highlights other differences in behavior across participant types for the full sample and a subset of participants in two donation treatments that stayed for the supererogatory task. The first two models use logistic regressions with a dependent dummy variable that takes on a value of one when an experimental subject proceeds with the second task and a value of zero otherwise. The first regression shows that the average effect of being recognized as a high-type participant upon completion of the first problem set translates into 14.5% higher chances of proceed-

Table 2.1: Regression analysis (logistic and log-linear models): Opt-in by participant type

	Opt-in 2nd task		Donation portion	
High status	0.145*		-0.169	
	(0.059)		(0.227)	
No. of points		0.057***		-0.063
		(0.017)		(0.074)
Time to completion	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
No. observations	180	180	93	93

Notes: $'p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Robust standard errors in parentheses.

ing with the supererogatory task, conditional on the demographic characteristics of participants. The second logistic regression operationalizes the level of performance through the number of correct answers, or the total number of points received in the first problem set. These regression results also align with the prior findings, showing that each additional correct answer increases the chances of continuing with the second task by almost 6%. The aforementioned regression results support the hypothesis that high-performers are more willing to complete the second task than low-performers. The question, whether these findings are attributed to the lower level of effort needed to complete problem sets for the high-performing subjects or to the impact from the recognition message, is discussed further.

The results of the study also show that less than 10% of participants, equally distributed between two charity treatments with more low-performing subjects in the second charity treatment, decided not to contribute to charity after proceeding with the supererogatory task, and only one subject directed the entire amount of their additional payoff to the social good. Based on the conclusions from the paper by Andreoni et al. (2017), these avoidance numbers might have been even higher if the experimenter, as a solicitor of the charitable donations, did not observe the rate of giving during the payoff distribution (i.e., a double-

Table 2.2: Regression analysis (log-linear models): Payoffs by participant type

	Payoff in donation groups			Total payoff		
High status	0.098*		0.044**	0.126***		0.068
	(0.036)		(0.165)	(0.031)		(0.141)
No. of points		0.042***	0.075**		0.049***	0.045**
		(0.011)	(0.022)		(0.009)	(0.016)
Status*points			-0.072*			-0.005
			(0.028)			(0.030)
Donation group 1				-0.088*	-0.086*	-0.086*
				(0.038)	(0.037)	(0.037)
Donation group 2				-0.132***	-0.136***	-0.134***
				(0.040)	(0.039)	(0.039)
Time to completion	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	93	93	93	180	180	180

Notes: $'p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Robust standard errors in parentheses.

blind payoff protocol).

As differences in payments come into place in the extra problem set, subjects did not experience differential payoffs when they decided to continue with problem-solving. Their decisions are solely attributed to their preferences for time, and effort contributed to the supererogatory task versus potential payoff. The third and fourth regressions reinforce the findings of negligible differences between the charitable donation of high- and low-performing experimental subjects as well as different donation schemes. Namely, there is no significant difference between high- and low-performing participants in terms of the realized donation portions of the total payoffs in both log-linear model specifications, regardless of whether a dummy variable for being recognized as a high-performer or the total number of correct answers are used as a predictor.

Table 2.2 provides the regression results that explore the relationship between performance levels and final payoff amounts in the experiment. High-performing participants

Table 2.3: Regression analysis by participant type (logistic and log-linear models)

	Opt-in 2nd task		Donation portion		Total payoff	
	High	Low	High	Low	High	Low
No. of points	0.039	0.050	-0.020	0.090	0.037*	0.033$'$
	(0.030)	(0.036)	(0.123)	(0.194)	(0.017)	(0.019)
Donation group 1					-0.021	-0.140*
					(0.055)	(0.056)
Donation group 2					-0.080	-0.168*
					(0.052)	(0.064)
Time to Completion	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	90	90	90	90	90	90

Notes: $'p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Robust standard errors in parentheses.

earned almost 10% more than low-performing ones across the two donation treatment conditions, and the premium for each additional correct answer goes up to about 4%. Including the interaction term leads to a reduction of the high-type status effect and an increase in the effect of the additional correct answer on the received payoff. Finally, total payoffs are heavily reliant on the subject's level of expertise, operationalized in both ways, as a dummy variable for high status and the number of correct answers in the first stage of the experiment. The payoffs were lower for treatments that include charitable donations while not materially different between the two charitable schemes. The results measured in the number of acquired points in the first stage of the experiment do not change with the inclusion of the interaction term. Thus, the overall preference for monetary rewards over indistinguishable charitable schemes corresponds to the larger amount of money collected at the end of the experiment and is in line with the findings of Imas (2014) and Schwartz et al. (2021) among others.

Finally, there might be a possible reinforcement of the recognition mechanism in the form of acknowledgment messages sent out to high-performers. To disentangle the effect of being a high performer from the effect of the message acknowledging their expertise,

the additional analysis includes the other iteration of the primary models' implementation. The same regression analysis was performed for high- and low-performing individuals separately. To begin with, Table 2.3 reveals that there is no relationship between the participant scores and the likelihood of them staying for the second stage of the experiment, therefore, the main effects comes from the recognition messages, following the prior literature (Ellingsen and Johannesson, 2007; Kosfeld and Neckermann, 2011; Bradler et al., 2016). Then the sub-sample analysis confirms no relationship between performance level, recognition and donations for both types. Lastly, the total payoffs are dependent on the score received at the first stage of the experiment for the high-performing individuals but not for the low-performing ones.

2.5.3 Sensitivity checks

The main limitation of the study comes from external validity concerns. The first sensitivity check includes the other iteration of the experiment where the dummy variable of being a high-performer was assigned only to one-fifth of the best-performing participants instead of the top half of the points distribution, though the recognition messages were distributed in a regular manner. The standard means and distribution tests, as well as regression analysis, did not show any material differences in relationships between the assigned level of expertise and donation amounts compared to the main analysis, as shown in Table A3 in the Appendix A. The distinctions observed are in the effect of the high status on the total payoff and decision to proceed with the supererogatory task: the higher the cutoff, the stronger the relationships.

Another sensitivity check involves comparisons of ten highest- and lowest-performing experimental subjects in their time to completion, scores, choices to stay for a supererogatory task, and charitable behavior. At the left tail of the distribution, participants earned from one to two points were all assigned to low-performers and stayed for the second round in 70% of all cases. In contrast, at the right tail of the distribution, the scores varied

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from nine to ten points; all subjects were assigned to the high-type group and continued with the task. Furthermore, the data exhibited no definitive patterns in terms of time to completion. Overall, the analysis revealed a lack of charitable behavior from the lowest-performing group while the highest-performing individuals all donated to charity a positive amount of up to 20% of their additional payoff in an extreme case.

2.6   Conclusions and discussion

The present study investigates differences in pro-social behavior between high- and low-performing subjects in their willingness to engage in pro-social behavior that uses their expertise. The experiment implements a two-stage design and tests various configurations of the target pro-social incentive. After the assignment of performance types, the research focuses on testing the hypotheses that the high-performing individuals would be more willing to participate in a supererogatory task for charitable giving, compared to the low-performing experimental subjects and whether they would be more willing to contribute to the charity if the first was true. The results help to understand whether there are differences in pro-social behavior between high- and low-performing subjects and whether these differences can be influenced by the use the incentive structure. The findings of the study might be of help to the charitable organizations to structure their donation campaigns and promotional partnerships.

The study results show that monetary rewards act as a stronger stimulus for both types of participants, high- and low-performing subjects in the lab, when the payoff is considered substantial for a studied population. The participants assigned to a high type appeared to be more likely to proceed with the supererogatory task due to the recognition effect and received higher overall payoffs, but they were not more willing to contribute to charity than the low-performers. By the same token, the study found no difference in charitable behavior regarding the decisions under risk: the experimental subjects were indifferent in terms of the portion of their payoff that they donated before and after their earnings were

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revealed to them. However, as high-performing individuals were more likely to stay for the supererogatory task and earn higher payoffs, then the aggregated donation pool increased substantially.

Combining skill contests and donation options can indeed be a potentially successful approach to raising money for charities. Firstly, skill contests attract participants who are interested in showcasing their abilities, skills, or talents to win prizes or recognition. By incorporating a charitable cause into these contests, organizers can engage a broader audience that otherwise would not necessarily go out of their way and participate in charitable activities. These practices likewise prompting customers to donate at the check-out might increase the overall fundraising potential but with less social pressure. Secondly, skill contests with charitable components can effectively raise awareness about the supported causes as the list of accessible charities might vary. Finally, organizations hosting these combined initiatives can showcase their commitment to social responsibility, and the contest itself might eventually gain even broader recognition.

The direction of future research emerges from a plausible task dependence on the results that might be acknowledged as a possible limitation of the current study: as the project investigates differences in pro-social behavior based on the particular type of expertise, the logical question is whether certain types of expertise lead to varying levels of charitable donations and that subjects with different skillsets might be recognized as high-performers based on the particular types of contest questions. Therefore, while the current experiment was not designed to evaluate the altruistic inclinations of specific population groups, the results may suggest the need for further research to explore the robustness of these findings. This could involve conducting similar experiments with different types of task sequences, such as those that involve verbal, finance, or art proficiency, and student sub-populations such as STEM and non-STEM scholars. By examining how pro-social behavior varies across different types of tasks, researchers may be able to better understand the factors that influence charitable behavior and how these factors may differ across different populations.

The results would allow charitable organizations to partner up with the most suitable skill

contests and events to potentially summon higher donation amounts.

CHAPTER 3

HIRING PROSPECTS OF ONLINE EDUCATION: EVIDENCE FROM A RANDOMIZED FIELD EXPERIMENT

3.1 Introduction

As the global workforce evolves to meet the demands of the current digital age, the traditional signals of academic achievements in a form of university diplomas are being supplemented with non-conventional educational opportunities such as ones offered by Massive Open Online Course (MOOC) platforms. These online platforms have emerged as a popular way of skill enhancement, allowing learners to access and pass high-quality courses at their own pace without the necessity to attend traditional classes at higher education institutions. As a result, the MOOC platforms have begun to award the certificates upon course completion to distinguish between a mere course-taker and the one who successfully completed all the requirements. Hence, this paper undertakes an exploration into the role of online certificates as signals of individual's capacity for continuous learning and accomplishments in obtaining in-demand skills within the labor market.

MOOCs have transformed the landscape of education, offering resources on a variety of disciplines, ranging from IT and data science to engineering and natural sciences to business and management, and beyond. Typically provided by prestigious global universities and corporate entities, these courses are characterized by their cost-effectiveness in comparison to traditional classroom-based instruction (Siemens, 2013; Chuang and Ho, 2016). Despite the large degree of accessibility and the low-stake environment, merely approximately 3% of online learning participants managed to successfully complete their courses and secure verified certificates in 2017-2018 (Reich and Ruipérez-Valiente, 2019). Consequently, those who eventually complete the courses or micro-degrees are even more likely

to be endowed with substantial motivation and pose the question whether their newly acquired skills are valued in labor markets, especially, in a rapidly developing fields of data science and artificial intelligence (Webb, 2019; Frank et al., 2019).

According to a Coursera survey, 86% of U.S. employers agree that earning an industry micro-credential strengthens a candidate's job application, while 74% believe that this credential improves a candidate's ability to perform in an entry-level position. Employers are on average 72% more likely to hire a candidate who has earned a professional certificate, and 88% of employers agree or strongly agree that a professional certificate strengthens a candidate's application (Coursera, 2023). Therefore, the present study focuses on the use of online certification as a major ability signal in the hiring process, utilizing a more objective research methodology of correspondence study. The certification is expected to play a substantial role in the hiring decision of potential employers as a proof of skill acquisition. The effect of the certification is twofold, showing that a potential worker has substantial ability and motivation to go beyond a traditional education path and that their skills were actually enhanced through the certification endeavor as approved by the official educational platform.

Additionally, the demand for professionals skilled in data analytics, machine learning, and artificial intelligence increased in recent years, and the resulting pressure on this specific labor pool placed a premium on analytics talent (Ransbotham et al., 2015; Sinclair, 2020). However, the supply of individuals seeking employment in this domain has not kept pace with the high wages offered in this field. The companies face the huge hurdle of finding the right talents due to the mismatch between the skills required by the evolving labor market and the skills offered through classic degree studies (McKinsey&Company, 2016; PWC, 2020). In their turn, in order to enhance the employability, many job seekers face a dilemma of returning to academia in pursuit of relevant degrees, that many times are falling behind in providing contemporary proficiencies, or remaining at the less technically sophisticated positions (BurningGlass, 2017). This is precisely when the option of online

learning becomes significantly important.

The project draws upon labor market discrimination literature and speaks to the growing interest in data science online education. First of all, the proposed randomized field experiment collects data on the attitudes of United States employers towards online certificates in data science. Furthermore, the amassed dataset allows to investigate whether the investments made with respect to these certificates lead to the desired labor market outcomes for the participants. Finally, the present study acknowledges the challenges and structural changes in online versus offline educational practices due to COVID-19. While online education thrived during the pandemic, it is still unclear whether possessing a relevant certification indeed is a credible evidence of certain level of proficiency for the potential employers as opposed to the in-person credentials.

Overall, the study outcomes address questions that are shared concerns for both the academic community and the broader community of data science job seekers and suppliers. The implications of the study's findings are of interest to job candidates as well as online learning platforms to assess the potential benefits associated with certificates earned online by collecting callback rates directed at fictitious resumes.

The next two sections are devoted to the theoretical framework and details of the experimental design. The following section describes the practical procedures incorporated into the current correspondence study, then the empirical results are discussed and interpreted for the whole dataset and sub-samples. The last section concludes the paper with a discussion of the findings and future research perspectives.

3.2   Theoretical framework

3.2.1   Hiring discrimination

It is important to acknowledge the scholarly discourse centered around hiring discrimination. The seminal work of Bertrand and Mullainathan (2004) inspired scholars across diverse disciplines to adopt the methodology of correspondence study. This approach in-

volves identifying employer perceptions of applicant characteristics to test for discrimination practices by comparing callback rates. The study implementation involves the submission of matched pairs of identical fictitious job applications, while deliberately introducing variations in specific predetermined attributes, to employers advertising various job opportunities (Rooth, 2014; Avivi et al., 2021).

This body of research includes studies by Neumark (2012); Chen (2020); Azmat and Petrongolo (2014); Booth and Leigh (2010); Nunley et al. (2016); Albert et al. (2011); Gaddis (2015), to name a few. A predominant portion of these scholarly inquiries is centered on various types of discrimination, the most common being racial discrimination (Baert, 2018). For instance, Dias (2020) examines instances of skin color discrimination within the Brazilian labor market. The author distributes fictitious resumes featuring photographs of entry-level job candidates, manipulating their skin color, gender, and socioeconomic class. The findings reveal strong evidence of a labor market discrimination against candidates with darker skin tones, particularly among female applicants, which disappears with an increase in socioeconomic status. Similarly, about a decade prior, Kaas and Manger (2012) conducted a parallel exploration of ethnic discrimination within the German labor market, getting similar results. Furthermore, while Agan and Starr (2018) and Cerda-Jara et al. (2020) primarily focus on examining the adverse effects associated with the disclosure of criminal records, Kroft et al. (2013), Eriksson and Rooth (2014) as well as Farber et al. (2016) employ the same methodology of correspondence experiments to investigate statistical discrimination against individuals with extended periods of unemployment.

Another branch of correspondence studies' literature investigate the impact of gender-based stereotypes on hiring outcomes. Chan and Wang (2018) identify a positive hiring bias in favor of female workers in female-dominated fields while none of those in male-dominated fields occupations. Adamovic and Leibbrandt (2023) also study hiring discrimination practices in male- and female-dominated fields. They find that males receive one and a half times more callbacks than women in male-dominated occupations and almost

one and a half times less in female-dominated ones. At the same time, there is a body of literature that explores hiring process in the IT and STEM-related occupations, using correspondence studies and quasi-experimental design, and proves a positive bias towards women for this type of vacancies to be present in this specific labor market (Piopiunik et al., 2020; Birkelund et al., 2022).

Finally, Blommaert et al. (2013); Gee (2019); Acquisti and Fong (2020); Kuhn (2014) expand upon this body of literature by utilizing fictitious profiles on online professional networking platforms to study the effectiveness of online methods of worker recruitment and job search. Acquisti and Fong (2020), in particular, examines the disparities in hiring practices based on religion and sexual orientation within the United States. The researchers generate job candidate profiles on major professional platforms and validate the fact that employers actively seek candidate information online. Their findings reveal that the online disclosure of specific personal characteristics has a comparable impact on hiring decisions as observed in the traditional offline context with various magnitude across employers.

Hence, being at the intersection of additional certifications in STEM careers and gender discrimination practices, this present paper fills in a very specific gap in the existing literature. It aspires to identify whether those certificates serve as a credible evidence of skill acquisition for potential employers and if there is a differential impact between genders.

3.2.2 Skill acquisition

Skill acquisition is a part of a broader field of human capital accumulation, skill development and labor market dynamics (Card and DiNardo, 2002; Cunha and Heckman, 2007; Becker, 2009; Méndez and Sepúlveda, 2012). According to Heckman (2006), skill acquisition is a dynamic and lifelong process on the crossroads of genetics, family, and social environments. The key idea in the skill acquisition literature is that skills are not innate so investments in education and training contribute are crucial for an individual's human capital, affecting their prospective labor market outcomes.

Skill acquisition usually happens through formal schooling and specific training. While the former is mostly associated with the acquisition of general purpose skills in colleges, and universities, the latter refers to acquiring specific skills for particular jobs and occupations either through in-person experience or online classes. In both scenarios, skill acquisition provides a signal of the workers unobserved ability, and having the relevant type of training increases workers chances of being a suitable candidate. In their turn, employers are making hiring decision based on observed education credentials, assuming that they are positively correlated with having greater ability. Therefore, acquisition of professional skills should follow hiring success closely.

The present study considers the major evidence of worker skill acquisition to be an online certification in a specific field that is different from the university degree obtained by the prospective employee. Therefore, a certification works in two directions: ensuring that a potential worker indeed is endowed with substantial ability and motivation to go beyond a traditional education path and that their skills were actually enhanced through the certification endeavor as approved by the official educational platform. Hence, the certification is expected to play a substantial role in the hiring decision of potential employers. However, being a correspondence study, the current research project addresses only the very first step of the hiring process such as an invitation to the interview or another next step of the selection procedure, measuring the differences between job applicants by the likelihood of a positive response. The details of the correspondence study design are discussed in the next section of this paper.

3.2.3 Online certification

The present paper evaluates the employment premium associated with online certificates in the field of data science. The research project is motivated by the growing demand for data science competencies across diverse industries, but supply is still trailing behind demand (LinkedIn, 2019a). Therefore, in addition to allowing for a better assessment of online

courses, our study contributes to the broader understanding of the market for data science skills. Given the rapid expansion of this market and the evolving nature of career pathways within the field, prospective learners are still uncertain about the most advantageous educational investments.

One major concern associated with online education pertains to its perceived lack of signaling power when compared to traditional education. The current research attempts to address that by offering insights into whether such concerns have a substantial basis. According to the surveying poll by Gallagher (2018), over 60% of HR leaders in the United States hold the belief that online learning generally matches the quality of traditional face-to-face instruction, and the institution's reputation matters the most for both instruction modes in regard to degree programs. Therefore, this paper puts this attitudinal perspective measure to an ultimate test using randomized field experiment.

The research objective is to elicit actual preferences of prospective employers towards online certification in the context of real-world hiring processes. Although, according to prior research, the certificates are already expected to have less impact than full degrees (Jepsen et al., 2014), this paper specifically estimates whether investments in online certificates enhance labor market outcomes for job applicants. This approach bridges the gap between perception and practice, providing valuable insights into the tangible impact of online credentials on employability.

3.3 Study methodology and research hypotheses

3.3.1 Correspondence study design

The present study quantifies the employment premium associated with online certificates using resumes as experimental instruments. Figure 3.1 illustrates a four-group experimental design to evaluate variations in employer responses regarding both gender and the inclusion or omission of an online learning certificate on job applicants' resumes. This way, the study examines not only the overall employment premium but also the potential interaction

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Female With certificate	Female Without certificate
Male With certificate	Male Without certificate

Figure 3.1: The experimental 2×2 design.

effects between gender and the certificate's inclusion.

The assessment of the value-added of an extra data science training is facilitated through the conferral of online certificates in data science. This approach is motivated by several considerations. Firstly, to have a competitive advantage in data analytics, collaborate with professionals from various fields, and enhance earning potential, one needs to have significant training in handling big data, machine learning, and data visualization, a proficiency typically imparted within undergraduate Computer Science and Mathematics programs, but not commonly found in other quantitative fields. Secondly, a standalone course in a completely new field is not enough to obtain sufficient expertise. To address this limitation, the design utilizes the Data Science Specialization on the Coursera platform, which consists of several courses culminating in a final capstone project. The successful completion of this comprehensive specialization program serves as an indicator of the applicant's competencies and proficiencies, thereby enhancing their appeal to prospective employers. Finally, a STEM-related specialization provides an avenue to investigate potential gender disparities in employer responses.

Therefore, the current 2×2 experimental design ensures that the treatment and control resumes possess comparable characteristics to mitigate self-selection bias. Hence, the treatment effect can be calculated as the difference in callback rates between these groups,

followed by the regression adjustments for controls. To cover all possible instances and provide sufficient statistical power, the desired sample size is determined based on response rate data obtained from a pilot study and evidence from previous research studies (Bertrand and Mullainathan, 2004; Gaulke et al., 2019; Piopiunik et al., 2020), power calculations following Cohen (1988), and possible bootstrapping of standard errors, originating from the regression analysis.

3.3.2   Study hypotheses

Within the framework of the experimental study, the query for job vacancies from the primary recruitment websites operating in the United States include the ones that satisfy the level of proficiency demonstrated by the created applicants. The data collection process involves soliciting responses through both telephone communication (i.e., voice mail and text messages) and email correspondence. This is done by the researcher receiving the callbacks using the phone numbers and email addresses provided in their resumes for the purpose of scheduling interviews or requesting additional documents by potential employers. Successful callbacks are defined as instances where the applicant receives an offer for a job interview, or a personalized and affirmative contact from a potential employer. Moreover, these callbacks are later conditioned on the employer characteristics such as remote or in-person modality of the job vacancy, their status as an equal opportunity employer and geographic location (Kline and Walters, 2019).

Formally, the current research is testing the two following hypotheses based on prior literature:

- If online data science certificates are perceived as evidence of applicant's competency, then they should have a positive impact on the response rate from potential employers for those with the certificates (Spence, 1973);

- Based on prior literature and aspirations to mitigate well-documented gender disparities in STEM careers, prospective employers should favor female applicants with

training in data science when compared to their male counterparts, holding other qualifications constant (Piopiunik et al., 2020; Birkelund et al., 2022).

Consequently, the anticipated results encompass heightened response rates among fictitious candidates who possess an additional online data science specialization certificate, in contrast to those lacking such certification. Additionally, it is expected that, while controlling for other candidate and potential employer attributes, female applicants will exhibit a higher likelihood of garnering responses when compared to their male counterparts.

3.4   Study implementation

The randomized field experiment was initiated as a job application process using fictitious resumes, e-mail addresses, and phone numbers from February — September 2023. The construction of the resume for the fictitious candidates was designed to align with the pre-requisites typically specified for entry-level positions in Data Analytics. A sample fictitious resume is presented in Appendix B. The targeted job postings commonly seek candidates holding at least a Bachelor's degree in quantitative disciplines. To ensure a controlled experimental setting with minimal variations between the treatment and control groups, all of the fictitious job applicants were to hold a Bachelor of Science degree in Economics from a large state public university. This choice is influenced by Deming et al. (2016) findings, which suggest that U.S. employers show a higher propensity to contact job applicants with academic credentials obtained from local public educational institutions. Therefore, within each group of four applicants, the fictitious resumes present identical formal educational qualifications, professional experiences, racial backgrounds, and citizenship status (as inferred from the assigned names), among other factors. The key distinguishing features between the two pairs of applicants in each group are their gender and the inclusion of an additional Coursera Certificate in Data Science from the Johns Hopkins University.

The fictitious resumes used for job applications utilized most popular first and last names in the US for someone born 20-25 years ago (SSA, 2020) and did not explicitly

reveal any extra information about the constructed applicant such as race, disability status, and other potentially sensitive topics during the application process. The job search targeted entry-level "Data Analyst" positions as a main search query on the primary online job boards in the United States. However, other queries such as 'Business Analyst", "Data Scientist", "Data Consultant", "Data Manager", "Finance Analyst" were also utilized as the presumed job responsibilities often overlapped for listed career options. The resume submission options included applications via e-mail, on the company website, or using online job boards directly. Most importantly, all information concerning the application process was collected and documented, including a job title, vacancy description and job posting URL, company's name and location, work contract modality and type of the contract as well as the company EOE (equal opportunity employer) status. The researchers were also responsible for tracking of employer's phone communications and e-mail callbacks. In case of a positive callback (i.e., request for additional information or invitation to an in-person or online interview), they reached out to the HRs and politely declined an offer per the IRB request, informing the employer that the applicant had just accepted another job offer.

Upon conducting the pilot study, scaling up an experiment relied on power calculations to detect a sample size given an expected effect size – the minimal difference between groups' characteristics of interest given the specified level of significance (Cohen, 1988). The present study required over 800 job applications, given the target significance level of 10%. The power calculations were based on the notion of the callback variable's binary nature and the effect size findings from prior literature such as Cerda-Jara et al. (2020); Acquisti and Fong (2020), and other more distant studies.

The research assistants serving as an applicants in this study were asked to apply for jobs and add all relevant information to the final *.CSV* document. The application was done using the following randomization mechanism: firstly, the participants search for a job posting and use the pre-programmed checker to ensure that nobody else applied for the same company before; secondly, they are randomly assigned with one out of four predeter-

mined resumes to apply for a chosen position; lastly, they fill in the information about the job posting and company selected.

The research project was heavily affected by the COVID-19 pandemic that had a significant impact on the labor market in the United States. Initially, the pandemic led to widespread job losses as many businesses were required to close or reduce their operations with uneven effect across industries and demographics. As such, women, minorities, and lower-income workers were disproportionately affected by job losses and economic hardships. Hence, during the pilot study in Spring — Summer 2020, there was more than a 50% reduction of data science jobs both in the state of Georgia and nationwide (LinkedIn, 2020; Glassdoor, 2020). Given the rapid decline in job postings the complete study was postponed until the labor market recovered from the natural shock.

Furthermore, as a result of the pandemic, many companies re-evaluated their remote work policies, with some adopting more flexible arrangements permanently even after COVID-19 has been determined to be over after the federal PHE declaration from May 11, 2023 (CDC, 2023). Thus, this structural change has the potential to reshape the geography of work and workforce dynamics forever. Finally, the pandemic highlighted the importance of digital skills and the need for adaptation to changing job requirements, especially the ones affected by automation and digitalization. Therefore, the current study is still useful to evaluate specific type of online certification for cutting edge data science techniques and professions.

3.5 Empirical results

3.5.1 Descriptive statistics

Overall, there are 25 positive callbacks out of a cleaned sample that consists of 849 submitted applications resulting in an overall response rate of 2.94%. The average response time is seven to ten days regardless of the outcomes which indicates a relatively quick advancement to the next round of application process. The callback rate is on the lower end but
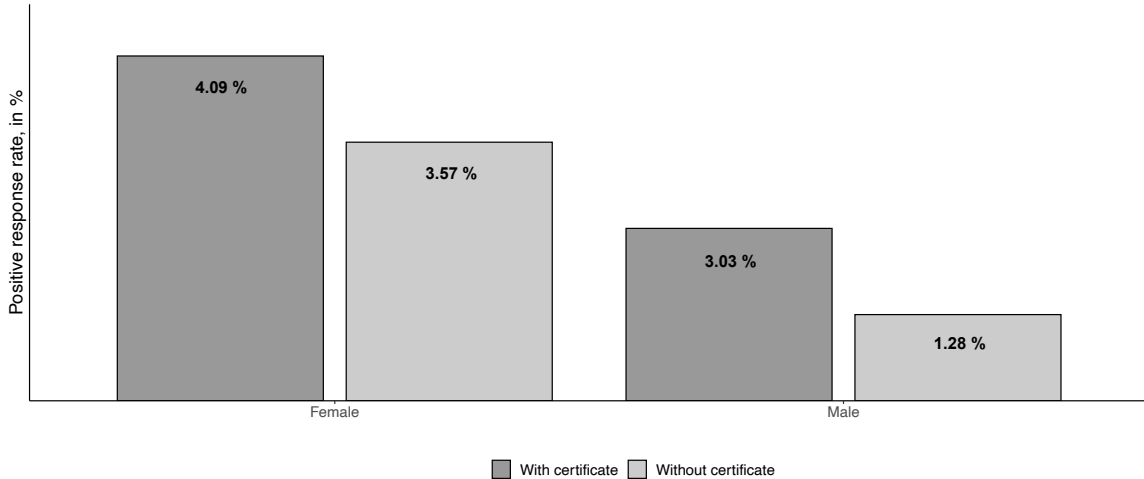
Figure 3.2: Positive response rates by certification and gender.

similar to previous research by Cahuc et al. (2019), which found a response rate of 3.3% and 4.5% in the private and public sector, respectively. The results also align with the 2.5% positive response rate in the pilot study undertaken in Spring 2020 at the very beginning of the COVID-19 pandemic.

The response rates in the final sample are 3.59% for the certification holders and 2.32% for others, 3.85% and 2.08% for female and male applicants, respectively. Both results generally align with the previously stated hypotheses and presented in Figure 3.2. Although, there is no significant differences between the sub-group callback rates: according to Student's t-tests, calculated p-values are equal to 0.277 and 0.130 for the sub-groups by certification status and gender, respectively. More precisely, nine out of 220 positive responses (4.09%) were attributed to a female candidate with a data science certificate and the other six out of 198 (3.03%) for a certified male candidate, respectively; while seven out of 296 positive responses (3.57%) were attributed to a female candidate without a data science certificate and the other three out of 235 (1.28%) for a non-certified male candidate, respectively.

The complete set of collected characteristics of the job postings is presented in Table 3.1, including the search query, type of work contract, and equity opportunity status of the potential employer. All vacancies are identified using four main US online job boards and

Table 3.1: Descriptive statistics

	With certificate		Without certificate		Overall
	Female	Male	Female	Male	
Percent of callbacks	4.09%	3.03%	3.57%	1.28%	2.94%
Percent of "Data Analyst" vacancies	51.36%	58.59%	67.34%	58.29%	58.66%
Percent of remote work contracts	33.18%	33.33%	38.27%	36.17%	35.21%
Percent of full-time work contracts	78.63%	81.82%	80.10%	76.17%	79.03%
Percent of EOE employers	65.00%	54.04%	62.76%	65.53%	62.07%
Callbacks	0.041	0.030	0.0357	0.013	0.029
	(0.199)	(0.172)	(0.186)	(0.113)	(0.169)
"Data Analyst" vacancies	0.514	0.586	0.673	0.583	0.587
	(0.501)	(0.494)	(0.487)	(0.494)	(0.493)
Remote work contracts	0.332	0.333	0.383	0.362	0.352
	(0.472)	(0.473)	(0.480)	(0.482)	(0.478)
Full-time work contracts	0.786	0.818	0.8010	0.762	0.790
	(0.481)	(0.387)	(0.485)	(0.485)	(0.407)
EOE employers	0.650	0.540	0.628	0.655	0.621
	(0.478)	(0.499)	(0.485)	(0.476)	(0.485)
Callback count	9	6	7	3	25
"Data Analyst" vacancies' count	113	116	132	137	498
Remote work contracts' count	73	66	75	85	299
Full-time work contracts' count	173	162	157	179	671
EOE employers' count	143	107	123	154	527
Observations	220	198	196	235	849

Notes: All application characteristics are listed as percentages, means and standard deviations, and counts: callbacks — positive responses from potential employers in a form of voice mail, text message, or email; "Data Analyst" vacancies — exact search query used at the online job board, with alternatives being "Business Analyst", "Data Scientist", "Data Consultant", "Data Manager", "Finance Analyst", and "Other"; remote work — work modality as opposed to in-person; full-time work — work modality as opposed to an internship, part-time work, and other; EOE — equal opportunity employer.

are located within the United States for both remote and in-person work modalities, with student's t-tests showing no significant differences between the baseline characteristics of job vacancies.

3.5.2 Regression results

The regression analysis examine whether there are differences in response rates for four types of fictitious job applicants, controlling for various factors such as the type of work contract, search query, and location fixed effects. Specifically, the estimation was done utilizing the following regression specification:

$$Callback_i = \beta_0 + \delta_1 Certificate + \delta_2 Female_i + \delta_3 Certificate_i * Female_i +$$
$$+ \beta_1' \sum Contract_i + \beta_2 Position_i + \beta_3 EOE_i + \beta_4 Remote_i + \varepsilon_i$$

where the dependent variable $Callback_i$ represents a presence of a positive response from potential employers in a form of voice mail, text message, or email; $Certificate_i$ is a dummy variable coded 1 if an applicant possess a data science certification and 0 otherwise; $Female_i$ is a dummy variable coded 1 if an applicant is a female and 0 if they are a male; $Certificate_i * Female_i$ is an interaction term between certification status and gender of a fictitious applicant; $Contract_i$ is a vector of work modality being full-time, part-time, internship, temporary contract, and other; $Position_i$ is coded as a dummy variable that is equal to 1 when the exact search query used at the online job board was "Data Analyst", and 0 if alternatives like "Business Analyst", "Data Scientist", "Data Consultant", "Data Manager", "Finance Analyst", and "Other" were used; EOE_i is a dummy variable indicating an equal opportunity employer; $Remote_i$ accounts for a work modality being remote (coded as 1) as opposed to in-person (coded 0) in Model 1, which is interchangeable with γ_i for the state fixed effects that refers to the precise company location (i.e., state); finally, ε_i is an individual error term. The main coefficients of interest for the whole sample are δ_1, δ_2 and δ_3, which represent whether there is a differential response according to the certification status and gender of the job applicant.

Table 3.2 summarizes the main regression results for the entire sample and two sub-samples of remote and in-person contracts. Column 1 exactly follows the regression model

Table 3.2: Regression analysis: full sample and sub-samples by work modality.

	Full sample		Remote	In-person
Constant	1.281	0.991	4.610	-5.648*
	(1.363)	(2.054)	(2.384)	(2.777)
With certificate	-1.182	1.570	0.377	2.304
	(2.460)	(1.435)	(2.543)	(1.690)
Female	2.187	2.224	-0.932	4.128*
	(1.535)	(1.470)	(2.013)	(1.976)
With certificate*female	-0.892	-1.499	0.813	-2.930
	(2.429)	(2.448)	(3.374)	(3.292)
Work contract: part-time	-3.502**	-3.218**	-3.234*	-2.229
	(0.995)	(1.020)	(1.336)	(1.769)
Work contract: internship	-2.408**	-1.989	-3.967*	-1.038
	(0.810)	(1.296)	(1.789)	(1.501)
Work contract: temporary	-2.592*	-2.741*	-2.234	-3.830**
	(1.226)	(1.280)	(1.786)	(1.480)
Work contract: other	6.230	5.206		0.951
	(9.725)	(10.883)		(2.512)
"Data Analyst" vacancy	0.884	1.003	1.069	2.146
	(1.351)	(1.360)	(2.169)	(1.711)
EOE employer	0.176	0.462	-0.853	1.207
	(1.206)	(1.322)	(1.686)	(1.845)
Remote work contract	-0.132			
	(1.337)			
Location	No	Yes	No	Yes
No. observations	849	849	299	550

Notes: $^{'}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Coefficients are converted to percentage points. Robust standard errors in parentheses.

form represented earlier. The model does not capture any significant differences between job seekers with and without an online certificate in data science, as well as between genders. The estimated gap in response rates between a full-time and other types of work contracts varies between -2.41 to -2.59 to -3.50 percentage points for internship, tempo-

rary contract and part-time job, respectively. Column 2 represents a model specification that replaces a $Remote_i$ dummy variable with location fixed effects. The regression results appear very similar to the previous model, with an exception of the difference between the positive response rates for a full-time position versus an internship not being statistically significant.

The regression models in Column 3 and 4 refer to the sub-samples, that divide the whole dataset on the basis of work modality: remote and in-person. The more in detail analysis is motivated by the substantial increase in full workdays from home after the pandemic and an overall acceptance of this work modality as a norm (Barrero et al., 2021). The regression in Column 3 examines the differential response rate between certified and non-certified, and male and female job seekers for remote vacancies. The findings follow the same pattern as for the whole sample: the coefficient estimates of the gender, certification status and their interaction term prove to be statistically insignificant, while the work modality does affect the callback rate. Lastly, the regression in Column 4 runs on the sub-sample of in-person vacancies and includes location fixed effects on top of other regular conditioning variables. This model yields a 4.13 percentage points gap between male and female job applicants, with a fictitious resume assigned with a female name being more likely to receive a positive response from a prospective employer in a form of a voice mail, a text message, or an email. This findings regarding initial hiring practices for IT skills in conventional in-person work arrangements might be a result of many companies actively seeking to enhance diversity and inclusion in the workplace (NSF, 2023). Such as, according to LinkedIn (2019b), women are 16% less likely to apply to a job after viewing it but 16% more likely than men to get hired after applying. Furthermore, the aspiration to reduce historical gender bias against women in the hiring process, especially in STEM fields, is consistent with evidence from prior review studies (Asanov and Mavlikeeva, 2023; Birkelund et al., 2022; Chavez et al., 2022).

Table 3.3: Regression analysis: sub-samples by certification status and gender.

	With certificate	Without certificate	Female	Male
Constant	4.217	-0.398	1.860	3.263
	(2.701)	(1.251)	(2.160)	(1.802)
With certificate			0.806	1.234
			(1.955)	(1.306)
Female	1.038	2.102		
	(1.855)	(1.553)		
Work contract: part-time	-3.774*	-3.323**	-3.696*	-2.852
	(1.732)	(1.275)	(1.430)	(1.552)
Work contract: internship	-3.725*	-1.309	-3.895*	-1.708*
	(1.451)	(0.890)	(1.570)	(0.855)
Work contract: temporary	-2.262	-2.994	-3.516*	-1.436
	(2.027)	(1.572)	(1.548)	(1.867)
Work contract: other	6.781	-3.408*	-4.107*	32.271
	(10.909)	(1.452)	(1.749)	(26.396)
"Data Analyst" vacancy	-0.193	2.186	2.292	-1.326
	(2.214)	(1.484)	(2.079)	(1.664)
EOE employer	-1.171	1.620	2.523	-2.546
	(1.919)	(1.414)	(1.799)	(1.607)
Remote work contract	-0.161	-0.053	-1.846	1.909
	(2.008)	(1.788)	(2.097)	(1.675)
No. observations	418	431	416	433

Notes: $'p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Coefficients are converted to percentage points. Robust standard errors in parentheses.

The overall sample can also be divided into certified versus non-certified applicants and male versus female job seekers. The regression model specifications are presented below:

$$Callback_i = \beta_0 + \delta Female_i + \beta_1' \sum Contract_i + \beta_2 Position_i + \beta_3 EOE_i + \beta_4 Remote_i + \varepsilon_i$$

$$Callback_i = \beta_0 + \delta Certificate + \beta_1' \sum Contract_i + \beta_2 Position_i + \beta_3 EOE_i + \beta_4 Remote_i + \varepsilon_i$$

where the former one is used to estimate gender effects within two separate sub-samples of

Table 3.4: Regression analysis: sub-samples by type of work contract.

	Full-time		Other	
Constant	0.619	0.053	1.934	2.466
	(1.957)	(2.382)	(2.212)	(2.613)
With certificate	0.837	0.800	5.379*	5.530*
	(1.987)	(2.053)	(2.254)	(2.425)
Female	2.674	2.868	-0.191	-0.556
	(1.998)	(2.066)	(2.221)	(2.350)
With certificate*female	0.038	-0.487	-5.358	-5.539
	(2.835)	(2.921)	(3.203)	(3.412)
"Data Analyst" vacancy	1.123	1.087	-0.315	-1.267
	(1.450)	(1.556)	(1.818)	(2.024)
EOE employer	0.755	1.303	-2.489	-2.756
	(1.495)	(1.612)	(1.603)	(1.733)
Remote work contract	-0.277		-0.491	
	(1.588)		(1.819)	
Location	No	Yes	No	Yes
No. observations	671	671	178	178

Notes: $'p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Coefficients are converted to percentage points. Robust standard errors in parentheses.

job seekers with and without data science certification and the latter evaluates the response differences, attributed to the certification, by gender. The regression results for these model specifications are presented in Table 3.3, confirming the patterns of the descriptive statistics and econometric model for the whole sample, with estimates only being statistically significant for work contract types but not for gender or certification subgroups. Specifically, the regressions from Columns 1 and 2 look into sub-samples of certified and non-certified workers to identify subtle differences in treatment by gender but do not find evidence of those. Similarly, the models shown in Columns 3 and 4 sub-divide the entire sample into female and male applicants to capture any differences by certification status, and again do not support this hypothesis, following the findings for the entire sample.

Finally, Table 3.4 exploits the presumed differences between sub-samples of full-time and other types of vacancies, comprising part-time occupations, internships and temporary contracts, using the first regression specification. Therefore, the job posting were classified into two categories and the initial dataset was split along this dimension. The findings from the regression for other than full-time contracts suggest a positive and significant relationship between a job seeker possessing an online data science certificate and receiving more callbacks from potential employers. In other words, certified applicants are about 5.5 percentage points more likely to be approached to participate in the next round of the application process than those without such a certificate, among companies offering nonstandard work arrangements, which is consisted while controlling for either remote contracts or location fixed effects. Nonstandard workers include temporary, part-time and contract employees, app-based, on-demand, freelancer, and gig workers, or those whose work facilitated by a digital online platform (GAO, 2015). The main distinctive feature of this type of working arrangements is that workers in nonstandard arrangements typically do not anticipate job permanence, regardless of their performance (Stone, 2004; Etzioni, 2018). Therefore, one possible interpretation for a favorable view of additional certification are the higher level of flexibility in terms of required training exhibited by nonstandard occupations and the focus on specific skills and knowledge relevance as the working arrangements themselves are less conventional. The results from the alternative logit and probit models are presented the Appendix B and confirm the main findings.

3.6 Conclusions and discussion

The current research undertakes an assessment of the potential employment advantages associated with online data science specialization certificates in the United States through a correspondence study. The project involves the collection of callbacks from potential employers for fictitious job applications that either include or omit online specialization certificates and are attributed to male or female job seeker. The main findings mostly align

with the anticipated outcomes as suggested by existing literature and commonly acknowledged practices within labor market. The obtained results show evidence of a positive relationship between response rate and being a certified professional in the field of data science for certain groups. Specifically, the online certificate might be a reasonable investment for those in nonstandard working arrangements as well as for females in regard to vacancies requiring in-person working conditions.

The study builds on prior studies on hiring practices and is hence subjected to the common limitations, the most concerning one being lack of generalizability. Firstly, the controlled nature of randomized field experiments might not fully capture the geographical differences and the complexity of hiring decisions in a real-world situations. Secondly, this experimental design does not provide potential employers with the rich contextual information that real job applicants would offer. That is the reason why the present paper focuses on the callback experience only as an invitation to the next round of application process but not as a certain job offer. Finally, this type of studies typically do not provide insights into long-term employment outcomes, such as final hiring decisions, job retention, career advancement, or job satisfaction. Thus, the present research project also aims at accessing only the initial rates of companies' positive responses to the constructed resumes without making any projections about the further hiring decisions.

Overall, this paper contributes to the broader academic discourse on the impact of online education and certification on employment outcomes, with a specific emphasis on the expanding domain of data science and analytics. The research findings bear significance for individuals seeking to improve their employability through online educational options, as the results demonstrate improvements in the likelihood of positive responses from potential employers for certain groups. This is particularly relevant for individuals looking for short-term or part-time contractual working agreements, which are common in the information technology and consulting fields in a form of freelancing. Furthermore, the research results hold relevance for online learning platforms, providing insights into the understanding and

communication of the value added by these certificates. As the demand for data scientists continues to rise, individuals with the necessary skills and certifications have a competitive edge in the job market for certain positions. In their turn, online learning platforms should emphasize the value of their certifications in improving employability and career prospects or even work with potential employers to validate the relevance and value of their certifications.

The possible avenues to extend this research project include incorporating more versatile approach to evaluate the role of online education and certification in the labor market. For instance, the relevant concern would be whether the certification itself has a signaling power or particular skills learnt in those classes (i.e., actual skill acquisition) matter more. To disentangle the effect of an official document from the educational credits received, one might add another level of complexity to the current design by allowing the fictitious candidates to vary in a number of classes completed out of the ten offered in a data science specialization. Hence, the final structure of the certification variable would be closer to the continuous one and allow to see subtle changes in employer behavior. All in all, this potential extension would require a substantial enlargement of the sample size needed to pick up differences between callback rates of the fictitious applicants and funding opportunities to disseminate a much larger number of resumes successfully.

CHAPTER 4

TRADE-OFFS BETWEEN EDUCATIONAL ATTAINMENT AND MARITAL DECISIONS IN DEVELOPING COUNTRIES

4.1 Introduction

Arranged marriages and self-selected, or love, marriages represent contrasting approaches to the institution of marriage with distinct characteristics and embedded within cultural contexts, including the significance of family consent and approval. Historically, arranged marriages at a younger age were a prevalent tradition across many cultures, where matrimonial alliances were agreed upon by families, with the parents of the prospective bride and groom making the decision and negotiating the terms of the union. While this practice still persists in numerous developing countries, driven by cultural, social, and economic factors, although recent research has shown a steady decline in the Middle East, East and Southeast Asia, and Africa (Jones, 2010; Ghimire et al., 2006; Vogl, 2012). This shift is generally attributed to factors such as a higher level of societal industrialization, greater investment in human capital and changes in the household composition, specifically the shift away from the extended families residing in close proximity toward nuclear family arrangements (Rubio, 2013, 2014).

An arranged marriage can be understood as a comprehensive package comprising a spouse, a specific geographic location, and potentially limited options in terms of occupations (Rubio, 2017). On one hand, arranged marriages involve families or intermediaries who propose potential partners based on various factors, including social standing and economic compatibility. As family consent and approval play a crucial role, parents often exert significant influence over the decision-making process. In this case, factors like wealth, education, and family background can all contribute to assessing the suitability of a potential

spouse and improving the social and economic status of the families through strategic alliances. Consequently, these marriages are perceived as a form of insurance for parents and their children against economic shocks, establishing an informal risk-sharing arrangement between extended households (Anukriti and Dasgupta, 2017).

On the other hand, arranged marriages can impose limitations on the mobility and relocation flexibility of the child, compared to self-selected marriages. For the latter, individuals select their life partner based on shared values, common interests, and emotional compatibility and, therefore, might pertain more flexibility in terms of labor migration. In contrast, arranged marriages often occur earlier in life and within close networks, which can restrict the geographic and social mobility of individuals involved (Akresh et al., 2018; Green and Canny, 2003; Sarkar, 2021). This restriction can potentially impact the expected income of the child and the quality of their prospective spouse, as they are less likely to relocate far away from their parents or their spouse's parents for the better employment opportunities.

This study aims to examine the following hypothesis both theoretically and empirically: acquiring a higher level of education is positively related to an increased likelihood of opting for self-selected spouses or even abstaining from the marriage market altogether. Previous research findings support this line of reasoning, with studies by Boulier and Rosenzweig (1984), Singh and Samara (1996) and Adams and Andrew (2019) indicating that women with higher educational attainment tend to marry at a later stage in life. This delay can be attributed to their increased bargaining power in looking for better quality partners through assortative mating and decreased relative financial benefits and insurance protection provided by institutionalized marriages. In their turn, Chiappori et al. (2009) and Asadullah and Wahhaj (2019) demonstrate that investment in schooling generates both the labor-market return in the form of increased wages and potential marital benefits, challenging the traditional division of domestic labor in a marriage.

Methodologically, the study builds upon Rubio's (2017) two-stage partial equilibrium

model that compares love and arranged marriages by allowing for the possibility that a child may choose to remain single. This trend is increasingly common in Western countries and is now being observed in regions where arranged marriages at a young age still exist. For instance, in the most economically developed areas in China, lower marriage rates are being documented as young individuals, especially highly educated women, opt to delay or even forgo marriage (Li, 2016). This trend is also becoming visible in various countries in Central Asia, despite the persistence of traditional practices such as child marriages in the region (CAI, 2016).

The present research specifically focuses on the early marriages and possibility of remaining single and employs an empirical regression model using data from the Chinese Household Income Project (CHIP) to compare the marital outcomes in rural and urban areas. As one primary reason for the prevalence of underage arranged marriages is the lack of education and future social roles of girls being restricted to traditional ones focused solely on housework and child-rearing, divergent living conditions are likely to contribute to the household marital decision-making process. Overall, underage marriages disproportionately affect female minors in developing countries, with 1 in 4 young women alive today married during their childhood (UNICEF, 2014). This perpetuates a cycle of social isolation, particularly due to poverty, geographical isolation, increased risk of domestic violence, and restricted access to healthcare.

The findings of this research have clear policy implications. The study highlights the significance of guaranteeing universal access to education as a crucial approach to tackle the problem of arranged marriages, particularly in the context of forced child marriages. By providing access to schooling, individuals are more likely to make autonomous decisions regarding their personal lives, including marital choices. Educational institutions provide opportunities to improve economic prospects, inform about legal rights and support services and allow to interact with diverse peer groups that might influence one's outlook on relationships and marriage. Therefore, developing countries should prioritize the goal of

achieving universal access to schooling and allocate increased investments in educational initiatives. Such efforts will contribute to fostering greater freedom and agency in personal life choices, thereby mitigating the prevalence of forced marriages and promoting individual empowerment.

4.2 Theoretical framework

The paper introduces a non-cooperative static two-period game, building upon the framework introduced by Rubio (2017), which involves parents (acting as a unified entity) and a child. The author theoretically explores the household choice of arranged versus self-selected, or love, marriages for the younger generation: an arrange marriage signifies an informal risk-sharing contract with another household while restricting geographic and social mobility; in contrast, a love marriage allows a child to choose a partner with higher labor market return and potentially increase their mobility and their own income prospects in the future.

The present paper extends the model described and incorporates an additional choice for the child at the beginning of the second period, allowing them to remain single, in addition to choosing between an arranged marriage and selecting a partner based on personal affection. Additionally, the Appendix C includes further model extensions: a three-period game incorporating an option of divorce at the later stage and a two-period framework including sibling interdependence.

The two-period model is constructed and formalized in the following way:

- in the first period, parents use an exogenous endowment for investing in the education of a child, and for searching for an arranged marriage partner for their offspring, while the child receives the level of education chosen by her parents (i.e., years of schooling);

- in the second period, the child makes a marital decision: they can choose to accept

an arranged marriage partner, decide to marry a love marriage partner or stay single; during this period, they enjoy the returns to schooling, face an additive shock to their income, and also transfer a fixed share of their family income back to their parents.

Following Rubio's (2017) setup, each agent maximizes a quadratic utility function,

$$u(c_{it}) = c_{it} - \frac{d_i}{2}c_{it}^2, \quad i = f, k, \quad t = 1, 2'$$

where c_{it} is consumption of agent i at time t, d_i is the degree of risk aversion ($u(c_{it}) > 0$, $u'(c_{it}) > 0$ and $u''(c_{it}) < 0$). For simplicity, all income endowments are normalized to 1 in each period.

In the first period, parents choose educational investment λ_k for the child and decide whether to put in high or low effort looking for a marriage partner, $I(e)$, where $e \in \{0, 1\}$. $I(e)$ determines the mate's quality in terms of risk-sharing gains, especially when the marriage is the most secure life insurance, as usually happens in arranged marriages. The first-period parents' budget constraint is, therefore:

$$c_{1f} = 1 - p\lambda_k - I(e = 1)e,$$

where p is the price of education, $I(e = 1)$ and e are an indicator of parents' high effort and its cost, respectively. In this period, the child exhausts schooling investment by receiving education at the level determined by their parents.

All children are assumed to make a decision concerning their possible marriage at the beginning of the second period and share the resources with their spouses equally within marriages. Parents are expected to receive a portion of the returns to schooling of the child anyway, regardless of their marital status (ϕ varies based on the matrimonial decision). Thus, when the marriage is inevitable, the consumption in the second period for the child

and parents respectively is given by:

$$c_{kh} = 1 + (1 - \phi)(\frac{x_{kh}\lambda_{kh} + \gamma x_{sh}\lambda_{sh}}{2} + \frac{\delta_k + \delta_s}{2}),$$

$$c_{fh} = 1 + \phi(\frac{x_{kh}\lambda_{kh} + \gamma x_{sh}\lambda_{sh}}{2} + \frac{\delta_k + \delta_s}{2}),$$

where the income that the child receives in the second period equals to $x_k\lambda_k + \delta_k$, with x_k as the known returns to their education λ_k (e.g., expected salary and wages) and $\delta_k \in N(0, \sigma_\delta^2)$ as an additive shock, and $x_s\lambda_s + \delta_s$ is the income of the child's spouse.

The present model specification allows children to reject any type of compulsory marriage in principle and choose to remain single. The acknowledgment of the possibility of remaining single signifies a social change to recognize different life trajectories beyond the traditional marital framework. Therefore, the child decision is operationalized as their decision between love and arranged marriages, or staying single at the beginning of the second period, using $\gamma \in \{0, 1\}$ as a probability of getting married. On top of that, term $\phi \in \{0, 1\}$ also varies for all three options due to differences in resulting family structure, assuming that the portion of the child's income transferred to their parents is the largest in case of the arranged marriage as it is essentially an insurance agreement and the lowest in the case of the love marriage that allows for more flexibility and autonomy. If the child stays single, they would be the only provider for the parental family and would most likely transfer some portion of their income that falls in between these two extremes, as shown below:

$$Max_{h \in \{S,A,L\}} E[u(c_{2kh}) + \alpha_{2h}]$$

$$s.t. \quad c_{kh} = 1 + (1 - \phi_h)[\gamma(\frac{x_{kh}\lambda_{kh} + x_{sh}\lambda_{sh}}{2} + \frac{\delta_k + \delta_s}{2}) + (1 - \gamma)(x_{kh}\lambda_{kh} + \delta_k)] =$$

$$= 1 + (1 - \phi_h)\left[\left(1 - \frac{\gamma}{2}\right)(x_{kh}\lambda_{kh} + \delta_k) + \frac{\gamma}{2}(x_{sh}\lambda_{sh} + \delta_s)\right],$$

given the child's utility in this period $u(c_{2kh}) + \alpha_{2h}$, where α_h is a realized love term for the married individual in a matrimonial decision of the type $h = single(S), love(L), arranged(A)$.

Therefore, anticipating the decision of the child, in the first period parents face the following problem:

$$Max_{\lambda_{kh}, e \in \{0,1\}} u(c_f) + \beta E[u(c_f)]$$

$$s.t. \quad c_{1f} = 1 - p\lambda_k - I(e = 1)e,$$

where

$$c_{fh} = 1 + \phi_h \left[\left(1 - \frac{\gamma}{2}\right)(x_{kh}\lambda_{kh} + \delta_k) + \frac{\gamma}{2}(x_{sh}\lambda_{sh} + \delta_s) \right] \Rightarrow$$

$$E[u(c_{fh})] = \left[1 + \phi_h \left(\left(1 - \frac{\gamma}{2}\right) x_{kh}\lambda_{kh} + \frac{\gamma}{2} x_{sh}\lambda_{sh} \right) \right] -$$

$$\frac{d_f}{2} \left[1 + \phi_h \left(\left(1 - \frac{\gamma}{2}\right) x_{kh}\lambda_{kh} + \frac{\gamma}{2} x_{sh}\lambda_{sh} \right) \right]^2 - \frac{d_f}{2} \phi_h^2 \left[\sigma_\delta^2 + \gamma \left(1 - \frac{\gamma}{2}\right) (\sigma_\delta^2 + \rho_{ks} I(e = 1)) \right]$$

The optimal level of educational investment λ_{kh} might be derived from the first order condition and the assumption of $x_{kh} = x_{sh}$ in equilibrium so that $\lambda_{kh} = \lambda_{sh}$. The latter assumption of equal division of resources in marriages comes from the concept of assortative mating introduced by Becker (1991) that implies that individuals match on an equal basis and marriage market participants cannot improve their household arrangements making others worse off. The optimal level of education depends on several factors including the cost of education, child's income and the share received by the parents, the effort put in by the parents to find a suitable marriage partner, and the probability of the child eventually getting married, and, consequently, the share of the child income transferred back to their parents:

$$\lambda(e)_{k,h}^* = \frac{(\beta \phi x_{k,h} - 2p)(1 - d_f) - 2p d_f e_{high} I(e = 1)}{d_f(2p^2 + \beta \phi^2(\frac{1+\gamma}{2}) x_{k,h}^2)}$$

However, the equality between returns to education for two partners does not need to hold. In this instance, the marital decision is taken by the child, given the level of education and effort provided by the parents in the first period of the model and cultural norms of financial contributions towards parental family. As the financial support provided by adult children to their parents is considered obligatory in many traditional societies, the marital

decision of the child goes hand in hand with an allocated portion of their income to support their parents. Consequently, even with the same level of education and parental effort to marry the child off, the choice of ϕ would also determine the choice of γ between marital options.

The present rational-agent model simplifies the complexities of the real-world marriage markets that are influenced by factors beyond economic considerations such as interpersonal and intergenerational relationships and expectations, cultural norms and social pressures, family expectations and personal values. The parties seeking matrimonial agreement might also suffer from information asymmetry. Additionally, the initial model does not fully capture the gender dynamics that shape marital decisions differently for male and female children, potentially overriding the impact of education. Therefore, while incorporating additive shocks and likelihood of different marital decisions, the theoretical model disregards the importance of non-economic factors, cultural influences, and power dynamics in developing countries.

4.3 Empirical implementation

4.3.1 Econometric models

The objective of this study is to investigate the relationship between education and marital arrangements in developing countries. Specifically, the study aims to answer whether individuals with higher levels of education are more likely to choose partners themselves and at a later stage in life; if education correlates with the postponement of marriage in developing countries or the renouncement of those; and what types of marital arrangements (i.e., types of matrimonial alliances, including arranged and love marriages) are prevalent in developing countries, and how do education levels influence those arrangements.

According to UNICEF (2014), there is a substantial gap in the prevalence of early marriages between the poorest and wealthiest segments of society. Moreover, it has been observed that arranged marriages, and particularly forced child marriages, are more likely

to be found in rural areas compared to urban regions. In terms of regression modelling, this study builds upon previous works by Ghimire et al. (2006), Munshi and Rosenzweig (2009) and Rubio (2013, 2014). The dependent variables correspond to two aspects: being married at a younger or older age. The conditional variables, ideally, include a range of factors such as education level, gender, current age and age at the time of marriage, parental wealth, residential location (urban or rural), religious beliefs and cultural traditions. The alternative specifications correspond to a linear model with years of education being a dependent variable and marital status acting as a treatment.

Formally, the empirical models are presented below: two standard logistic models with binary outcomes, one multinomial logistic model to formalize the choice between three marital decision categories of engaging in a love or arranged marriage or remaining single at the time of observation, and a linear regression to estimate the opposite relationship – how marital decisions affect education level. These models primarily correspond to the second stage of the theoretical model, when the younger generation makes a decision about their matrimonial alliance or absence of those. The parental influence could be extracted from the educational level of a child while conditioning on the industry a child works in affects their returns to schooling. Data features and limitations of the employed dataset and how that affect the ultimate set of dependent and independent variables are further discussed in the next section.

- Logistic regression comparing the choices of getting married vs. staying single:

$$M_{ilt} = \beta_0 + \beta_1 educ_{ilt} + \beta_2 male_{ilt} + \beta_4 urban_{ilt} + \beta_5 work_{ilt} + f_l + \theta_t + \varepsilon_{ilt}$$

where M_{ilt} is a dummy variable that equals 1 if an individual i in location l (country or province) and year t (for several survey waves) is married and 0 if single, $educ_{ilt}$ represents years of schooling, $male_{ilt}$ has a value of 1 for male respondents (for mixed samples), $urban_{ilt}$ is a dummy for the residence type (1 if urban, 0 if rural),

$work_{ilt}$ takes the value of 1 if respondents is in the labor force, f_l is a set of location dummies (country or province fixed effects), θ_t is a set of time dummies for several survey waves if present, and ε_{ilt} is an error term.

- Logistic regression modelling the choice between love and arranged marriage (child marriage included), conditional on getting married:

$$T_{ilt} = \beta_0 + \beta_1 educ_{ilt} + \beta_2 male_{ilt} + \beta_4 urban_{ilt} + \beta_5 work_{ilt} + f_l + \theta_t + \varepsilon_{ilt}$$

where T_{ilt} is a dummy variable that equals 1 if an individual i in location l (country or province) and year t (for several survey waves) has married at a age below the minimum required age legally, $educ_{ilt}$ represents years of schooling, $male_{ilt}$ has a value of 1 for male respondents (for mixed samples), $urban_{ilt}$ is a dummy for the residence type (1 if urban, 0 if rural), $work_{ilt}$ takes the value of 1 if respondents is in the labor force, f_l is a set of location dummies (country or province fixed effects), θ_t is a set of time dummies for several survey waves if present, and ε_{ilt} is an error term.

- Multinomial logistic regression model with marital status as the dependent variable which takes up the values of *single (never married)*, *in a love marriage*, and *in an arranged marriage*:

$$P_{ilt} = \beta_0 + \beta_1 educ_{ilt} + \beta_2 male_{ilt} + \beta_4 urban_{ilt} + \beta_5 work_{ilt} + f_l + \theta_t + \varepsilon_{ilt}$$

where P_{ilt} indexes the variations in marital status of an individual i in location l (country or province) and year t (for several survey waves), $educ_{ilt}$ represents years of schooling, $male_{ilt}$ has a value of 1 for male respondents (for mixed samples), $urban_{ilt}$ is a dummy for the residence type (1 if urban, 0 if rural), $work_{ilt}$ takes the value of 1 if respondents is in the labor force, f_l is a set of location dummies (country or province fixed effects), θ_t is a set of time dummies for several survey

waves if present, and ε_{ilt} is an error term.

- Linear regression model with years of schooling as the dependent variable:

$$educ_{ilt} = \alpha_0 + \alpha_1 P_{ilt} + \alpha_2 male_{ilt} + \alpha_4 urban_{ilt} + \alpha_5 work_{ilt} + f_l + \theta_t + \epsilon_{ilt}$$

where $educ_{ilt}$ represents years of schooling P_{ilt} indexes the variations in marital status of an individual i in location l (country or province) and year t (for several survey waves), $male_{ilt}$ has a value of 1 for male respondents (for mixed samples), $urban_{ilt}$ is a dummy for the residence type (1 if urban, 0 if rural), $work_{ilt}$ takes the value of 1 if respondents is in the labor force, f_l is a set of location dummies (country or province fixed effects), θ_t is a set of time dummies for several survey waves if present, and ϵ_{ilt} is an error term.

4.3.2 Data

According to East Asian Social Survey (EASSDA, 2006), which examines five birth cohorts spanning from the 1930s to the 1980s, arranged marriage practices affect less and less part of the Chinese population: the proportion of individuals involved in arranged marriages has decreased significantly from approximately 17% to around 4% (Rubio, 2013). The prior research by Xiaohe and Whyte (1990); Riley (1994); Huang (2005) and Zang (2008) supports these findings, showing a notable reduction in parental involvement in marital arrangements in urban areas of China, where young people are now taking more control over their decision-making process regarding mate selection. Also, Xiaohe and Whyte (1990) underscore that choosing a partner independently leads to a higher level of relationship satisfaction among females compared to arranged marriages, regardless of the length of the marriage and other individual and couple characteristics.

Furthermore, data from the National Bureau of Statistics of China (NBS, 2020) shows that the proportion of never-married individuals in the country has remained relatively sta-

Table 4.1: Sample statistics

	Arranged Marriage	Love Marriage	Single	*p-value (Married vs. Single)*
Education (Years)	8.153	8.193	9.720	0.000
	(2.455)	(3.702)	(3.182)	
Sex (Male)	0.560	0.508	0.562	0.000
	(0.496)	(0.499)	(0.496)	
Age (Years)	17.415	45.531	21.451	0.000
	(1.994)	(12.444)	(6.089)	
Location (Urban)	0.140	0.385	0.284	0.000
	(0.348)	(0.486)	(0.451)	
Observations	769	130,484	31,324	$\sum = 162,577$

Notes: p-value for the two-sided t-test (95% confidence interval); Standard errors in parentheses;

For categorical variables, means are equivalent to sample proportions.

ble at around 18-19% over the past two decades. According to the Chinese Ministry of Civil Affairs (SC, 2017), there are about 200 million single people in China and this figure continues to grow. There are several possible factors contributing to this trend: the gender imbalance resulting from the implementation of the country's one-child policy between 1979 and 2015; changing social attitudes towards marriage and family; and economic factors such as rising housing prices and increased job competition.

Overall, China appears to be a suitable candidate for the empirical model implementation, as the country's marriage market trends align closely with the developed theoretical and empirical frameworks. The proposed model is performed on the data from the Chinese Household Income Project (CHIP), which was conducted in four waves in 1995, 2002, 2007, and 2013 (CIIDBNU, 2020). The surveys were carried out as a part of a collaborative research project conducted by Chinese and international researchers with assistance from the National Bureau of Statistics of China (NBS). The data sets include comprehensive information on income and expenditure for both urban and rural households, and have been previously analyzed by researchers such as Gustafsson et al. (2008); Griffin et al. (1993); Riskin and Li (2001); Kong et al. (2010).

The CHIP data imposes some natural limitations to the present study such as the absence of readily available measure of parents' investment in education in the dataset. To address this, the study operationalized parental investment in their child's schooling through years of education: as compulsory education in China spans nine years from the ages of 6 to 15 years and is funded by the government, the excessive schooling embodies parental investments in child education. Another limitation to the empirical model implementation relates to the unavailability of a direct measure of returns to education generated by the child. Given challenges associated with isolating the child's personal income from the their household income, the regression analysis controls for the types of occupations to isolate the effect of educational level on the matrimonial decision of the child. Finally, for the purpose of the present research, being under-aged and in the arranged marriage is defined as being younger than 20 years old for females and 22 years old for males and being in the legally recognized marriage, according to Chinese regulations on the minimal marital age. Therefore, the dependent variable was constructed by assigning a value of "underage arranged" to those who got married before the legal age of marriage and a value of "love" to those who got married later and under less coercion from a parental family, according to the overall trend mentioned before.

The process of data preparation for regression analysis included inspecting the initial questionnaires that vary across years, unifying the coding structure of variables, aggregating and harmonizing separate datasets for each year and location type. Table 4.1 presents the variables employed in the successive regression analysis by the type of marital choices, including years of education, sex and age of children, and their residential location. As shown, there is no statistical difference between subsamples of married and single survey respondents, while individuals in arranged marriages are statistically different from both singletons and love matches.
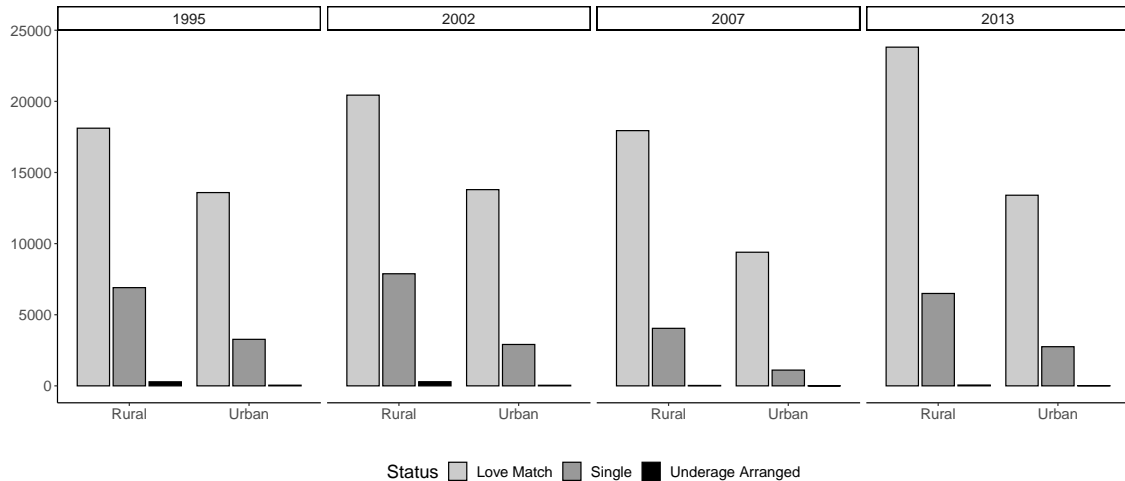
Figure 4.1: Types of matrimonial alliances by location and year.

4.4 Results

Figure 4.1 shows the distribution of the types of marital choices by location and survey year while Table C1 in the Appendix C provides more in-depth information on population proportions of married student by cohort. Table 4.2 presents an analysis of the variations in marital status and educational level, influenced by a number of individual and community characteristics. The first model utilized is a logistic regression, with a binary dependent variable indicating marriage (in any form) coded as 1, and remaining single coded as 0. The model incorporates a range of independent variables, including years of schooling, gender, the interaction between years of schooling and gender to capture differential outcomes for males and females, residential location and employment type at the time of taking a survey as well as cohort dummies. The findings of the regression analysis suggest a negative relationship between years of schooling as well as being a male and the likelihood of being married. This might be attributed to various factors, such as different level of social pressure, overall urbanization of the society and expanded employment opportunities outside of the household.

The second model employs the same set of conditioning variables as the first model and conducts a logistic regression analysis to examine the likelihood of entering into mar-

	Married vs. Single	Arranged vs. Love	Arranged vs. Love vs. Single		Education
			Arranged	Love	
Education (Years)	-0.234***	0.007	-0.120***	-0.239***	
	(0.004)	(0.032)	(0.019)	(0.004)	
Married					
Arranged					-0.798***
					(0.094)
Love					-0.727***
					(0.051)
Sex (Male)	-0.584***	0.326	-0.148	-0.592***	0.088**
	(0.042)	(0.259)	(0.214)	(0.049)	(0.030)
Education*Sex	0.060***	-0.101**	0.022	0.061***	
	(0.004)	(0.037)	(0.025)	(0.004)	
Location (Urban)	-1.376***	-1.479***	-0.640	-1.416***	2.471***
	(0.025)	(0.383)	(0.214)	(0.025)	(0.039)
Employment Type	Yes	Yes	Yes		Yes
Province	Yes	Yes	Yes		Yes
Cohort	Yes	Yes	Yes		Yes
Observations	162,577	131,253	162,577		162,577

Notes: $'p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. Robust standard errors in parentheses.

riage at the early age compared to a selection of a proper mate at the later stages of life. As the primary focus of this paper is early marriages, that are predominately forced, especially among female minors, and given the overall declining trend for arranged marriages in China, the assumption is that majority of the marriages happening in adulthood is not arranged by the parental family but follows the younger generation personal choices. Therefore, the resulting subset of the individuals in married early in life accounts for approximately one-half percent of the total number of observations. The results of the analysis did not reveal any evidence of significant differences in the probability of arranged versus love marriages occurring, except for the location parameter and the interaction term between

years of schooling and gender of the respondent. Thus, the findings suggest that being an urban citizen as well as an more educated male has a negative impact on the likelihood of entering into early marriages compared to marriages at the older age.

The multinomial model compares the three potential marital outcomes: being in an arranged marriage, a love marriage, or remaining unmarried, as a reference category. By analyzing the results of the multinomial logistic regression, it is observed that there is a negative relationship between the level of education and the probability of entering into a matrimonial alliance at the older age as compared to staying single. In contrast to that, being a more educated male slightly increases the likelihood of getting married as observed in this and the first model, comparing married and single survey respondents.

Table 4.2 also shows that being an urban citizen reduces the probability of marriage, with a particularly pronounced negative impact on the likelihood of entering into a love marriage as compared to an arranged marriage or staying unmarried in the last model. Table C2 in the Appendix C provides a robustness check by assigning 18 years to be a cut-off for early marriages and confirms the present regression results. These findings also align with theoretical expectations and are supported by previous empirical research in the field.

Finally, Table 4.2 represents the regression results for the linear regression with a dependent variable of education level and a number of independent variables, including a marital status as treatment. The presented findings refer to the complete sample for 16 to 24 years old and to each cohort separately. This specific age limits were selected to include both possible cut-offs for early marriages and to see the differences between survey respondents around them. The regression results show significant negative effect of being in any matrimonial alliance at that age and substantial positive impact of being urban resident on educational level received.

4.5 Conclusion and discussions

The persistence of matrimonial alliances involving minors in specific countries can be attributed to various factors, including low levels of education among the broader population, particularly among women, generational poverty, ongoing conflicts, religious beliefs, and cultural norms that favor traditional social structures and division of labor. This paper investigates both theoretical and empirical implications regarding the trade-off between educational attainment and different marital choices in developing countries, with a particular focus on China. The theoretical contribution proposes that as the optimal educational level increases, the probability of getting married decreases when marriage (of any kind) is not mandatory. The results from the regression analysis conducted using the CHIP data on the subset of the Chinese citizens highlight that marital outcomes are influenced by a range of individual and community factors, including education level and level of local urbanization. These findings underscore the complex social and cultural factors in shaping current marriage practices in China.

The direction of future research emerges from acknowledging the limitations of the present study. First and foremost, acknowledging the endogeneity issue between educational attainment and marital choices suggests ambiguity of which one is the cause and which one is an outcome: does more education lead to later marriage or does later marriage lead to more education? The presented regression analysis attempted to study both educational and marital decisions that are heavily influenced by the social norms and practices as well as financial stability of the parental household, especially in more traditional societies. However, the endogeneity issue cannot be solved in the current dataset that does not represent any quasi-experimental pre- and post-policy intervention data.

Additionally, marital practices might vary among families, aspiring to find a compatible spouse for the child, and are likely to be influenced by their financial and cultural non-economic conditions. Therefore, accounting for the broad range of socio-economic

characteristics of the parental family and community as a whole might bring additional empirical insights.

Finally, expanding a dataset to include other developing countries would allow for a more comprehensive analysis of the region. For instance, within the Former Soviet Union country members, early marriages have been particularly common in Kyrgyzstan, with over 20% of women being married before the age of 18; while in Kazakhstan and Turkmenistan, the rates were around 15% and 10%, respectively UNICEF (2005). Therefore, future research could involve constructing a comprehensive dataset for Central Asian countries through partnerships with international and local human rights organizations, and examining the impact of the aforementioned regional factors on the marriage markets in these countries.

CHAPTER 5

CONCLUSION

The dissertation encompasses three essays on skills and individual decision-making, examining concept of skills, knowledge, expertise and education from various angles. The research findings hold broader significance for policy development and individual decision-making.

The first essay utilizes the GSU EXCEN facilities to conduct a controlled laboratory experiment in order to test whether participants with significant expertise differ in responding to monetary and charitable incentives within a skill contest. The research findings have policy implications for organizations and charities seeking to optimize their strategies for eliciting support and enticing charitable contributions. Specifically, the results are relevant in relationship to individuals possessing substantial skills and knowledge to enhance their participation and donation level through contest activities.

The second essay aspires to to learn impact of online certificates in data science on the employment prospects of job seekers through a randomized field experiment, given the growing interest in data science education and careers. The study contributes to the broader discourse on the intersection of education and employment outcomes, specifically focusing on the role of data science skills and offering valuable insights for both online learning platforms and job seekers. The last essay elaborates on the partial equilibrium model of marital choice conditional on the educational level. The project highlights a significant policy implication regarding investments in education beyond compulsory schooling to address early marriage practices in developing countries. Hence, policymakers might work towards mitigating this societal issue, particularly among young women, by enabling them to make more informed and autonomous choices regarding marriage.

In summary, the implications drawn from these three dissertation essays extend beyond

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the area of academic research and offer valuable guidance to organizations and charities, job seekers and online learning platforms as well as policymakers. The findings center on the strategic importance of recognizing and leveraging on the potential of individuals with substantial expertise, the transformative power of data science education in the labor market, and importance of extended investments in education to address societal challenges in developing countries.

Appendices

APPENDIX A

SUPPLEMENTARY NOTES AND TABLES

A.1 Study sample size and drop-out rate

Table A1. Descriptive statistics by performance level

| | Treatment | | | |
	Monetary	Donation 1	Donation 2	Total
Opt-in high type	30/30	27/30	24/30	81/90
Opt-in low type	30/30	22/30	20/30	72/90
Total	60/60	49/60	44/60	153/180

The necessary sample size allows detecting of whether the comparison groups are really different and to what extent in a particular study. According to List et al. (2011), the current sample size was calculated based on the conventional significance level of 95% and test power of 80%. The minimum detectable effect size was adjusted based on the preliminary results from the first 9 out of 15 experimental sessions. The calculations revealed $N = 174$ to be the minimum size of the overall participant pool with a minimum of $n = 29$ for each experimental cell. Therefore, the total sample of 180 students meets the criteria and allows the detection of supposed differences between groups.

Table A1 shows that 90% of all high-performers and 80% of low-performers participated in the supererogatory task. All participants subjected to the monetary treatment stayed for the second stage, while two other donation schemes exhibited certain drop-out levels. The drop-out rates vary by participant performance level, but the differences are not statistically significant, nor are the differences between the two charity treatments. The observed student behavior might be rooted in the total available payoff amount and single-blinded payment mechanism, intensifying subjects not to participate in charitable giving versus withholding the donations upon committing to the supererogatory stage of the game.

Table A2. Demographic characteristics

	High	Low	Total
Age			
18-25	86	89	175
26-30	3	1	4
Over 30	1	0	1
Ethnicity			
Non-Hispanic White	8	4	12
Hispanic and Latino (of any race)	2	10	12
Black or African American	41	57	98
Asian	32	14	46
Two or more races	6	3	9
Other	1	2	3
Gender			
Male	32	20	52
Female	55	69	124
Non-binary	3	1	4
Origin			
Northeast	3	10	13
Midwest	1	1	2
South	61	58	119
West	0	1	1
Outside of the US	25	20	45
Family income			
Less than $20,000	14	21	35
$20,000 to $60,000	35	35	70
$60,000 to $100,000	26	24	50
Over $100,000	15	10	25
Charitable activities			
Never	8	24	32
Sometimes	73	58	131
Regularly	9	8	17
Total	90	90	180

Table A2 provides the summary of the demographic characteristics of the collected sample. These characteristics were used as conditioning variables in all regression specifications used in the analysis.

A.2 Selection of charitable organizations

List of charity organizations featured on the contribution page shown to participants in the both pro-social incentive conditions:

- American Cancer Society

- Piedmont Park Conservancy

- Atlanta Community Bank

The choice of charities was based on the location and size/popularity criteria. Participants were more likely to contribute towards the health or malnourishment causes rather than for environmental one, though the differences are not statistically significant at 95% level.

A.3 Sensitivity check results

Table A3 shows the regression results with a different performance split than the main specification. In this case, the participants are assigned to be high-performing when they solved more exercises than 80% of all subjects. The results are aligned with the primary analysis.

A.4 Other studies conducted

Before proceeding with the full study, the instruments were verified via a pilot study and PISA expert consultations. The questions were originally produced based on the PISA tests

Table A3. Sensitivity Checks

	Opt-in 2nd task		Donation amount		Pro-social payoff		Total payoff	
High status	0.205**	0.126	-0.182	0.306	0.094*	0.408	0.176***	-0.011
	(0.076)	(0.856)	(0.296)	(3.000)	(0.044)	(0.433)	(0.042)	(0.467)
No. of points		0.047*		-0.058		0.044**		0.039**
		(0.023)		(0.116)		(0.016)		(0.012)
Status*points		-0.006		-0.038		-0.051		0.009
		(0.102)		(0.361)		(0.052)		(0.056)
Pro-social group 1							-0.074	-0.081*
							(0.037)	(0.037)
Pro-social group 2							-0.135***	-0.135***
							(0.040)	(0.039)
Time to Completion	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	180	180	93	93	93	93	180	180

Notes: $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

(OECD, 2019) which are traditionally used to evaluate the application of functional numerical thinking to domains of all sorts (Gal and Tout, 2014). The students were presented with a multiple choice questions and allowed to use scratch paper. All notes made by the participants were collected at the payment stage along with the signed consent protocols. That ensured no leakage of questions and prevented the inflation of the task completion results in the further sessions.

There were a couple issues that came up during the pilot that were addressed prior to running the actual sessions:

- The complexity of questions was adjusted based on the received feedback to be adequate for anyone graduated from a high school.

- The *zTree* environment required participants to select the charity and the amount donated being anything between 0% and 100% as the pilot revealed that a few subjects opted-in the extra task with the option of charitable contribution but did not actually

specify neither the charity organization nor the portion of their payoff.

The only concern left was the different timing of the first stage completion. Some participants were able to complete the task earlier than others but were bound to wait for the rest as the ranking was assigned upon the whole session completion. Although, 90% of high-performing subjects stayed for the supererogatory task, their attrition might have slightly declined due to somewhat boredom.

A.5 Sample participant instructions and real task questions

A.5.1 General subject instructions

Please do not talk. If you have a question, please raise your hand and the experimenter will come to answer your question.

Stage 1

You will be presented with a problem set. Please, solve as many problems as possible in 30 min. You may use scratch paper. The ones getting to the top 50% of the participants will be classified as experts upon completing this task.

Stage 2

Please, follow the instructions further on: you will learn how and how much you will earn as the experiment progresses.

Post-Experiment Questionnaire

Please, answer each question as accurately as possible by selecting the answer or filling in the space provided.

List of questions for the Stage 1

1. Anna and Ron together have 20 packs of cookies. 40% of them are chocolate chip cookies, 25% are key lime and 35% are oatmeal flavor. How many packs of cookies does Anna have if 75% of chocolate chip and 20% of key lime cookies are Ron's?

    (a) 8

    (b) 13

    (c) 12

    (d) 7

2. A special kind of building material consists of 1/3 sand, 3/5 water, and 12 kg of soil. What is the total weight (in kg) of the mixture?

    (a) 98

    (b) 180

    (c) 120

    (d) 58

3. What are some possible positions of the larger and smaller clock arrows that yield 60 degrees between them?

    (a) 10:10pm

    (b) 12:10pm

    (c) 6:50am

    (d) 11:20am

4. All first-year students at State University must take calculus, English composition, or both. If half of the 4,800 first-year students take calculus and half do not, and one-

third of those who take calculus also take English composition, how many students take both English composition and calculus?

   (a) 800

   (b) 1,600

   (c) 2,400

   (d) 3,200

5. The chance of winning $100 in the first lottery is 3%, while the chance of winning $50 in the second one is 7%. Which one would you prefer to participate in if tickets for both cost $2?

   (a) Second lottery

   (b) They are equivalent

   (c) Neither one generates profit

   (d) First lottery

6. A man is eating an apple pie. During the first day he eats a half of the apple pie. On the second day he eats 1/3 of the remaining part of the apple pie. The third day he eats 1/4 of what is left, and the forth day he eats 1/5 of what still remains. He then stops because the last piece was not fresh. What fraction of the original apple pie is still available?

   (a) 1,234/10,000

   (b) 1,234/2,345

   (c) 1/5

   (d) 1/4

7. A farmer can pick 7kg of apples in 1 hour. Working at the same rate, how long in hours would it take two farmers to pick 28kg of apples?

(a) 4

(b) 3

(c) 2

(d) 1

8. To convert degrees Fahrenheit to degrees Celsius, subtract 32 from the first one and multiply by 5/9: (degrees F - 32) × 5/9 = degrees C. What is the temperature in degrees Celsius when we observe 32 degrees Fahrenheit?

(a) 50

(b) 33

(c) 0

(d) 10

9. Alan can follow one of the study routines: (1) he can study for two hours twice a week reading 25 pages in the first hour and 80% of that in the second hour; or (2) he can study for one hour three times a week with the mentioned productivity of the first hour of reading. Which study routine should he choose to acquire more knowledge in a week?

(a) The results are equivalent

(b) First

(c) Second

(d) Not enough information to answer

10. Which of the following when rounded to the nearest hundredths, is rounded to 4.17?

(a) 4.16849

(b) 4.17401

    (c) 4.16501

    (d) All of the above

Subject instructions for the high-performers

Congratulations! You have shown a high expertise at problem solving! Would you like to proceed with the experiment?

- Yes, complete 5 extra questions

  Keep all the money / Donate a part of your earnings to charity. Then select what percentage from your expected earning you want to donate to the charity and select a charity from the list below. You will receive a confirmation about the charity donation in a few days.

  - Donate to American Cancer Society

  - Donate to Piedmont Park Conservancy

  - Donate to Atlanta Community Food Bank

- No, collect $10 as your payoff for participation in the experiment upon completing the following questionnaire

Subject instructions for the low-performers

Unfortunately, you were not classified as an expert. Would you like to proceed with the experiment?

- Yes, complete 5 extra questions

  Keep all the money / Donate a part of your earnings to charity. Then select what percentage from your expected earning you want to donate to the charity and select a

charity from the list below. You will receive a confirmation about the charity donation in a few days.

  - Donate to American Cancer Society

  - Donate to Piedmont Park Conservancy

  - Donate to Atlanta Community Food Bank

- No, collect $10 as your payoff for participation in the experiment upon completing the following questionnaire

List of questions for the Stage 2: Random selection of 5 out of 10 questions

1. Mark drinks coffee 2 times more frequently than David does. Another day they bought 6 shots of espresso for two. How many drinks did Mark have?

   (a) 4

   (b) 3

   (c) 1

   (d) 2

2. At a motorbike store, 1/5 of the motorbikes are Honda products and 1/9 of the products are Yamaha. If it had exactly 270 motorbikes, how many of them are either Honda or Yamaha made?

   (a) 54

   (b) 84

   (c) 86

   (d) 30

3. What are some possible positions of the larger and smaller clock arrows that yield 30 degrees between them?

(a) 5:45am

(b) 10:55pm

(c) All of the above

(d) None of the above

4. All first-year students at State University must take calculus, English composition, or both. If half of the 4,800 first-year students take calculus and half do not, and one-third of those who take calculus also take English composition, how many students take English composition only?

(a) 1,600

(b) 2,400

(c) 800

(d) 1,200

5. The chance of winning $80 in the lottery is 5%. What should be a maximum price for a lottery ticket?

(a) 4

(b) 2

(c) 8

(d) 5

6. Sarah ate 1/3 of 3/4 of a pizza. How much pizza is left?

(a) 2/3

(b) 1/3

(c) 1/4

(d) 3/4

7. An artist finished her last work in 3 hours. How many hours should she work to finish four art pieces if every next art work requires half an hour more than the previous one?

   (a) 3

   (b) 12

   (c) 15

   (d) 18

8. To convert degrees Fahrenheit to degrees Celsius, subtract 32 from the first one and multiply by 5/9: (degrees F - 32) × 5/9 = degrees C. What is the temperature in degrees Celsius when we observe 77 degrees Fahrenheit?

   (a) 25

   (b) 30

   (c) 35

   (d) 40

9. Alex went to the gym for 2 hours twice this week and for 75% of that time three times last week. Which week did he spent more time exercising?

   (a) Last week

   (b) This week

   (c) Same time

   (d) Not enough information to answer

10. Round 46.72653 to the number with 3 integers after the decimal point:

   (a) 46.726

   (b) 46.727

(c) 46.73

(d) 46.7265

APPENDIX B

SUPPLEMENTARY FIGURES AND TABLES

EMILY SMITH

(470) 296-5590 ⋄ emily.v.smith357@gmail.com

EDUCATION

Georgia State University   2019-2023
B.Sc. in Economics
GPA: 3.8/4.0
Minor in Global Studies
Member of Robinson Management Consulting Club and Spanish Club

CISabroad Intern in Barcelona, Spain   May 2022

CERTIFICATION

Coursera Specialization Certification "Data Science" from Johns Hopkins University
The Data Scientists Toolbox, R Programming, Getting and Cleaning Data, Exploratory Data Analysis,
Reproducible Research, Statistical Inference, Regression Models, Practical Machine Learning, Developing Data Products, Data Science Capstone

PROFESSIONAL EXPERIENCE

Grubhub, Inc.   May 2020 - July 2020
Contact Center Specialist
- Supported a high volume of contacts through e-mail, tickets, and inbound and outbound calls
- Classified the incoming complaints into the categorical structure based on content
- Analyzed trends across the categories

United States Postal Service   June 2021 - August 2021
Sales Enablement Intern
- Designed and implemented new training strategies across 12 sales segments and industries
- Coordinated cross-functional weekly meetings with senior leadership teams
- Tracked project progress amongst cross-functional team members' tasks

LEADERSHIP EXPERIENCE

V.I.S.A. Leader Program   2020 - 2022
- Assisted with orientation check-in
- Managed a four-hour group session of about 15 new international students (campus tour and information session)
- Provided information about course registration, housing options, banking, and campus life

SKILLS

Coursework	Statistics and Econometrics (multiple regression and forecasting)
	Calculus and Optimization, Business and Communications
Projects	In-class capstone project on Grubhub logistics system (Fall 2020)
Languages	Spanish (fluent)

Table B1. Logit regression: full sample and sub-samples by work modality and type of work contract.

	Full sample		Remote	In-person	Full-time		Other	
Constant	-4.351***	-4.403***	-2.882***	-23.013	-4.416***	-4.520***	-21.987****	-22.265***
	(0.679)	(0.898)	(0.692)	(40.396)	(0.712)	(0.931)	(0.792)	(2.971)
With certificate	0.805	0.833	0.154	1.553	0.409	0.409	20.431***	20.431***
	(0.713)	(0.736)	(0.999)	(1.146)	(0.771)	(0.811)	(0.975)	(1.927)
Female	1.003	1.022	-0.512	2.003*	0.976	1.031	-0.208	-0.463
	(0.704)	(0.698)	(1.207)	(0.993)	(0.704)	(0.706)	(0.975)	(1.735)
With certificate*female	-0.695	-0.850	0.494	-1.761	-0.210	-0.371	-20.418***	-20.308***
	(0.926)	(0.946)	(1.517)	(1.284)	(0.951)	(0.987)	(1.365)	(2.140)
Work contract: part-time	-15.238**	-17.091***	-15.143***	-16.394***				
	(0.398)	(0.439)	(0.511)	(1.039)				
Work contract: internship	-14.802***	-16.648***	-15.437***	-16.246***				
	(0.416)	(0.601)	(0.873)	(0.790)				
Work contract: temporary	-1.483	-1.519	-1.186	-17.134***				
	(1.040)	(1.044)	(1.148)	(0.512)				
Work contract: other	1.070	0.818		0.915				
	(1.165)	(1.544)		(1.551)				
"Data Analyst" vacancy	0.304	0.326	-0.421	0.652	0.349	0.303	-0.165	-0.702
	(0.492)	(0.502)	(0.840)	(0.612)	(0.480)	(0.481)	(2.392)	(2.025)
EOE employer	0.055	0.104	-0.363	0.233	0.231	0.337	-19.714***	-19.668***
	(0.420)	(0.461)	(0.687)	(0.569)	(0.471)	(0.502)	(0.828)	(1.061)
Remote work contract	-0.030				-0.083		-0.628	
	(0.468)				(0.490)		(2.391)	
Location	No	Yes	No	Yes	No	Yes	No	Yes
No. observations	849	849	299	550	671	671	178	178

Notes: $^{'}$ $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Coefficients are converted to percentage points. Robust standard errors in parentheses.

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Table B2. Probit regression: full sample and sub-samples by work modality and type of work contract.

	Full sample		Remote	In-person	Full-time		Other	
Constant	-2.236***	-2.216***	-1.591***	-7.162	-2.267***	-2.289***	-5.953***	-6.679***
	(0.272)	(0.375)	(0.308)	(4.737)	(0.292)	(0.399)	(0.513)	(1.949)
With certificate	0.349	0.393	0.056	0.721	0.182	0.209	5.054***	5.658***
	(0.288)	(0.308)	(0.433)	(0.445)	(0.312)	(0.340)	(0.675)	(1.231)
Female	0.423	0.422	-0.236	0.909*	0.417	0.437	0.013	-0.072
	(0.286)	(0.298)	(0.483)	(0.386)	(0.292)	(0.307)	(0.457)	(0.181)
With certificate*female	-0.298	-0.382	0.225	-0.816	-0.091	-0.171	-5.168***	-6.030***
	(0.390)	(0.414)	(0.636)	(0.542)	(0.403)	(0.436)	(0.802)	(1.251)
Work contract: part-time	-3.802**	-4.123***	-3.947***	-4.214***				
	(0.147)	(0.163)	(0.227)	(0.454)				
Work contract: internship	-3.638***	-4.005***	-4.029***	-4.080***				
	(0.156)	(0.254)	(0.256)	(0.355)				
Work contract: temporary	-0.594	-0.617	-0.521	-4.626***				
	(0.387)	(0.393)	(0.436)	(0.335)				
Work contract: other	0.505	0.421		0.441				
	(0.581)	(0.750)		(0.756)				
"Data Analyst" vacancy	0.113	0.107	-0.185	0.265	0.145	0.117	-0.159	-0.553
	(0.213)	(0.226)	(0.363)	(0.274)	(0.211)	(0.221)	(1.253)	(1.094)
EOE employer	0.010	0.012	-0.175	0.047	0.080	0.116	-5.009***	-5.547***
	(0.184)	(0.210)	(0.295)	(0.274)	(0.207)	(0.234)	(0.494)	(1.198)
Remote work contract	0.011				-0.017		-0.340	
	(0.203)				(0.216)		(1.262)	
Location	No	Yes	No	Yes	No	Yes	No	Yes
No. observations	849	849	299	550	671	671	178	178

Notes: $^{\cdot}\,p < 0.1$; $^{*}\,p < 0.05$; $^{**}\,p < 0.01$; $^{***}\,p < 0.001$. Coefficients are converted to percentage points. Robust standard errors in parentheses.

APPENDIX C

SUPPLEMENTARY NOTES AND TABLES

C.1 Additional sample characteristics

Table C1. Sample proportions for students by cohort

	Arranged Marriage	Love Marriage	Single
1995			
Male	85 (47.49%)	4 (0%)	1,737 (31.79%)
Female	82 (53.59%)	4 (0%)	1,576 (33.44%)
2002			
Male	107 (56.61%)	4 (0%)	2,210 (36.89%)
Female	94 (65.28%)	7 (0%)	1,899 (39.56%)
2007			
Male	1 (6.67%)	0 (0%)	3 (0%)
Female	0 (0%)	2 (0%)	7 (1.52%)
2013			
Male	22 (45.83%)	13 (0%)	2,118 (39.19%)
Female	6 (22.22%)	29 (0%)	2,049 (53.29%)
Total			
Male	215 (49.88%)	21 (0%)	6,068 (34.66%)
Female	182 (53.85%)	42	5,531 (40.02%)
Observations	769	130,484	31,324

Table C1 confirms the fact that most of the marriages happening at the time of schooling are considered arranged in this analysis. Looking at each cohort individually, females and males are equally likely to stay in school after marriage for all years except 2013, where the shift to being singles while studying is exceptionally visible among females.

Table C2. Robustness Check

	Married vs. Single	Arranged vs. Love	Arranged vs. Love vs. Single	
			Arranged	Love
Education (Years)	-0.234***	0.007	-0.149***	-0.237***
	(0.004)	(0.032)	(0.023)	(0.004)
Sex (Male)	-0.584***	0.326	-0.149	-0.585***
	(0.042)	(0.259)	(0.278)	(0.043)
Education*Sex	0.060***	-0.101**	-0.018	0.061***
	(0.004)	(0.037)	(0.032)	(0.004)
Location (Urban)	-1.376***	-1.479***	-0.872**	-1.400***
	(0.025)	(0.383)	(0.374)	(0.025)
Employment Type	Yes	Yes	Yes	
Province	Yes	Yes	Yes	
Cohort	Yes	Yes	Yes	
Observations	166,621	131,253	166,621	

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; Robust standard errors in parentheses.

C.2 Robustness check

Table C2 shows the regression results with an age cut-off of 18 years for both males and females to identify underage marriages. The findings confirm the robustness of the primary analysis.

C.3 Model with divorce

Given the marriage of any kind in the second period, the child observes the realization of the love term, α_h, at the beginning of the next period, and decides on her future marital status: whether to remain married or not. If she divorces, she gets only her personal income, pays a divorce utility cost of $\mu > 0$, and faces the realization of her shock δ_k by herself in this period. In the initial model by Rubio (2017), she necessarily finds a new partner in the love market in the fourth period regardless of the previous marriage type – this exact assumption is relaxed in the present paper.

Therefore, the child divorces if the utility from the divorce and further marriage, or the absence of those, exceeds the utility of staying in the first marriage, conditional on having a spouse during previous periods:

$$\alpha_h + u(c_k)^{M,h} + \beta\{E[u(c_k)]^{M,h} + \alpha_h\} <$$

$$u(c_k)^D - \mu + \beta\{E[u(c_k)]^{M,L} + \nu E(\alpha_L)\}, \quad h = L, A$$

where M and D is the utility of married and divorced individuals respectively, h refers to the type of the first marriage, α_h is a realized love term, and $\nu \in \{0, 1\}$ stands for the probability of the second marriage.

Since the distribution of the love term differs by the marriage type, α_h influences the probability of divorce. Thus, if the child chooses a love marriage in the second period, then α_L is captured by the following threshold:

$$\alpha_L^* < (1+\beta)^{-1}\left[-\mu + \frac{d_k}{2}(1-\phi)^2\sigma_\delta^2\left[\frac{\rho_{ks}(e, I(L=1))}{2} - \frac{1}{2}\right] + \nu\beta E(\alpha_L)\right]$$

If the child chooses an arranged marriage in the second period, then:

$$\alpha_A^* < (1+\beta)^{-1}\left[-\mu + \frac{d_k}{2}\frac{(1-\phi)^2}{4}\sigma_\delta^2[\rho_{ks}(e, I(L=1)) - \rho_{ks}(e, I(L=0))]\right] +$$

$$\frac{d_k}{2}(1-\phi)^2\sigma_\delta^2\left[\frac{\rho_{ks}(e, I(L=0))}{2} - \frac{1}{2}\right] + \nu\beta E(\alpha_L)$$

The lower realization of the love term in the first marriage corresponds to the lower probability of the second marriage as the decision not to remarry might depend on the individual experiences in the first marriage.

The empirical testing of this model extension would require an access to the longitudinal dataset to track respondents' matrimonial decisions throughout their lifetime. Otherwise, the survey questionnaire would incorporate a block of questions regarding the

longevity of marriages and successive partnerships.

C.4 Model with siblings

As the number of children increases, parents take into account the characteristics of the households where their children may be married to (controlling for the correlated shocks), so they have incentives to arrange marriages for only some children. The model by Rubio (2017) treats all children as homogeneous within gender but heterogeneous between gender in the price of education ($p_g \neq p_b$) and the returns to schooling ($x_g \neq x_b$). The present paper relaxes the necessity to get married and fixes the price of education at the same level regardless of the child's gender ($p_g = p_b = p$).

Thus, the problem faced by the parents of two siblings of different genders in the first period is given by:

$$Max_{\lambda_g, \lambda_b, e \in \{0,1\}} u(c_f) + \beta E[u(c_f)]$$

$$s.t. \quad c_f = 1 - \frac{1}{2}p\lambda_g - \frac{1}{2}p\lambda_b - \frac{1}{2}e^g I(e_g = 1) - \frac{1}{2}e^b I(e_b = 1)$$

The solution for the case when children are heterogeneous is analogous to the solution for the model with one child. Thus, the given parents' effort level is $e = \frac{1}{2}e^g I(e_g = 1) + \frac{1}{2}e^b I(e_b = 1)$.

Parental investments into girl's and boy's education respectively, λ_g and λ_b, are:

$$x_g > x_b \Rightarrow \lambda_g^* = \frac{(\beta\phi x_g - 2p)(1 - d_f) - 2pd_f e}{d_f(2p^2 + \beta\phi^2 \frac{(1+\gamma)}{2}x_g^2)} > 0, \lambda_b^* = 0$$

$$x_g < x_b \Rightarrow \lambda_b^* = \frac{(\beta\phi x_b - 2p)(1 - d_f) - 2pd_f e}{d_f(2p^2 + \beta\phi^2 \frac{(1+\gamma)}{2}x_b^2)} > 0, \lambda_g^* = 0$$

Hence, the hypothesis about higher level of education needed to forego a marriage of

any type in the second period is supported in a case of siblings as well:

$$\gamma_g^* < 1 - 2\left[\frac{(\beta\phi x_g - 2p)(1 - d_f) - 2pd_f e}{\lambda_g d_f \beta\phi^2 x_g^2} - \frac{2p^2}{\beta\phi^2 x_g^2}\right]$$

$$\gamma_b^* < 1 - 2\left[\frac{(\beta\phi x_b - 2p)(1 - d_f) - 2pd_f e}{\lambda_b d_f \beta\phi^2 x_b^2} - \frac{2p^2}{\beta\phi^2 x_b^2}\right]$$

The present model shows the same tendency for all genders, however, the theoretical literature review suggests a more prominent effect for female minors.

BIBLIOGRAPHY

Acquisti, A. and Fong, C. (2020). An Experiment in Hiring Discrimination via Online Social Networks. *Management Science*, 66(3):1005–1024.

Adamovic, M. and Leibbrandt, A. (2023). A Large-Scale Field Experiment on Occupational Gender Segregation and Hiring Discrimination. *Industrial Relations: A Journal of Economy and Society*, 62(1):34–59.

Adams, A. and Andrew, A. (2019). Preferences and Beliefs in the Marriage Market for Young Brides. Technical report, IFS Working Papers.

Agan, A. and Starr, S. (2018). Ban the Box, Criminal Records, and Racial Discrimination: A Field Experiment. *The Quarterly Journal of Economics*, 133(1):191–235.

Akresh, R., Halim, D., and Kleemans, M. (2018). Long-term and Intergenerational Effects of Education: Evidence from School Construction in Indonesia. Technical report, National Bureau of Economic Research.

Albert, R., Escot, L., and Fernández-Cornejo, J. A. (2011). A Field Experiment to Study Sex and Age Discrimination in the Madrid Labour Market. *The International Journal of Human Resource Management*, 22(02):351–375.

Andreoni, J. (1989). Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence. *Journal of political Economy*, 97(6):1447–1458.

Andreoni, J. (1990). Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal*, 100(401):464–477.

Andreoni, J., Rao, J. M., and Trachtman, H. (2017). Avoiding the Ask: A Field Experiment on Altruism, Empathy, and Charitable giving. *Journal of Political Economy*, 125(3):625–653.

Anukriti, S. and Dasgupta, S. (2017). Marriage Markets in Developing Countries. In *The Oxford Handbook of Women and the Economy*.

Asadullah, M. N. and Wahhaj, Z. (2019). Early Marriage, Social Networks and the Transmission of Norms. *Economica*, 86(344):801–831.

Asanov, I. and Mavlikeeva, M. (2023). Can Group Identity Explain the Gender Gap in the Recruitment Process? *Industrial Relations Journal*, 54(1):95–113.

Avivi, H., Kline, P., Rose, E., and Walters, C. (2021). Adaptive Correspondence Experiments. In *AEA Papers and Proceedings*, volume 111, pages 43–48. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Azmat, G. and Petrongolo, B. (2014). Gender and the Labor Market: What Have We Learned from Field and Lab Experiments? *Labour Economics*, 30:32–40.

Baert, S. (2018). Hiring Discrimination: an Overview of (Almost) All Correspondence Experiments Since 2005. In *Audit studies: Behind the scenes with theory, method, and nuance*, pages 63–77. Springer.

Barrero, J. M., Bloom, N., and Davis, S. J. (2021). Why Working from Home will Stick. Technical report, National Bureau of Economic Research.

Becker, G. S. (1974). A Theory of Social Interactions. *Journal of political economy*, 82(6):1063–1093.

Becker, G. S. (1991). A Treatise on the Family.

Becker, G. S. (2009). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. Third Edition.* University of Chicago press.

Bertrand, M. and Mullainathan, S. (2004). Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review*, 94(4):991–1013.

Birkelund, G. E., Lancee, B., Larsen, E. N., Polavieja, J. G., Radl, J., and Yemane, R. (2022). Gender Discrimination in Hiring: Evidence from a Cross-National Harmonized Field Experiment. *European Sociological Review*, 38(3):337–354.

Bjork, E. L., Soderstrom, N. C., and Little, J. L. (2015). Can Multiple-Choice testing Induce Desirable Difficulties? Evidence from the Laboratory and the Classroom. *The American journal of psychology*, 128(2):229–239.

Blommaert, L., Coenders, M., and Van Tubergen, F. (2013). Discrimination of Arabic-Named Applicants in the Netherlands: An Internet-Based Field Experiment Examining Different Phases in Online Recruitment Procedures. *Social forces*, 92(3):957–982.

Booth, A. and Leigh, A. (2010). Do Employers Discriminate by Gender? A Field Experiment in Female-dominated Occupations. *Economics Letters*, 107(2):236–238.

Boulier, B. L. and Rosenzweig, M. R. (1984). Schooling, Search, and Spouse Selection: Testing Economic Theories of Marriage and Household Behavior. *Journal of political Economy*, 92(4):712–732.

Bradler, C., Dur, R., Neckermann, S., and Non, A. (2016). Employee Recognition and Performance: A Field Experiment. *Management Science*, 62(11):3085–3099.

Brock, J. M., Lange, A., and Ozbay, E. Y. (2013). Dictating the Risk: Experimental Evidence on Giving in Risky Environments. *American Economic Review*, 103(1):415–437.

Burkart, J. M., Schubiger, M. N., and van Schaik, C. P. (2017). The Evolution of General Intelligence. *Behavioral and Brain Sciences*, 40.

Burkhardt, H. (2007). Functional Mathematics and Teaching Modeling. *Mathematical Modelling: Education, Engineering and Economics*, pages 177–186.

BurningGlass (2017). The Quant Crunch: How the Demand for Data Science Skills is Disrupting the Job Market. Technical report.

Cahuc, P., Carcillo, S. L., Minea, A., and Valfort, M.-A. (2019). When Correspondence Studies Fail to Detect Hiring Discrimination.

CAI (2016). Central Asia Institute: Education Can End Child Marriage.

Card, D. and DiNardo, J. E. (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of labor economics*, 20(4):733–783.

Cassar, L. and Meier, S. (2017). Intentions for Doing Good Matter for Doing Well: The (Negative) Signaling Value of Prosocial Incentives. *National Bureau of Economic Research*.

Cassar, L. and Meier, S. (2018). Nonmonetary Incentives and the Implications of Work as a Source of Meaning. *Journal of Economic Perspectives*, 32(3):215–38.

CDC (2023). End of the Federal COVID-19 Public Health Emergency (PHE) Declaration. *URL: https://www.cdc.gov/coronavirus/2019-ncov/your-health/end-of-phe.html*.

Cerda-Jara, M., Elster, A., and Harding, D. J. (2020). Criminal Record Stigma in the College-Educated Labor Market.

Chan, J. and Wang, J. (2018). Hiring Preferences in Online Labor Markets: Evidence of a Female Hiring Bias. *Management Science*, 64(7):2973–2994.

Chavez, K., Weisshaar, K., and Cabello-Hutt, T. (2022). Gender and Racial Discrimination in Hiring before and during the COVID-19 Pandemic: Evidence from a Field Experiment of Accountants, 2018–2020. *Work and Occupations*, 49(3):275–315.

Chen, M. (2020). *The Value of US College Education in Global Labor Markets: Experimental Evidence from China*. Princeton University Industrial Relations Section.

Chiappori, P.-A., Iyigun, M., and Weiss, Y. (2009). Investment in Schooling and the Marriage Market. *American Economic Review*, 99(5):1689–1713.

Chuang, I. and Ho, A. (2016). HarvardX and MITx: Four Years of Open Online Courses–Fall 2012-Summer 2016. *SSRN 2889436*.

CIIDBNU (2020). Chinese Household Income Project (CHIP) by China Institute For Income Distribution.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences*, volume 699. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Coursera (2023). New Coursera Survey Shows High Demand for Industry Micro-Credentials from Students and Employers in Tight Labor Market. *URL: https://blog.coursera.org/from-higher-education-to-employment/*.

Cox, J. C. and Harrison, G. W. (2008). Risk Aversion in Experiments: An Introduction. In *Risk aversion in experiments*, pages 1–7. Emerald Group Publishing Limited.

Crumpler, H. and Grossman, P. J. (2008). An Experimental Test of Warm Glow Giving. *Journal of Public Economics*, 92(5-6):1011–1021.

Cunha, F. and Heckman, J. (2007). The Technology of Skill Formation. *American economic review*, 97(2):31–47.

DellaVigna, S. and Pope, D. (2018). What Motivates Effort? Evidence and Expert Forecasts. *The Review of Economic Studies*, 85(2):1029–1069.

Deming, D. J., Yuchtman, N., Abulafi, A., Goldin, C., and Katz, L. F. (2016). The Value of Postsecondary Credentials in the Labor Market: An Experimental Study. *American Economic Review*, 106(3):778–806.

Dias, F. A. (2020). How Skin Color, Class Status, and Gender Intersect in the Labor Market: Evidence from a Field Experiment. *Research in Social Stratification and Mobility*, page 100477.

DOL (2022). Georgia Department of Labor. Minimum Wage since 2009. Retrieved: https://dol.georgia.gov/minimum-wage.

Downen, T. (2012). A Supplemental Tutorial for Using z-Tree in a Non-interactive Accounting Experiment. *Adv Account Behav Res*, 15.

EASSDA (2006). East Asian Social Survey.

Eckartz, K. (2014). Task Enjoyment and Opportunity Costs in the Lab: The Effect of Financial Incentives on Performance in Real Effort Tasks. Technical report, Jena Economic Research Papers.

Ellingsen, T. and Johannesson, M. (2007). Paying Respect. *Journal of Economic Perspectives*, 21(4):135–150.

Eriksson, S. and Rooth, D.-O. (2014). Do Employers Use Unemployment as a Sorting Criterion when Hiring? Evidence from a Field Experiment. *American economic review*, 104(3):1014–39.

Erkal, N., Gangadharan, L., and Koh, B. H. (2017). Monetary and Non-monetary Incentives in Real-effort Tournaments.

Erkal, N., Gangadharan, L., and Nikiforakis, N. (2011). Relative Earnings and Giving in a Real-Effort Experiment. *American Economic Review*, 101(7):3330–48.

Etzioni, A. (2018). Benefits for Gig Workers. *Challenge*, 61(3):255–268.

Evren, Ö. and Minardi, S. (2017). Warm-Glow Giving and Freedom to be Selfish. *The Economic Journal*, 127(603):1381–1409.

Fahle, S. and Sautua, S. I. (2021). How Do Risk Attitudes Affect Pro-Social Behavior? Theory and Experiment. *Theory and Decision*, 91(1):101–122.

Farber, H. S., Silverman, D., and Von Wachter, T. (2016). Determinants of Callbacks to Job Applications: An Audit Study. *American Economic Review*, 106(5):314–18.

Fehr, E. and Schmidt, K. M. (2006). The Economics of Fairness, Reciprocity and Altruism – Experimental Evidence and New Theories. *Handbook of the economics of giving, altruism and reciprocity*, 1:615–691.

Fischbacher, U. (2007). z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental economics*, 10(2):171–178.

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wangk, D., Younk, H., and Rahwana, I. (2019). Toward Understanding the Impact of Artificial Intelligence on Labor. *Proceedings of the National Academy of Sciences*, 116(14):6531–6539.

Gaddis, S. M. (2015). Discrimination in the Credential Society: An Audit Study of Race and College Selectivity in the Labor Market. *Social Forces*, 93(4):1451–1479.

Gal, I. and Tout, D. (2014). Comparison of PIAAC and PISA Frameworks for Numeracy and Mathematical Literacy.

Gallagher, S. (2018). Educational Credentials Come of Age: A Survey on the Use and Value of Educational Credentials in Hiring. *URL: https://www. northeastern. edu/cfhets/wpcontent/uploads/2018/12/Educational_Credentials_Come_of_Age_2018. pdf*.

GAO (2015). U.S. Government Accountability Office. Contingent Workforce: Size, Characteristics, Earnings, and Benefits. *GAO-15-168R.Washington, DC.*

Gaulke, A., Cassidy, H., and Namingit, S. (2019). The Effect of Post-Baccalaureate Business Certificates on Job Search: Results from a Correspondence Study. *Labour Economics*, 61:101759.

Gee, L. K. (2019). The More You Know: Information Effects on Job Application Rates in a Large Field Experiment. *Management Science*, 65(5):2077–2094.

Ghimire, D. J., Axinn, W. G., Yabiku, S. T., and Thornton, A. (2006). Social Change, Premarital Nonfamily Experience, and Spouse Choice in an Arranged Marriage Society. *American Journal of Sociology*, 111(4):1181–1218.

Glassdoor (2020). Glassdoor Economic Research: U.S. Job Openings -29% Since Early March As Weekly Decline Slows to 1%.

Gneezy, U., Meier, S., and Rey-Biel, P. (2011). When and Why Incentives (Don't) Work to Modify Behavior. *Journal of Economic Perspectives*, 25(4):191–210.

Green, A. E. and Canny, A. (2003). *Geographical Mobility: Family Impacts*. Policy Press.

Griffin, K. B., Zhao, R., et al. (1993). *The Distribution of Income in China*. Springer.

Gustafsson, B. A., Shi, L., and Sicular, T. (2008). *Inequality and Public Policy in China*. Cambridge University Press.

Hanushek, E. A., Machin, S. J., and Woessmann, L. (2016). *Handbook of the Economics of Education*. Elsevier.

Hanushek, E. A., Schwerdt, G., Wiederhold, S., and Woessmann, L. (2015). Returns to Skills around the World: Evidence from PIAAC. *European Economic Review*, 73:103–130.

Harbaugh, W. T. (1998). The Prestige Motive for making Charitable Transfers. *The American Economic Review*, 88(2):277–282.

Heckman, J. J. (2006). Skill Formation and the Economics of Investing in Disadvantaged Children. *Science*, 312(5782):1900–1902.

Holderness JR, D. K., Kari Joseph Olsen CMA, C., et al. (2019). Making Performance Feedback Work. *Strategic Finance*, 100(8):46–51.

Holt, C. A. and Laury, S. K. (2002). Risk Aversion and Incentive Effects. *American economic review*, 92(5):1644–1655.

Huang, W.-J. (2005). An Asian Perspective on Relationship and Marriage Education. *Family process*, 44(2):161–173.

Imas, A. (2014). Working for the "Warm Glow": On the Benefits and Limits of Prosocial Incentives. *Journal of Public Economics*, 114:14–18.

Jeffrey, S. (2004). The Benefits of Tangible Non-Monetary Incentives.

Jepsen, C., Troske, K., and Coomes, P. (2014). The Labor-Market Returns to Community College Degrees, Diplomas, and Certificates. *Journal of Labor Economics*, 32(1):95–121.

Jones, G. W. (2010). Changing Marriage Patterns in Asia. *Asia Research Institute. Working Paper Series No. 131*.

Kaas, L. and Manger, C. (2012). Ethnic Discrimination in Germany's Labour Market: a Field Experiment. *German economic review*, 13(1):1–20.

Kahnemann, D. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47:263–292.

Kline, P. and Walters, C. (2019). Audits as Evidence: Experiments, Ensembles, and Enforcement. *arXiv preprint arXiv:1907.06622*.

Kong, S. T. et al. (2010). Rural – Urban Migration in China: Survey Design and Implementation. *Chapters in Xin Meng, Chris Manning, Li Shi and Tadjuddin Noer Effendi: "The Great Migration: Rural-Urban Migration in China and Indonesia"*.

Kosfeld, M. and Neckermann, S. (2011). Getting More Work for Nothing? Symbolic Awards and Worker Performance. *American Economic Journal: Microeconomics*, 3(3):86–99.

Kroft, K., Lange, F., and Notowidigdo, M. J. (2013). Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment. *The Quarterly Journal of Economics*, 128(3):1123–1167.

Kuhn, P. J. (2014). The Internet as a Labor Market Matchmaker. How Effective are Online Methods of Worker Recruitment and Job Search? *URL: https://wol.iza.org/uploads/articles/18/pdfs/internet-as-a-labor-market-matchmaker.pdf*.

Lazear, E. P., Malmendier, U., and Weber, R. (2012). Sorting in Experiments with Application to Aocial Preferences. *American Economic Journal: Applied Economics*, 4(1):136–163.

Lee, J. S. and Keil, M. (2018). The Effects of Relative and Criticism-Based Performance Appraisals on Task-Level Escalation in an IT project: A Laboratory Experiment. *European Journal of Information Systems*, 27(5):551–569.

Li, X. (2016). China's Marriage Rate is Plummeting – and it's because of Gender Inequality.

LinkedIn (2019a). Emerging Jobs Report. Technical report, LinkedIn Talent Solutions.

LinkedIn (2019b). Gender Insights Report.

LinkedIn (2020). LinkedIn Economic Graph. Workforce Report. United States. May 2020. Technical report, LinkedIn Talent Solutions.

List, J. A., Sadoff, S., and Wagner, M. (2011). So You Want to Run an Experiment, Now What? Some Simple Rules of Thumb for Optimal Experimental Design. *Experimental Economics*, 14(4):439–457.

McKinsey&Company (2016). The Age of Analytics: Competing in a Data-driven World. Technical report.

Meier, S. (2007). *A Survey of Economic Theories and Field Evidence on Pro-social Behavior*. Mit Press.

Méndez, F. and Sepúlveda, F. (2012). The Cyclicality of Skill Acquisition: Evidence from Panel Data. *American Economic Journal: Macroeconomics*, 4(3):128–152.

Munshi, K. and Rosenzweig, M. (2009). Why is Mobility in India So Low? Social Insurance, Inequality, and Growth. Technical report, National Bureau of Economic Research.

NBS (2020). National Bureau of Statistics of China.

Neumark, D. (2012). Detecting Discrimination in Audit and Correspondence Studies. *Journal of Human Resources*, 47(4):1128–1157.

Niss, M. and Højgaard, T. (2019). Mathematical Competencies Revisited. *Educational Studies in Mathematics*, 102(1):9–28.

NSF (2023). National Science Foundetion. Diversity and STEM: Women, Minorities, and Persons with Disabilities.

Nunley, J. M., Pugh, A., Romero, N., and Seals Jr, R. A. (2016). College Major, Internship Experience, and Employment Opportunities: Estimates from a Résumé Audit. *Labour Economics*, 38:37–46.

OECD (2019). *PISA 2018 Assessment and Analytical Framework*.

Piopiunik, M., Schwerdt, G., Simon, L., and Woessmann, L. (2020). Skills, Signals, and Employability: An Experimental Investigation. *European Economic Review*, 123:103374.

PWC (2020). What's Next for the Data Science and Analytics Job Market?

Ransbotham, S., Kiron, D., and Prentice, P. K. (2015). The Talent Dividend: Analytics Talent is Driving Competitive Advantage at Data-oriented Companies. Technical report.

Reich, J. and Ruipérez-Valiente, J. A. (2019). The MOOC Pivot. *Science*, 363(6423):130–131.

Riley, N. E. (1994). Interwoven Lives: Parents, Marriage, and Guanxi in China. *Journal of Marriage and the Family*, pages 791–803.

Riskin, C. and Li, S. (2001). Chinese Rural Poverty Inside and Outside the Poor Regions. *China's Retreat from Equality, Income Distribution and Economic Transition*.

Rooth, D.-O. (2014). Correspondence Testing Studies. *IZA World of Labor*.

Rubio, G. (2013). The Love Revolution: Decline in Arranged Marriages in Asia, the Middle East and Sub-Saharan Africa. *Mimeo*.

Rubio, G. (2014). How Love Conquered Marriage: Theory and Evidence on the Disappearance of Arranged Marriages.

Rubio, G. (2017). The Mating Game: (Potential) Intergenerational Conflict on Marital Arrangements. *A part of the job market paper "How love conquered marriage: Theory and Evidence on the Disappearance of Arranged Marriages."*.

Sarkar, S. (2021). Local Crime and Early Marriage: Evidence from India. Technical report, WIDER Working Paper.

SC (2017). Ministry of Civil Affairs of the People's Republic of China.

Schoenfeld, A. H. (1992). Learning to Think Mathematically: Problem Solving, Metacognition, and Sense Making in Mathematics. eds. D. A. Grouws. In *Handbook of research on mathematics teaching and learning: A project of the National Council of Teachers of Mathematics*, pages 334–370. Macmillan Publishing Co, Inc.

Schwartz, D., Keenan, E. A., Imas, A., and Gneezy, A. (2021). Opting-in to Prosocial Incentives. *Organizational Behavior and Human Decision Processes*, 163:132–141.

Siemens, G. (2013). Massive Open Online Courses: Innovation in Education?" eds. Commonwealth of Learning. *Perspectives on Open and Distance Learning: Open Educational Resources, Innovation, Research and Practice*, page 5.

Sinclair, T. (2020). The Role of AI in Hiring and Workforce Development at the AAAS Human Impacts of AI Symposium.

Singh, S. and Samara, R. (1996). Early Marriage among Women in Developing Countries. *International family planning perspectives*, pages 148–175.

Sorauren, I. F. (2000). Non-monetary Incentives: Do People Work Only for Money? *Business Ethics Quarterly*, pages 925–944.

Spence, M. (1973). Job Market Signaling. In *The Quarterly Journal of Economics*, volume 87, pages 355–374.

SSA (2020). Social Security Administration: Popular Baby Names.

Stone, K. V. (2004). *From Widgets to Digits: Employment Regulation for the Changing Workplace*. Cambridge University Press.

Swan, R. H., Plummer, K. J., and West, R. E. (2020). Toward Functional Expertise through Formal Education: Identifying an Opportunity for Higher Education. *Educational Technology Research and Development*, 68(5):2551–2568.

Tonin, M. and Vlassopoulos, M. (2015). Corporate Philanthropy and Productivity: Evidence from an Online Real Effort Experiment. *Management Science*, 61(8):1795–1811.

UNICEF (2005). Early Marriage: A Harmful Traditional Practice. Technical report.

UNICEF (2014). Ending Child Marriage: Progress and prospects. Technical report.

Vogl, T. (2012). Marriage Institutions and Siblings Competition: Evidence from South Asia. *National Bureau of Economic Research. Working Paper 18319*.

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. *Available at SSRN 3482150*.

WorldSkills (2023). *WorldSkills: About Us*.

Xiaohe, X. and Whyte, M. K. (1990). Love Matches and Arranged Marriages: A Chinese Replication. *Journal of Marriage and the Family*, pages 709–722.

Zang, X. (2008). Gender and Ethnic Variation in Arranged Marriages in a Chinese City. *Journal of Family Issues*, 29(5):615–638.