STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Master's thesis in Economics
Academic year 2015-2016

Participation in the Digital Transformation: The Case of Women and IT Majors in Sweden

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Abstract

Even in a country of high gender equality like Sweden, women are to a lesser extent taking part in the shaping of society. They neither hold leading positions to the same extent as men, nor are they well-represented in key industries. Much of this considerable power gap between the sexes can be attributed to occupational choice. With the purpose of evaluating policies that could change this, we examine the choice of college major, focusing on IT education. We conduct an information experiment on approximately 800 Swedish high school students, where respondents are divided into three different groups and treated with information on IT. Only younger female students respond to an affirmative action policy suggesting that they will not need to repay their student loans after IT studies, but not to an extent that would increase the share of women in the sector noticeably. In contrast, an information campaign on the employability of IT graduates only has positive effects on certain sub-samples of male students. A low degree of baseline interest in IT, and a lack of belief in their IT abilities is prevalent among the women. Thus, short-term interventions aimed at quickly increasing the share of women will not be effective until attitudes are altered and self-confidence is increased.

Keywords: college major, labor supply, gender equality, public policy, information experiment, affirmative action
JEL: J24, I24, I28, D03

Supervisor: Chloé Le Coq
Date submitted: May 23, 2016
Date examined: June 2, 2016
Discussants: Robin Ringkvist & Karin Örbom
Examiner: Martina Björkman-Nyqvist

Acknowledgments

First of all, we would like to thank the participating teachers and students without whom this thesis would never have been possible. We would further like to thank our supervisor, Chloé Le Coq, and those who offered guidance along the way: Magnus Johannesson, Erik Lindqvist, Juanna Joensen and Roman Bobilev. Infinite gratitude goes to our friends and family for always being available for discussion. A special thanks to Edmund Bennett and Clara Schultz.

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1 Introduction

Sweden is generally known to be a country with a high level of gender equality.[1] Yet, a quick look at some statistics reveals the following: women make up 20% of listed companies' management groups and only hold 6% of CEO positions (Lundeteg et al., 2016). These figures are surprising considering that Sweden has had more women than men pursue academic degrees since 1977 (UKÄ, 2015). In fact, 64% of those who earned a tertiary degree in 2014 were female (UKÄ, 2015). Furthermore, women in Sweden continue to outperform their male counterparts during all years of compulsory and secondary schooling in terms of grades (Skolverket, 2015). Given all this, it seems that the power gap between the sexes should be rapidly diminishing. Why, then, are women still lagging behind?

Before attempting to answer such a question, it is important to note that the conditions listed above are not unique to Sweden. OECD statistics show that only 6% of managers are female (OECD, 2015). Fortune 500 companies in 2015 reached an all-time high number of female CEOs: 24 (Swanson, 2015). This amounts to just under 5% of the largest U.S. corporations having female leaders.

One of the most cited explanations for the power and wage gap between the genders is occupational choice (Albrecht et al., 2003; Eide, 1994; Machin & Puhani, 2003). Men and women select into different fields of study and accompanied careers that lead to large gaps later in life. Occupational gender differences are persistent across all countries, and there is even evidence that they are larger in Sweden than in the US and non-Scandinavian Europe (Dolado et al., 2003). Looking at the choices men and women in Sweden make, the two most popular university programs among women are nurse and preschool teacher, compared to engineering among men (Statistics Sweden, 2015).

One may ask, however, if this even matters. Individuals are free to choose whichever field of education and job they prefer. Under these circumstances, we would expect men and women to optimize by selecting into the profession for which they have the highest skills and potential. However, research has established that abilities play little role in explaining gender differences in the choice of college major. Instead, preferences seem to be what lead men and women down vastly different college major paths (Dickson, 2010; Gemici & Wiswall, 2014; Turner & Bowen, 1999; Wiswall & Zafar, 2015). This implies that entire sectors miss out on skilled labor that is self-selecting into other occupations not because of lack of ability, but because of robust gender differences in preferences. For companies looking to hire, this poses a restriction. Instead of having all of the most able candidates to choose from, the choice is limited to only one side of the gender spectrum; an issue both for male and female dominated sectors. This brings with it hindrances to economic development, as research has shown that diversity and female representation in top management improves performance and leads to better decision making (Campbell & Mínguez-Vera, 2008; Dezsö & Ross, 2012; Erhardt et al., 2003). Having a diversity of both genders represented in all fields is, therefore, socially optimal.

Regardless of whether one personally views the power gap as a societal problem, politicians do. And as politicians tend to fund their policies with tax money, the issue concerns everyone; implementing ineffective interventions can be very costly to society. A widely debated and common way for policy makers to try to increase diversity is through affirmative action. This

[1] The United Nations Development Programme (UNDP) ranks Sweden sixth in the world in terms of gender equality (UNDP, 2014).

can take many forms, one of which is the introduction of quotas to increase the presence of the underrepresented group. It is, however, not only politicians who define increased workplace diversity as an objective; employers, for example in the IT industry, have expressed a need for it as well (IT&Telekomföretagen, 2015).

The IT sector poses an especially interesting case. We are currently living in what is referred to as the Digital Age, during which a wide array of new products and services are constantly emerging, along with shifts to digitalized processes in traditional industries. Not surprisingly, 42% of the productivity growth in Sweden during 2007-2011 stemmed from the ICT sector (IT&Telekomföretagen, 2015). However, only 23% of those who are pursuing an IT major at Swedish colleges are female (SOU 2015:91), and this share is projected to decrease in the future (Statistics Sweden, 2014). Thus, women today are to a lesser extent taking part in shaping society, as the sector creating most innovations is dominated by men. When women lack influential power both in terms of managerial positions and in terms of innovation, they are ultimately not in a position to take part in shaping what the world will look like tomorrow.

Along with the rapid digital developments, the need for skilled IT workers is constantly growing. Sweden alone is projected to have a shortage of 60,000 IT professionals in 2020 (IT&Telekomföretagen, 2015). In order to develop a strategy on how to meet the demands the digitalization era is putting on the country, the Swedish government appointed a commission of experts in 2012: the Digitalization Commission *(Digitaliseringskommissionen)*. One of the proposed policy measures it put forward to the government in December 2015 suggests that females who choose to study IT at university will not have to repay their student loans. The estimated cost of the proposal is between MSEK 208 and MSEK 1044 (USD 25-126 million) (SOU 2015:91). Before implementing an expensive intervention of this magnitude, it is imperative to evaluate its consequences and effectiveness.

The purpose of this thesis is to investigate one possible approach to increasing the share of females in influential positions in society–namely to make women select into key professions by choosing an associated college major. We focus on the IT industry for two main reasons; first, the industry exhibits a sharp under-representation of the female gender. Second, it is one of the key industries in the modern economy with a high level of growth, innovation rate and influence. We test whether two alternative policy measures would be successful at increasing the share of female applicants to IT majors, the first of which relates directly to the suggestion by the Digitalization Commission. The second intervention focuses on the job security associated with IT majors. That is, getting employed is not a difficult task for an IT graduate. Research has shown that female students are more concerned about job security than are male students (Belzil & Leonardi, 2007; Reuben et al., 2015), and that females are less concerned with the pecuniary outcomes of their college major choice than are men (Marini et al., 1996; Morgan et al., 2001; Reuben et al., 2015; Wiswall & Zafar, 2015). This implies that money may not be the most efficient way to influence women, as they could be more responsive to job security.

In surveying 793 senior high school students, we conduct an information experiment where we test the two policies on those whom they would be targeted at if implemented. These students are close in time to making their choice of college major and will graduate from university around the year of 2020. The Swedish government has explicitly expressed the goal of increasing the share of women in IT by 2020 (Näringsdepartementet, 2010). In our experiment, one treatment group is given information on the free student loan for women, and another is given information on the high demand for IT graduates.

By testing a form of affirmative action targeted at women, and, alternatively, an informational campaign regarding the employability of IT professionals, we estimate the potential effects on young women in Sweden today. Adding to the complexity of attracting students to IT is the fact that Sweden faces an overall shortage of professionals in the field. Ideally, female students should be attracted through measures that do not demotivate male students from also applying. In order to additionally evaluate the effect of the policies on men, the sample of students surveyed includes both males and females. Our findings have the potential to enable policy makers to make well-informed, evidence-based decisions regarding how to meet the demand for IT professionals, and how to increase the share of women in the field. Doing so would be one important step in ensuring that women and men have equal opportunities to participate in the shaping of society.

The remainder of this thesis is organized as follows: Section 2, Background, reviews the relevant literature, provides an overview of the education system in Sweden, and presents our research question. The next Section, 3 Analytical Framework, develops a model for analyzing the choice of college major. Section 4, Method, outlines how the research question will be approached. Next, Section 5 details our Empirical Strategy, including the survey procedure. Section 6 presents the Data, followed by the empirical Results in Section 7. Finally, Sections 8 and 9 provide Discussion and Conclusions.

2 Background

To evaluate interventions aimed at increasing the share of women in IT, we first consider the existing research on affirmative action. Furthermore, there is a vast body of literature on college major choice and behavioral differences between the sexes, which helps us hypothesize how a student's choice can be affected. Finally, before presenting our research question, understanding the context in which the interventions would be implemented requires some basic background on the Swedish education system.

2.1 Previous Research

2.1.1 Affirmative Action

The implementation of affirmative action to counter imbalances in the education and job market has historically provoked debate. An example of an often recurring topic in Sweden is that of quotas for company board compositions (see, for example, Elias, 2015; Silva, 2013; Sundkvist, 2013). While currently not implemented in Sweden, neighboring country Norway has since 2008 required that publicly listed company boards have at least 40% of either sex represented. Evaluation of the law in Norway has been mixed, with findings indicating that only representation of female employees at the very top of the earnings distribution has improved, with limited to no trickle-down effects (Bertrand et al., 2014; Seierstad & Opsahl, 2011).

Nevertheless, research on the effects of affirmative action has yielded some positive results as well. Quotas have been found to be an efficient manner to increase female entry into competition (Balafoutas & Sutter, 2012; Niederle et al., 2013). When assessing equal opportunity laws in a tournament setting,[2] Schotter and Weigelt (1992) find that such laws increase the effort level of all subjects, which increases output and profits. However, the effects depend on the severity of a group's cost disadvantage; only where the disadvantage is severe do programs significantly increase effort levels.

Opinions on affirmative action are often mixed. There may be a stigma of incompetence associated with such policies, as shown in a study by Heilman et al. (1997). Subjects in the study rated female affirmative action hires as less competent and suggested smaller salary raises for this group. How the affirmative action policies are framed has also proven to be of importance for attitudes (Fine, 1992; Jordan-Zachery & Seltzer, 2012). Kravitz and Platania (1993) find that women evaluate affirmative action programs more positively than men, even when the program is not directed at women. In a study on college students, Heilman et al. (1996) show that preferential selection can produce negative reactions among the non-beneficiaries, even if these reactions are not always uniform. Kinder and Sanders (1990) find that whites strongly oppose affirmative action both in the workplace and in college admissions, irrespective of how it is framed. However, the strongest opposition is seen when the action is framed as "reverse discrimination."

Having a closer look at affirmative action for college admissions, Arcidiacono (2005) shows that removing financial aid for blacks attending college in the US would have a very small

[2]The tournament setting here implies that the agent's payoff depends on the rank of their performance relative to others in the tournament.

effect on the expected earnings of black men. This is largely due to the individuals at the margin of attending being those with the lowest treatment effect of college attendance. Furthermore, Card and Krueger (2005) use SAT scores to evaluate if the elimination of affirmative action in California and Texas led to changes in students' SAT-sending behavior to colleges.[3] They find no change in behavior for highly qualified black and Hispanic students, only in relatively less qualified students, who reduce their sending behavior. Looking instead at the elimination of affirmative action in Washington state, Brown and Hirschman (2006) find that the proportion of minority high school seniors who went on to college decreased temporarily after the elimination. The decrease stemmed primarily from declines in application rates, rather than admission rates. This indicates that affirmative action programs may play a role in signaling a welcoming environment to minority students and, thus, impact their application decision.

2.1.2 College Major Choice

The literature on college major choice is extensive and the analytical and empirical approaches to explaining the differences between men and women in this regard have developed over time. Paglin and Rufolo (1990) reason that individuals self-select into occupations (and thus, majors) in which they would have a comparative advantage. Using measures of SAT scores and high school GPA, they conclude that men have a higher endowment of quantitative skills, and that they are premiered for this scarce resource in the labor market. Similarly, Arcidiacono (2004) finds that mathematics abilities are rewarded in the labor market as individuals with these abilities sort into lucrative majors. However, he also concludes that the earnings differences between majors remain even after controlling for ability sorting. Instead, he finds that the ability sorting is primarily related to preferences for particular majors, and also, but to a lesser extent, the preferences for the workplace. In addition, Gemici and Wiswall (2014) find that differing tastes, and not abilities, are the most important in explaining uneven gender distributions across majors, and Turner and Bowen (1999), and Dickson (2010) find a persistent gender gap in major choice even after controlling for SAT scores. Finally, Weinberger (2004) concludes that females with high SAT scores are no less likely than other females to state that an IT major would be too time consuming or difficult.

Ruling out skills and pre-collegiate performance as main drivers of the gendered major choices, researchers have paid a lot of attention to differences in tastes for majors and certain characteristics of the majors. Modeling such aspects of the college major choice has, however, proven quite challenging. In particular, the actual choice of major a student has made may bias them to think that their abilities, earnings and job prospects are better in that particular major, as opposed to in counterfactual majors. Thus, it becomes problematic to distinguish between a student's preferences and the relative importance of different college major characteristics. Analyzing data on college major choices already made would require invoking assumptions regarding students' expectations in their chosen as well as other majors. For example, Montmarquette et al. (2002) assume that the students' earnings expectations are always realized when showing that earnings are an important factor in the choice, but less so for females than for males. Also assuming rational expectations, and assuming a normal distribution of tastes, Beffy et al. (2012) find that earnings have a significant but small impact. Moreover, Arcidiacono (2004) assumes an extreme value distribution of tastes.

[3] Both Texas and California have high SAT participation rates and both states require SAT scores for admission to public colleges and universities. Test-takers list a number of schools to receive their SAT scores, and while this is not the same as actually applying to the school, the correlation between the two is strong.

Since data on observed major choices may have been the result of several combinations of expectations and preferences, making an assumption such as the expectation forming process being rational and homogeneous for all students may lead to incorrect conclusions (Manski, 2004; Wiswall & Zafar, 2015). Indeed, Wiswall and Zafar (2015) find that invoking such assumptions biases the ability estimate upward. A way of circumventing the issue of invalid assumptions regarding students' expectations is to incorporate reported subjective expectations into models depicting the decision making process (see, for example, Arcidiacono et al., 2012; Stinebrickner & Stinebrickner, 2011; Zafar, 2013). This implies analyzing expectations among individuals who are yet to make their choice, instead of those who have already selected into a major.

Nevertheless, with such an approach, it would still not be possible to separately identify the preference for a major from other factors, such as earnings and ability for the major, without making further assumptions. Wiswall and Zafar (2015) avoid making such assumptions by using experimental variation in the students' beliefs; first, the students report their beliefs regarding their earnings and other major-specific outcomes. Second, they obtain information on the population distribution, and re-state the beliefs about themselves. The authors find that the students update their self-beliefs after accessing correct information. Moreover, Arcidiacono et al. (2012) model that 7.5% of their sample of male Duke students would switch majors, had they been correctly informed regarding future earnings. These findings imply that access to and variation in information should be considered when estimating the decision making process.

Numerous researchers have dug deeper into the relative importance of different work values, or different weights put on characteristics of majors and their associated occupations, and how these vary by gender. Wiswall and Zafar (2015) find that earnings differences across majors are less important and ability differences more important to women than to men, but that tastes are the main driver of the choice for both sexes. Eccles et al. (1999) find that females put more weight on helping others and doing something worthwhile for society at work. For the males, on the other hand, fame, earning a lot of money, having challenging tasks, and using mathematics and computers is more important. Moreover, Marini et al. (1996) show that women place more value on intrinsic, social and altruistic rewards, and Morgan et al. (2001) find that women report more interpersonal work goals and less status work goals than men. Physical or mathematical science careers were viewed as less likely to afford interpersonal goals and more likely to afford high pay and status goals. In the Swedish context, Dunér (1972) finds that for both sexes, being interested in the occupation is especially important. However, status, earnings, and having the power to make decisions is more important for boys, whereas girls view varying tasks and working with people more important.

2.1.3 Behavioral Gender Differences

Turning to cognitive and behavioral differences, preferences for risk and competition may have an impact on the choice of college major. Research has established robust differences between the genders when it comes to risk preferences (Byrnes et al., 1999; Croson & Gneezy, 2009; Eckel & Grossman, 2002, 2008), and women have been shown to be more risk averse both in lab settings and in field decisions on investments (Croson & Gneezy, 2009). Differences in risk aversion further translate into preferences for types of employment and job security. More specifically, studies have found that a higher level of risk aversion is associated with selection into public sector employment (Bellante & Link, 1981; Pfeifer, 2011), since workers feel the most secure in permanent public sector jobs (Clark & Postel-Vinay, 2009). Women have also been shown to be more sensitive to cyclical shifts in the economy, as more women apply to higher education during recessions (Andersson & Hagsten, 2010). A study by Sapienza et al. (2009) illuminates the connection to testosterone, showing that individuals high in testosterone and low in risk aversion are more likely to choose risky careers in finance.

Gender differences in competitiveness could play a crucial role if certain college majors, and their associated careers, are perceived as being more competitive. Previous research in the field has found that men and women respond differently to competitive environments, leading to women being under-represented in high profile jobs (Niederle & Vesterlund, 2007). Buser et al. (2014) find that males are more likely to choose prestigious paths. When controlling for differences in competitiveness, most of the gender differences disappear. Moreover, women have been shown to dislike competitive environments and perform less well when competing against men (Gneezy et al., 2003). There is also evidence that women shy away from competition only in the male stereotypical (mathematical) task, and that they shy away from competing against men but not against other women in a single-sex setting (Große & Riener, 2010). Beyond being less inclined toward competition, females may also exhibit lower confidence in their skills, irrespective of actual ability (Beyer, 1990; Buser et al., 2014). Further research has found that females are less likely to study and pursue careers linked to mathematics and physical science, as a result of them being less confident in their mathematics and physical science abilities (Cunningham et al., 2006; Eccles, 2011).

When considering college major choices related to STEM (Science, Technology, Engineering, and Mathematics), it is crucial to understand the stereotypes associated with these particular fields. The presence of strong stereotypes may encourage certain applicants while deterring others (Cunningham et al., 2006). Weinberger (2004) finds that classroom and workplace climate appear to be important factors for women who avoid IT majors. Other factors of relevance for both sexes include IT not being interesting, too difficult, or too time consuming. Furthermore, classroom stereotypes have been found to deter women from enrolling in computer science courses even when their gender is well represented (Master et al., 2016). When trying to encourage female applicants with role models, female role models have been no more effective than male role models at increasing women's beliefs about their potential success in STEM fields. Instead, the deciding factor appears to be how much the role model embodies STEM stereotypes, where stereotype embodiment negatively impacts females (Cheryan et al., 2011).

When it comes to parental role models, Dryler (1998b) finds that both boys and girls are more likely to choose a specific Swedish senior high school program if their parents pursued it, or if it is related to their parents' occupation. Same-sex stereotyping is not likely to be an important driver behind gendered choices, as children are affected by both parents. Moreover, the author finds that both boys and girls were more likely to choose a field of study dominated by the opposite sex if their parents were highly educated. Analyzing over time and across cohorts how Swedish children have identified with their parents, in terms of which one they want to be most alike, Bengtsson (2001) finds that Swedish children identify increasingly less with their parents, and that the identification remaining is not exclusively related to the parent with the same sex. Nonetheless, in a Swedish survey conducted in 2015, females who had parents working in IT reported twice as high willingness to try out a related profession compared to other females (Insight Intelligence, 2015).

In the same Swedish survey, 36% of women aged 16-30 not active in IT reported that they would be willing to consider such a career. Young women aged 16-20, and especially young women in the Stockholm region, were somewhat more interested in the field compared to the rest of the sample. The most cited reason for why the women did not find IT appealing was that it did not match with their personality, reported by 51% of the women. Furthermore, 28% did not find it interesting enough and 21% said they would not be comfortable in such a male-dominated environment. Whether they viewed themselves skilled at it was not an available option in the survey. However, the women thought that technical abilities, problem solving skills, patience, and independence were the most important characteristics of a successful IT professional. Especially the first two, technical and problem solving skills, few women associated themselves with (Insight Intelligence, 2015).

One may note that the literature related to gender and schooling in Sweden is quite limited. As interesting as the aforementioned survey carried out in 2015 may be, the reported statistics are not further analyzed. Thus, no conclusions regarding causations can be drawn. The few academic studies available were mainly carried out by sociologists prior to the 2000's (Dryler, 1998a,b; Dunér, 1972). Hence, there is a need for updated research on the topic that tests whether findings from other countries have bearing in Sweden too. Furthermore, there is a need for analyzing how the choice of major can be affected, as opposed to merely mapping underlying causes of it, which has been the main focus of previous literature. We aim to fill this void by evaluating ways policymakers can increase the share of women in influential and powerful positions in society.

2.2 The Swedish Education System

In Sweden, senior high school, or upper secondary school, is called *gymnasium*, and constitutes the final three years in school. That is, the tenth through twelfth year of schooling. It is not mandatory, but in principle all ninth graders choose to proceed to *gymnasium* (Skolverket, 2016b). The students attend one of 18 different educational programs, of which six programs prepare them for higher studies at the university. The other programs are vocational. For more details on the different programs, see Appendix A.1. The six academically oriented programs contain a common set of core courses, as well as courses specific to each program. Students from the Natural Science Programme and the Technology Programme are eligible to apply for virtually all existing IT majors (Utbildningsinfo, 2016a).

Admission to *gymnasium* is based on the student's ninth grade GPA. Students can apply to any *gymnasium* in their municipality, and some schools also accept applicants from neighboring municipalities or from anywhere in the country. Thus, students need not study in the same district as they live. Since students enroll in a program, they belong to one specific class of students, with a typical size of 25-32 students. However, some courses, such as foreign languages, may be taught in groups consisting of students from several classes.

At the start of the academic year of 2015-2016, there were about 66,000 Swedish senior high school students enrolled in either the natural science or the technology program, in all grades. 24% of these attended private schools, and the rest attended public schools, which are run by the municipalities. 53% of the natural science students and 16% of the technology students were female (Skolverket, 2016b). Today, all Swedish high school students are provided with a computer by their schools (Skolverket, 2016a).

Having attended one of the non-vocational high school programs, the students are eligible to attend higher studies. There are two types of colleges in Sweden; *universitet* and *högskola*. Nowdays, there are no general differences between the two regarding type of education, achievable academic degrees, teaching styles, or reputation. For this reason, the terms *university* and *college* are used interchangeably in this thesis. Students are able to choose from a wide range of programs at the university level, the majority of which make up a three-year Bachelor's degree (180 ECTS), or a full five-year Bachelor's and Master's degree combined (300 ECTS). In addition, it is possible to enroll in independent courses without formally pursuing a degree. Note that the typical student chooses their major by choosing a program and makes this decision before enrolling at a specific university. In general, it is not possible for an undergraduate to be admitted to a school and choose major after enrollment. The two main ways in which students compete to get admitted to undergraduate studies are their senior high school GPA and the University Test, *Högskoleprovet*. The University Test is a voluntary one-day exam divided into two main parts: a quantitative part, and a verbal part consisting of four tests each. A more detailed overview of the college application process is provided in Appendix A.1.

No tuition fees are charged for EU citizens attending college in Sweden, and financial student aid is provided to Swedish citizens by the authority *Centrala Studiestödsnämnden* (CSN), the Central Council for Student Aid. The student aid consists of grants as well as loans, and the repayment of the loan begins after graduation. The weekly maximum amount of aid is SEK 2,476 (USD 304), of which SEK 704 (USD 86) is a grant and SEK 1,772 (USD 218) a loan. Student aid can be granted for a maximum of 240 weeks, or 12 semesters of full time study, in total (CSN, 2015).

2.3 Research Question

An important step in ensuring a sufficient and diverse labor supply of IT specialists is to increase the interest among young females in these types of majors. As politicians are considering affirmative action, it is time for research to catch up. In this thesis, we examine the choice of college major, focusing on IT education. However, in contrast to previous literature on the topic, we are primarily interested in evaluating how the choice can be influenced through policy. To our knowledge, this has not been done by other researchers. If the interventions we test prove efficient, they have the potential to serve as a step in securing equal opportunities for men and women to take on key roles in society.

The two potential policies subject to evaluation in this thesis are a monetary intervention where information is provided on a proposal that women do not have to repay their student loans, and an intervention relating to information on job security. Evaluating the effectiveness of policies under consideration is crucial to allow socially optimal actions to be put in place. By contrast, implementing policies that will have no effect is costly and may spur anger and distrust among the public.

Thus, the research question of this thesis is the following:

How can female students be encouraged to apply for an IT major?

In Sweden today, we see a sharp under-representation of women in higher IT education. This is the motivation for the proposal by the Digitalization Commission; to allow women to avoid repaying their student loans after having completed a Bachelor's degree in IT (SOU 2015:91). We use this proposal as our first incentive. By treating students with information on it, we estimate the response of both genders by measuring their stated probabilities of applying to an IT program at university.

In addition to the information treatment of not repaying student loans, we also appeal to the gender differences in risk aversion found in the literature. Since previous findings indicate that the monetary aspects of the choice of higher education are not the most important factor for women (Eccles, 2011; Marini et al., 1996; Morgan et al., 2001; Reuben et al., 2015; Wiswall & Zafar, 2015), they may respond more strongly to a treatment giving information on the ease with which they can find employment post-graduation. This leads us to our first hypothesis:

Hypothesis I. *For female students, the effect of the job security treatment will be stronger than the effect of the student loan treatment on their probability of applying for an IT major.*

Moreover, if women are more risk averse than men (Croson & Gneezy, 2009; Eckel & Grossman, 2002), they may exhibit a stronger treatment effect than men when given information on the ease with which they will find employment post-graduation. Our second hypothesis is, therefore:

Hypothesis II. *Female students will be more affected by the job security treatment than the male students.*

Finally, we want to estimate how men will respond to the proposal of student loan repayment for women. If they feel discriminated against as a result of the gender-based treatment, they may lower their probability of applying to IT majors. This would, in turn, make the proposal even more efficient at raising the proportion of female students, although not in the way the Digitalization Commission may have intended. On the contrary, this potential consequence would be quite unfortunate given the overall lack of labor supply in the IT sector, which would not be able to afford losing any future professionals, irrespective of their gender. This potential effect is tested through our third hypothesis:

Hypothesis III. *Motivating female students through the affirmative action proposal will come at the cost of male students reducing their probability of pursuing an IT major.*

Thus, the focus of our research is to analyze the effectiveness of the two treatments on women, and, additionally, the potential consequences for men. The outcome variable of interest is a stated probability of applying to an IT major, which we compare across treatments and genders. If we, for example, find support for *Hypothesis I*, we can conclude that it would be far more cost effective to implement the treatment relating to job security. Alternatively, we may find that none of the treatments have an effect.

3 Analytical Framework

In the economic literature, Random Utility Models (RUMs) have traditionally been applied to analyze discrete choices already made, where a seminal paper by McFadden (1974) on consumer decisions was the starting point. The latent variable underlying the decision outcome is the utility from making that particular decision. Over time, the literature has evolved to also use RUMs for modeling choices that are expected to be made in the future, and to predict choices in counterfactual choice settings (Walker & Ben-Akiva, 2002).

In the context of college major choice, the students as decision-makers act with partial information on the outcomes of the choice, and are assumed to form probabilistic expectations and maximize their expected utility (in line with Manski, 2004). The utility of a college major is assumed to be a function of individual and major-specific characteristics. The utility for student i choosing major j is expressed as:

$$U_{ij}(X_i, M_{ij}, \epsilon_{ij}) = \alpha_j X_i + \beta_{ij} M_{ij} + \epsilon_{ij} \tag{1}$$

The vector X_i represents the student's individual characteristics, and vector M_{ij} represents the major-specific factors that affect both the in-school utility while studying and the post-graduation utility of the associated career. These major-specific factors do not impact students uniformly, resulting in students estimating, for example, abilities and success in a given major differently. It is implicitly assumed that factors pertaining to outcomes realized a given time after initiation of college studies are discounted to a present value at the time of decision, which is reflected in the differing weights students put on the different components of the two vectors of characteristics. Any uncertainty about the outcome of the choice is captured in the error term ϵ_{ij}.

The RUM assumes utility maximization; hence, an IT major is chosen if the expected utility from studying IT exceeds the expected utility from all other schooling and non-schooling alternatives:

$$\begin{aligned} &\text{Student } i \text{ chooses major } j \text{ if and only if } U_{ij} \geq U_{ik} \text{ for all } k \in K_i, \\ &\qquad\qquad \text{where } K_i \text{ is the set of alternatives faced by student } i. \end{aligned} \tag{2}$$

Applying the model to an IT major, and viewing the outcome choice Y as binary–i.e., either the IT major is chosen or not–reduces the structural Equation (1) to a limited dependent variable:

$$Y = \begin{cases} 1 & \text{if } U_{i,IT}(X_i, M_{i,IT}, \epsilon_{i,IT}) \geq U_{ik}(X_i, M_{ik}, \epsilon_{ik}) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Deciding whether to study IT at university is in reality a discrete choice, but we allow the respondents of our survey to express uncertainty regarding the outcome by reporting probabilities as opposed to a definite yes or no. The main reason for this is that in the hypothetical scenario, i.e., the survey setting, students have less information than they would have in an actual choice setting. Thus, the students report the probability of ending up in the state where Equation (3) takes on the value $Y = 1$. Our focus is, therefore, on the effects of the two treatments on the probability of ending up in the $Y = 1$ state. The empirical estimation method used for evaluating RUMs depends on which assumptions are imposed on the error term ϵ_{ij}. Section 2.1.2 outlined assumptions made in previous research, and our approach will be presented in Section 5.6 Choice of Estimator.

4 Method

Research on the choice of college major aims to predict students' choice behavior. In this study, students' IT probabilities, and how they vary depending on two different treatments, are predicted. Our chosen method for evaluating students' IT probabilities is to conduct an information experiment by collecting survey data; however, other methods may also be fruitful. In the current section, we provide the reasoning behind our approach.

4.1 The Survey Instrument

While much of previous research has focused either on the use of observed choice data or the collection of probabilistic expectations data, there are other methods through which students' choices could be analyzed. We are interested in influencing reported choice probabilities for an IT major and attempt to do this through appealing to two specific factors that could impact the choice; money and risk. As such, a laboratory setting may have been a viable option to conducting a survey.

Our treatments relate to the importance of monetary aspects, and the previously found connection between job security and risk aversion. In other research, risk aversion and monetary incentives have been studied in experimental lab settings, and such a setup could map and highlight gender differences in our case too. Lab arrangements could, therefore, potentially be suited for analyzing these two specific components of the college major choice. What such an approach would miss, however, is the direct association to an IT major. It has already been documented that females place less value on monetary goals (Eccles, 2011; Marini et al., 1996; Morgan et al., 2001; Reuben et al., 2015; Wiswall & Zafar, 2015), and are more risk averse than males (Croson & Gneezy, 2009; Eckel & Grossman, 2002). However, without placing this in the context of IT, it is of little help in answering our research question of how to encourage more female applicants. Furthermore, being able to draw inference on two treatments requires a sufficiently large sample; gaining access to an adequately large pool of students implies requesting minimal time and effort from the approached teachers. The survey approach facilitates this.

The survey method has further appealing advantages. More specifically, we are able to physically oversee and control the data collection as we visit each of the surveyed classes and distribute the questionnaires in paper format. This allows for a sense of formality, and while it is not possible for us to directly observe the students' thinking, we can evaluate the atmosphere of the class and the level of seriousness applied to the survey. Later, when processing the data, we are also able to evaluate the face validity of the answers, which implies that each question measures what it intends to measure. We can do this by examining the degree to which a person gives internally consistent and sensible answers (Manski, 2004) (see Section 6.4). According to Manski (2004), studies largely possess face validity when questions concern well-defined events that are relevant to respondents' lives. We believe the choice of college major to be such a well-defined and relevant event for the students in question.

4.2 Expressing Expectations

As we have mentioned briefly already, previous research on students' choice behavior has largely been carried out in two distinct ways. The first method is called revealed preference analysis, which entails trying to map the decision making process behind choices already made. More recently, however, economists have turned to expected choice analysis, where data on students' probabilistic expectations is used to infer the most likely choice (Manski, 1999). In approaching high school students who have not yet made their choice of major, we use an expected choice analysis. The primary reason for this is that testing the effectiveness of the two treatments requires approaching the group that they will be directed at, would they be put in place. Moreover, there are compelling theoretical arguments in favor of expectations data put forward by researchers. For example, Manski (2004), Wiswall and Zafar (2015), and Van der Klaauw (2012) highlight that using observed choices requires imposing strong assumptions regarding the distribution of expectations for the chosen as well as counterfactual majors, such as assuming that the expectations are rational, an issue we outlined in Section 2.1.2. Collecting probabilistic expectations circumvents this issue entirely.

Further advantages of the probabilistic expectations approach can be found in the literature. More specifically, although the survey method entails that stated choices may differ from actual choices later made (largely a result of respondents being provided with less information than they would have in reality), a stated probability reflects this uncertainty, as opposed to yes or no responses (Blass et al., 2010). Moreover, unease about how well respondents would deal with reporting probabilities may be largely unfounded. For instance, Wallsten et al. (1993) report that virtually all of their respondents were willing to communicate their beliefs numerically, if the situation warranted it. In a study on birth control choice, Delavande (2008) found that the women surveyed used the whole scale of zero to 100 to answer open-ended questions on subjective probabilities.

Given the positive results implied by previous research using survey data to elicit choice probabilities, the method is well-suited for this study. Alternatively, rather than a binary $\{0, 1\}$ outcome or a probabilistic outcome on the [0,1] interval, a shorter scale of, say, 1-10 could have been used. However, for the purpose of measuring students' interest in IT, such a scale would be too crude. It would overstate the probability of the students very reluctant to IT, since all in the tenth percentile would choose 1 on such a scale. Furthermore, the scale would be unable to capture a small treatment effect, or it could, alternatively, overstate the treatment effect, due to its large increments. Ornstein (2013) points out that if respondents are expected to have highly differentiated views, which we expect among the surveyed students, a longer scale would be able to capture this. Furthermore, asking for probabilities allows us to more accurately estimate the overall interest in IT among high school students today, by examining the answers of the control group. Finally, when considering the use of probabilities, we recognize that our target group is second and third year senior high school students in the natural science and technology programs, both of which are mathematics intensive. The students surveyed are, therefore, expected to be comfortable with the concept of probabilities.

4.3 Consistency

In Section 2, we noted that Wiswall and Zafar (2015) find upward bias in ordinary least squares (OLS) estimates on the impact of the characteristics of a major on the choice of major, due to correlation of personal preferences and major characteristics, including the student's ability for that major. They separate preferences from characteristics by creating experimental variation in probabilities of pursuing a major, and in subjective expectations on major characteristics. This is done by asking the same student to give answers on the two matters both before and after receiving information on the population distribution of earnings and other major characteristics. Thus, a panel structure is created where separation in time is a matter of seconds. Comparing the relative changes in preferences (measured as the probability of pursuing the major) to changes in beliefs about major characteristics makes the authors conclude that preferences are the main component of the choice.

We are, however, somewhat skeptical of the approach of Wiswall and Zafar (2015). While it is an innovative way of dealing with the issue of the close link between preferences and characteristics (including abilities), we see other, quite serious sources of bias being enhanced when one person answers the same question twice. For example, issues such as hypothetical bias, where respondents behave differently in the survey compared to real life, and agree response bias, under which respondents answer positively to questions regardless of their content, could seriously hamper the results. More specifically, being presented with the earnings distribution for a college major one just stated one's preferences for may induce the students to change their stated preferences just because they feel they "should" do so, even if earnings are not particularly important to them. Alternatively, they may convince themselves that earnings are not an important factor for them, and refrain from changing their stated preferences. These types of bias and their potential presence under our chosen research design will be further elaborated upon in Section 6.4.

Our contribution to the literature is of a slightly different nature compared to that of Wiswall and Zafar (2015). Taking the abilities for a certain major in the population (and thus, also in the sample) as given, we test whether our sample would adjust their preferences in response to treatment enough to have implications for their probability of applying for an IT program. In theoretical terms, the treatment effects would be illustrated in a higher expected utility for the IT major. Although we take the abilities for the major of interest as given, the preferences we try to adjust will be correlated with the abilities. Complete separation of preferences and abilities in the same manner as Wiswall and Zafar (2015) would be too costly for us in terms of the other forms of bias that this approach could cause. A more suitable way of handling this remaining correlation in the setting of the current study is, therefore, to ask students to estimate their IT ability and thereafter control for it in the regression analyses. When holding stated abilities for IT constant, the potential remaining bias arising from the preference measures being infused by abilities should be much smaller than the bias from constructing a panel where the observations from the same unit are separated merely by seconds. The coefficient on the ability measure in a cross-sectional analysis should, however, be interpreted with caution due to the simultaneity issue. Ideally, we would like to obtain an objective measure of the students' IT abilities, for example through a test. When students estimate their abilities themselves, the matter may be more complex than suggested by previous research. We will discuss this in depth later on.

Not using the procedure of having the same student re-state their application probabilities for an IT major after exposure to treatment implies that a control group is required to create a counterfactual baseline scenario. The drawback of having another student as counterfactual is, of course, that they do not possess the exact same characteristics as the first student. It is hard to control for all such characteristics, and estimations would be prone to omitted variable bias. We deal with this issue by randomizing the students into treatment groups.

Through our information experiment, we test if either of the two different policies have the potential to nudge female students to apply for IT. We do so by attempting to influence their stated preferences for IT through interventions whose effects have the potential to be immediate. A priori, we expect such policies to only have the potential to adjust preferences, whereas long-term policies would be favorable to permanently shift the preferences *and* abilities (both self-perceived and actual) for a major, in which case separating abilities from preferences would be of greater importance in evaluation of the policies. Our focus lies on short-term interventions for two primary reasons; firstly, there is a need for policy to increase the supply of skilled professionals as soon as possible, and such policies are currently being discussed by politicians in Sweden. Secondly, these types of policies can more easily be estimated from a cross-section, whereas shifting abilities normally requires more time for both implementation and evaluation of the treatment, the effect of which may appear with some lag.

5 Empirical Strategy

After concluding that a survey is the most suitable option for the purpose of our research, the next step is to decide on its design. The complete list of survey questions can be found in Appendix A.3, along with corresponding English translations. In what follows, we present the designing process.

5.1 Sampling and Randomization

To answer the research question of how to encourage female students to apply for IT majors, the targeted students are those close in time to making their actual choice of college major. Survey data was collected on a sample of 793 Swedish senior high school students in their second and third year, equivalent to the eleventh and twelfth year of schooling. Since the third year students were at the time of the survey only a few months away from finishing high school, all students were surveyed prior to the last day of university application for the upcoming fall semester; April 15, 2016. Thus, applying for an IT major remained a hypothetical choice for all respondents, and our dataset consists of expectations data, not revealed choices.

Furthermore, only students actually eligible to apply for an IT major were targeted. This limits our sample to students in the natural science and technology programs. Since the data collection process was conducted and monitored by us in person, the respondents all study at senior high schools in the Stockholm area. The sampling procedure employed is commonly referred to as *cluster sampling*, and the generated data have a four-level hierarchical structure. First, schools were randomly sampled from a list filtered on the programs of interest. Second, individual teachers of the relevant programs were contacted. Third, the recruited classes within these programs were visited and the students within each class were randomized into one of three groups; *Treatment 1* of student loan repayment, *Treatment 2* of job security, and a *Control* group. Within-class randomization was achieved by distributing three versions of the questionnaire in paper format in each classroom. The three versions pertaining to the different treatments and the control group were randomly mixed in a pile and handed out by us in person. In other words, the two different treatment groups and the control group each contain respondents from all classes surveyed in this study. The result of our sampling procedure is a dataset with three levels of clusters: schools, programs and classes of students. Elements within a cluster are, in principle, always more similar than elements from different clusters (Ornstein, 2013). In spite of such similarities, randomization within each classroom should prevent bias arising from it. Our randomization proved efficient and is analyzed in detail in Section 7 Results.

Ideally, we would have liked to survey all students of all schools simultaneously. For practical reasons, however, this was not possible. Furthermore, in our sample, four of the schools were visited during more than one day since it was not possible to meet with all of the classes on the same day for scheduling reasons. The implication of us not being able to survey everyone at the same time is that students may have communicated with each other. A student in a class that has been surveyed may have discussed the survey with his or her peers in a non-surveyed class. This would imply that the un-surveyed student entered the survey setting with additional information. However, the most crucial parts of this would be captured by the survey itself, for example in an included control question, which checks for prior awareness of the free student loan proposal, a variable that will be explained more in detail and will be dealt with appropriately below. While we hope that students in the same school did not extensively discuss the survey with each other, this is not something we were able to prohibit, or observe.

During data collection, none of the students in the visited classes declined to answer the survey. Hence, selection bias on the student level is not present in our study. However, in the process of recruiting teachers, some declined to participate, and some did not answer their phone. It could, for instance, be the case that teachers of well-disciplined students were more likely to be willing to participate, or more likely to answer their phones in the first place, and disciplined students may respond more, or less, to the treatments than undisciplined ones. Important to note is that this type of teacher-level selection concerns participation in the survey as a whole, and that selection into treatments was not possible since students within each class were assigned randomly to the treatments. In general, estimation suffers from selection bias if selection into treatments is correlated with an omitted variable affecting outcomes. This implies that in the current study, selection poses a problem for the external validity of the results, rather than their internal validity. In other words, if teachers have selected into the survey in a way that makes participating classes vary systematically from nonparticipating ones, our results may not hold for the population as a whole. We cannot rule out that this is the case, but we note that generally, teachers who did pick up their phones were quite willing to have us visit them. If our sample is different due to teacher selection, the correct label for the phenomenon is exogenous sample selection. It is exogenous since sample selection is random, and, thus, OLS estimates will not be biased (Wooldridge, 2015).

A further selection issue is attrition, which would cause bias in our estimates if the reason for it is correlated with an omitted variable that has implications for treatment outcomes. Two recruited classes did not participate in the end due to rescheduling of the course we were to visit. However, these classes belonged to two different schools from which we met with other classes. Since teachers teach multiple classes, and since the rescheduling had nothing to do with the survey and was made by the school administrations and not the teachers, these two events were most likely random and had nothing to do with school, teacher, or class characteristics. Hence, attrition on the class level should not confound our results. Furthermore, on an ordinary school day, one or several students are normally sick or absent for some other reason, which was the case also in our sample. Fortunately, the absent students did not deliberately opt out of the survey since the students did not find out about our visit until sitting in the classroom. Those who did cut class did so for other reasons unknown to us. Therefore, equivalent to the case of abstaining teachers, attrition both on the class and student levels primarily pose an issue for external validity. We do not expect absence to be completely random; some students may skip classes frequently, and others may have frequent health issues. However, we do not believe that the absent students differ systematically from the students present in such a way that their characteristics would have an implication for their IT probabilities, or for their propensity to be affected by the treatments.

5.2 Treatments

When meeting with classes, we randomized the students into one of three groups by randomizing within each class which of the tree versions of the questionnaire they received. The only difference between the three versions of the questionnaire is the information provided in one question. In this question, the students received their treatment information and thereafter stated their probability of applying to an IT major. The information provided to students in the treatment groups can be seen below (translated into English). The control group was immediately asked to state their IT probability without any additional information.

Treatment 1: *According to a suggestion from the Digitalization Commission (SOU 2015:91), women who choose to study IT at university will not have to repay their student loans after graduation.*

Treatment 2: *Today, there is a skill shortage in the IT sector. In 2020, a lack of 60,000 IT professionals is projected for Sweden, according to IT&Telekomföretagen.*[4] *SACO*[5] *also predicts continuously low competition on the job market for IT professionals in 2020.*

The first treatment targets women, but also aims to measure the reactions to such a policy among men. *Hypothesis III*, stating that men reduce their probability of applying to an IT major as a result of the affirmative action benefiting women, was formulated to test this. The second treatment speaks to all students in our sample, and targets them specifically as the predicted shortage of IT professionals is given for the year of 2020, which approximately corresponds to the year in which our sample will graduate from university. Their exact graduation year depends on their current grade, whether they take a gap year, and the length of their chosen university program. As stated in *Hypothesis I*, we predict Treatment 2 of job security to have a greater impact on female students than Treatment 1 of student loan repayment. We also predict that female students are more affected by the job security treatment than are the male students (*Hypothesis II*).

By treating the students with additional information, we aim to make the application decision (measured as the decision of what probability to state) more informed. As previous studies have already indicated, students are not necessarily well or correctly informed (Arcidiacono et al., 2012; Wiswall & Zafar, 2015). Thus, even though students may have an idea of the employability for IT professionals, they may not have the correct idea of it. For this reason, a control question of their own impression of how easy it is to get employed after completing an IT degree is included in the questionnaires. Similarly, and as mentioned previously, students may or may not be aware of the proposal from the Digitalization Commission, which is also checked in the questionnaire and controlled for in the empirical analysis.

Regardless of how well informed the students were at the start of the survey, through our treatments we force them to make the provided information an active part of their decision making process. Naturally, a risk of hypothetical bias remains; that is, respondents may behave differently in real life. We are not able to rule out this possibility completely, but we can perform an analysis of the quality of the answers (see Section 6.4). Generally, the quality of the generated answers proved high, which indicates a low risk of hypothetical bias.

5.3 Data Collection Procedure

In every classroom, students were given identical instructions. Limited information was provided about the survey beforehand–the students were simply told they would answer an

[4] IT&Telekomföretagen is the Swedish employer organization for the IT and ICT industry.

[5] SACO stands for *Sveriges akademikers centralorganisation*, the Swedish Confederation of Professional Associations, a central organization for 23 labor unions.

anonymous survey about their plans after high school, for the purpose of a Master's thesis in economics. Moreover, the students were instructed to be silent when filling out the survey and to direct any potential questions to us, not to their fellow students. The students were also asked to fill out the questions in the order that they appear in the survey, and not jump between questions. This point was crucial for successful implementation of the treatments. For instance, the question on awareness of the Digitalization Commission's student loan proposal appears at the end of the survey. If students in Treatment 2 of job security or in the control group would go back and alter their stated IT probability after reaching the end of the survey and learning about the proposal, they would have been exposed to a treatment intended only for the first treatment group. The same problem could arise if students were to engage in extensive sneak peeking, but would then require the student to specifically read the treatment information of the person sitting next to them. By monitoring the survey process in person, we could do our best to ensure that such behavior did not occur.

Finally, the students were told that they were welcome to ask any general questions they may have after everyone had completed the survey. Avoiding answering questions beforehand ensured that no one knew that IT was the focus of the thesis, nor did they know that they were given one of three different questionnaires. Awareness of this could otherwise have biased the results. Furthermore, not answering questions about ourselves beforehand minimized any potential experimenter effects; i.e., that our personal characteristics and how we were perceived by respondents could have affected how they answered the survey. For instance, our presence may have increased the interest among the students for economics, business, or our school. Potentially, some experimenter effects may have remained since our mere presence may have increased the interest for economics regardless of whether we answered questions about it, or it may have reminded the students that this field of study exists. This may, in turn, have had some negative effects on the interest in IT majors, although this potential effect is likely to be negligible.

An important step in designing the survey was a pilot study conducted in four classrooms in two different schools, Bromma Gymnasium and Kärrtorps Gymnasium, in March 2016. The two pilot rounds resulted in exclusion of some questions and inclusion of others, as well as some rewording and clarification of existing questions. An important finding of the pilot study was that the students were comfortable with answering in probabilities ranging from zero to 100, and willing to do so. Thus, we decided to stick to the probabilistic expectations approach outlined in Section 4. Moreover, a general conclusion we were able to draw from the pilot study was that third grade students tend to be much better informed than second grade students, for example regarding awareness of different majors, and what GPA one has. This is reasonable since the third year students were just one month away from making their college major choice for the fall semester.

5.4 Control Variables

The questionnaires each contain 20 questions in total; thus, in addition to our main variable of interest–the probability of applying to an IT major–we generate a rich set of controls, including factors important to the students when making their choice of major. A comprehensive list of all variables is found in Appendix Tables 11-12. When selecting and formulating questions to include, there is a tradeoff between getting access to detailed information that may be useful for analysis, and tiring the students with too many questions. Tiring the students would reduce the quality of the answers, and take up a lot of time from the teachers;

the longer the survey, the less likely is receiving access to classes. The questionnaires were designed with this tradeoff in mind.

Including factors likely to be of relevance for the average student when choosing major reflects the M_{ij} component of the utility function in Equation (1), and partly the component X_i of individual characteristics. In the end, ten factors of likely relevance were chosen. The English translations are listed below:

- Earning a lot of money
- Status of the major
- Studying what I am interested in
- Studying what I am good at
- To be able to help others/make a difference
- To be able to have work-life balance
- Studying with like-minded people
- Share of women (if you are a woman)/men (if you are a man) in the major
- Getting a job working with people
- Easily getting a job after your studies

The chosen factors build upon previous research in Section 2.1.2 and what has been found to be of importance for students. Eccles (2011) puts forward that the choice is a dynamic process in which different factors are of differing importance over time. For this reason, several of the ten chosen factors are those we consider most essential to Swedish high school students, at their particular phase of life. Other factors were included since they may differ in importance between the genders, or between students in general, and thereby create variation in the data that may have explanatory power for the preference for IT. The share of students of the same gender and future earnings are two such examples. One of the key objectives of the pilot study was to evaluate what factors to include.

One may argue that the choice of major does not only depend on the characteristics of the major, but also on the characteristics of the chosen university or college and the area in which it is situated. For example, a student may wish to stay in the area they grew up in, or be keen on leaving it. Similarly, the student may be inclined to apply for a specific university because of its reputation, or for some other reason. We decided not to explicitly model such potential effects for two main reasons. First, IT majors are available at the majority of larger colleges in Sweden; therefore, the potential effect of a desire to live in a specific area is unlikely to have an explicit impact on the probability of applying for IT studies. Second, in the pilot study, the students generally did not state factors related to the area or other characteristics of a specific college as being part of their considerations. Although locality considerations are likely to be part of the final application decision, it is thus unlikely that they will have a significant impact on our dependent variable. For these reasons, we remained parsimonious when designing the survey and focused on factors related to characteristics of the major and its associated occupation, keeping in mind the aforementioned tradeoff.

During the pilot study, the factors were evaluated by including an open-ended question asking students to state freely any further factors that they considered important, in addition to the ten factors covered. This enabled us to conclude that there were no overlooked factors mentioned by several students. The main purpose of including the factors in the surveys is to use them as control variables, rather than achieving a complete mapping of each student's considered factors. However, there is a risk in not always capturing the main driver for each student, since it may confound estimates and make treatments look ineffective. Had we identified a factor mentioned by more than one student in the pilot study, it would have been included. Randomization of treatments is intended to avoid bias stemming from omitted variables in the form of unobserved factors, or any other variables affecting outcomes.

Further building on the utility function in (1), questions aimed at capturing the ability vector X_i were included. In particular, students were asked to disclose their current GPA as well as how they perceived their own abilities compared to their class. The self-perceived ability was ranked on a scale from one to ten by the students themselves, both relative to their current class, and in the consecutive question, relative to their hypothetical future IT class. Furthermore, students were asked to state which, if any, of the ten factors they associated with an IT major. One of the factors they could then choose was "I am good at it", which also gives an indication of their perceived IT ability.

Additionally, peer influence was estimated by asking whom the students had consulted about their college major choice and if they had people close to them working with or studying IT. Students were also asked to report their parents' level of education, proxying socioeconomic background. This parental education control also exists on the program level for each school, as does the proportion of foreign-born students in the program, which could capture potential cultural differences with implications for college decisions. The program level control variables will be presented in more detail in upcoming Section 6.

Two other important variables generated during the survey process are the students' estimates of what probability of applying to IT their classmates will state. We ask students to estimate their female classmates' and male classmates' preferences for IT separately, reported as average probabilities. These variables are not used as controls in the same way as the others mentioned above. Instead, they enable us to see whether students believe that other students will be affected by the treatments but not themselves, and serve as a robustness check for the potential impact of the treatments on our main variable of interest, the students' own probability of studying IT.

5.5 Econometric Model

To analyze our data, we use the following econometric model:

$$\begin{aligned} Prob\_IT_i = \alpha_0 \ + \ \beta_1 t1_i \ + \ \beta_2 t2_i \ + \ \beta_3 female_i \ + \ \beta_4 t1_i * female_i \\ + \ \beta_5 t2_i * female_i \ + \ \alpha_1 X_{1ikps} \ + \alpha_2 X_{2kps} \ + \alpha_3 X_{3ps} \ + \alpha_4 X_{4s} \ + \ u_{ikps} \end{aligned} \tag{4}$$

Individual i, in class k and program p, in school s, states his or her probability of applying to an IT major; *prob_IT*. The variables *t1* and *t2* are dummy variables indicating if the student belongs to either of the treatment groups. The baseline is assignment to the control group. The variable *female* is a dummy indicating female gender, and the interactions with the treatment dummies that follow illuminate any potential gender differences in treatment effects. The stated *prob_IT* of student i relates back to the utility function in Equation (1). How the treatments affect the maximization of the utility function depends on the weights given by the student to different factors, and other controls. All control variables are included in the X vectors, which differ in subscripts since our control variables are defined on either of the individual, class, program, and school levels. Similarly, the error term u has the subscript *ikps* since we expect it to have an idiosyncratic, individual component, along with common fixed components for each of the higher levels. This illustrates that individuals within clusters are likely to be more similar to each other than are individuals across clusters. Only two of the schools in the sample have both programs represented, implying that for the majority of the observations, the program and school level coincide.

5.6 Choice of Estimator

As described in the Method section, students reported their IT probabilities and not a binary answer regarding their interest in IT majors. In addition to the fact that this approach allows for expression of uncertainty, it generates much richer data. Our dependent variable can now take on any value on the [0,1] interval. We utilize this richness by using OLS as an estimator. Now, we assume that the error term in utility function (1) is normally distributed.

Nonetheless, the majority of previous studies on college major choice have used multinomial models to analyze the probability of choosing one of a limited number of majors. See, for example, Montmarquette et al. (2002), or Dickson (2010). However, as we focus our analysis on IT majors specifically, as opposed to a broader class of majors (such as STEM-related ones), the available counterfactual choices are the full spectrum of existing university programs. Asking the students to disclose choice probabilities for hundreds of majors is not viable. Thus, the classes of estimators dealing with such data are not applicable to our study. Note, however, that the counterfactual of relevance when estimating the effect of a treatment is the control group. By constructing three different questionnaires, we obtain the outcome of the counterfactual scenario (i.e., receiving no treatment)–one of the benefits of an experimental research design. What we cannot do with our results is to state the probability of choosing IT relative to one or several other, specific programs. Our objective is to answer how the relative IT probability changes due to the treatments, a probability that is defined in terms of pursuing an IT major as opposed to doing something else. What this "something else" is exactly, we do not model, but it could serve as an interesting extension of this study.

Concluding that multinomial methods are not appropriate, maximum likelihood estimation (MLE) could still have been used also in the current setting. One would then model the binary outcome of IT or not IT. Doing so assumes that the error term of the utility function in (1) follows an extreme value distribution. In other words, the subjective choice probabilities of the students are assumed to take on the extreme values zero or one under MLE (Blass et al., 2010). Assuming that the students exhibit no uncertainty regarding outcomes would imply asking for yes or no answers instead of probabilities. As previously discussed, this is not a reasonable assumption.

In addition to inference based on OLS, we will also test the treatment effects using Tobit estimation to check the robustness of our results. When using Tobit, we account for the corner solution outcome; 11% of the sample (86 students) report a zero probability of applying for an IT program (for histograms, see Figures 1 & 2 in Section 6). The corner outcome of the IT probabilities is reasonable, since it can be expected that a proportion of the students have a very small interest in the field. For consistency, both Tobit and OLS hinge on the classical linear model assumptions (CLM). Amongst other things, this implies that the dependent variable must have a normal, homoscedastic distribution with a linear conditional mean. In the case of Tobit, it is the latent variable which is assumed to not take on a corner solution response that must follow a conditional normal distribution. Whereas homoscedasticity is dealt with by clustering the standard errors, normality is of a greater concern. Visual inspection of the distribution of the self-reported IT probabilities in Figures 1 and 2, and performing standard tests of normality in Stata, questions the normality assumption, even when the zero-observations are excluded. For OLS, we can refer to the asymptotic consistency of our results, but this is not possible for Tobit, though moderate departures from the CLM assumptions should not be of a great concern, according to Wooldridge (2015).

In spite of this, as previous research has concluded that imposing the CLM assumptions on expectations data can bias the results (Blass et al., 2010; Manski, 2004; Wiswall & Zafar, 2015), we will also test running our main specifications with an alternative semi-parametric estimator that allows us to relax the normality and homoscedasticity assumptions, called censored least absolute deviations (CLAD). The CLAD estimator was introduced by Powell (1984) and allows us to estimate the conditional median of our outcome variable of IT probability: $Med(Prob_{IT}|X)$. Unlike the standard least absolute deviations (LAD) method, CLAD is robust to heteroscedasticity and estimates standard errors by bootstrapping, and it is possible to specify corner solution responses just as for Tobit estimation (Jolliffe et al., 2000). The various procedures and methods undertaken when drawing inference from the data will be evaluated in Section 7.4.

6 Data

Having collected a rich set of variables, it is now time to get to know the students in our sample and some of their characteristics. Thereafter, we will evaluate the quality of the responses that the survey generated.

We begin by noting that the sample consists of 793 students surveyed in a total of 33 classes at eight schools in the greater Stockholm area. Of the 793 students, 424 are male and 364 are female. Reporting gender was voluntary and five students declined to do so. The distribution between genders and across control and treatment groups is shown in Table 1 below. We see a balanced number of students across the three groups.

Table 1: Gender Distribution Across Treatments

Treatment	All	Males	Females
Control	265	145	117
Treatment 1	265	137	127
Treatment 2	263	142	120
Total	793	424	364

The surveyed students are all natural science and technology students in their second and third years of senior high school. The distribution between grades and programs is shown in Table 2. The size of the surveyed classes ranges from 13 to 31 students, with an average size of 25. Randomization carried out within each class enables us to create a balanced sample, and the success of the randomization process is described in Section 7.

Table 2: Grade and Program Distribution Across Treatments

Treatment	Grade 2	Grade 3	Natural Science	Technology
Control	156	109	218	47
Treatment 1	155	110	214	51
Treatment 2	157	106	211	52
Total	468	325	643	150

The majority of the variables in our dataset are defined on the individual level, reported by the students in the survey. Available class level variables are; *class size*, *class female share* (proportion of female students in the class), *technology* (dummy for technology program), *grade 3* (dummy for students in their third year), *median GPA*, and *day surveyed* (count variable for day surveyed, ranging from one to 28). Data on median GPA is taken from *Gymnasieantagningen Stockholms Län*[6] and refers to the students' grades from the ninth year of schooling with which they were admitted to their senior high school class (Gymnasieantagningen Stockholms Län, 2016).

Program level variables are *program female share* (proportion of female students in the program), *program higher educ* (the proportion of students in the program with parents who have attended higher education), and *program foreign-born* (the proportion of foreign-born students in the program). The school level variables in the dataset are *school size*, *school*

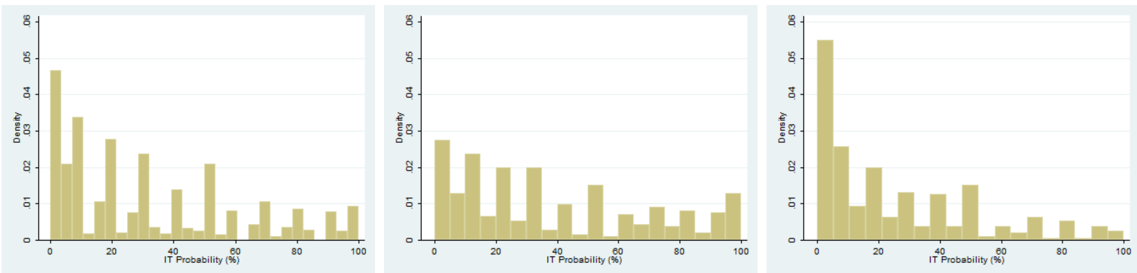
[6] *Gymnasieantagningen Stockholms Län* handles all admissions to senior high schools in Stockholm county and is run by the municipalities in the area.

share start college (share of students that continue on to college) and *private* (dummy variable indicating the ownership of the school). Out of the 33 classes surveyed, only one belongs to a private school. Program and school level data is taken from SIRIS.[7] As previously mentioned, only two of the surveyed schools have both programs represented in the sample. For the rest of the schools, the program level coincides with the school level. See Appendix Tables 11-12 for a comprehensive list of all variables, and Appendix Table 10 for descriptive statistics for each school in the sample.

Since our sample consists of students from two different programs, this may be reflected in the responses in the survey. Looking at summary statistics in Appendix Table 13 confirms that preferences differ according to the student's program belonging, captured by the control variables. Students in the technology program have lower GPAs, both men and women, and are less likely to continue on to higher studies, compared to the natural science program. Ability perceptions defined relative to the current class do not vary depending on the program. Furthermore, the women in the technology program do not view themselves significantly more able at IT than do the women in the natural science program. As one may expect, the outcome variable of IT application probability takes on significantly higher values if the student is in the technology program, irrespective of their gender.

6.1 Dependent Variables

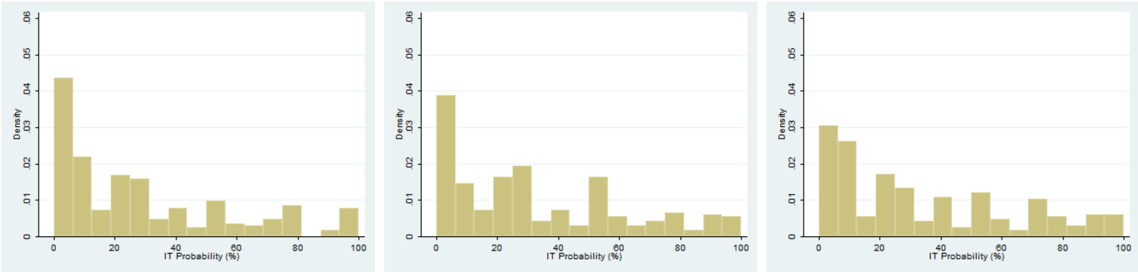
Our primary dependent variable of interest is the reported probability of applying to an IT major. Figure 1 below displays the distribution of this variable for all students, and for males and females separately. We see that female students report lower IT probabilities than do their male counterparts. The reported probabilities range from zero to 100% with 68 unique values. This implies that using a shorter scale would have been too crude. Although we see some rounding to the nearest 5%, appearing as spikes in the graphs, the students seem to handle the scale quite well. We are further interested in looking at the distribution of the probability of applying to an IT major across treatments. Figure 2 displays this, for all students. Histograms of the distribution of how the students estimated their classmates' probabilities are reported in Appendix A.5.



(a) All students (b) Males (c) Females

Figure 1: Probability of applying to an IT major across genders

[7]SIRIS stands for *Skolverkets Internetbaserade Resultat- och Kvalitetsinformationssystem*, and is a statistical database run by *Skolverket*, the Swedish National Agency for Education; the government agency overseeing the Swedish school system (Skolverket, 2016b).



(a) Control (b) Treatment 1 (c) Treatment 2

Figure 2: Probability of applying to an IT major across treatment groups

6.2 Control Variables of Particular Interest

Our dataset contains three control variables of special interest, hereafter dubbed "special controls." These controls are: prior proposal awareness, high prior interest in IT, and assessment of job market conditions for IT graduates. Table 3 shows the number of students who were familiar with the student loan proposal from the Digitalization Commission before the survey. Overall, we see the highest proportion of students being familiar with the proposal in the group treated with this information (Treatment 1), especially among males. Female students show most previous familiarity with the proposal in the control group. To prevent this from causing bias in our estimates, these individuals will be given special attention when drawing inference from our data in Section 7. This is done both by controlling for proposal awareness, and by excluding these individuals entirely from the sample.

Table 3: Mean Previous Familiarity with Student Loan Proposal By Treatment

	Control	Treatment 1	Treatment 2
All	0.179	0.192	0.121*
	(0.024)	(0.024)	(0.020)
Males	0.151	0.216	0.137
	(0.030)	(0.036)	(0.029)
Females	0.200	0.168	0.103**
	(0.037)	(0.034)	(0.028)

Note: Standard errors are displayed in parentheses. Asterisks indicate a significant difference in means compared to control, where ***$p < 0.01$, **p< 0.05 and *$p < 0.1$.

Table 4 shows how students evaluate the level of job security provided by an IT major. The students reported how easy they think it is to get a job after a completed IT major on a scale of one to ten, where a score of ten indicates maximum job security. Here, we expected students treated with the job security information to display higher values, on average, as these students have through their treatment been made aware of the actual job market situation for IT professionals. However, only male students in the job security treatment group estimate a significantly higher average job security compared to control. The men in the sample may therefore be more likely to show a treatment effect from the job security information, which will be analyzed further in Section 7. As students report high average values across all groups, they appear to have a relatively accurate view of the job market opportunities for IT graduates. This implies that Treatment 2 may not be providing the students with new information. Yet, it is still induces the students to make the job security information an active part of their decision making.

Table 4: Beliefs About IT Job Security by Treatment

	Control	Treatment 1	Treatment 2
All	7.574	7.669	7.724
	(0.107)	(0.114)	(0.105)
Males	7.464	7.754	7.835*
	(0.151)	(0.169)	(0.141)
Females	7.739	7.598	7.590
	(0.140)	(0.150)	(0.158)

Note: Standard errors are displayed in parentheses. Asterisks indicate a significant difference in means compared to control, where ***$p < 0.01$, **p< 0.05 and *$p < 0.1$.

Before any information about IT is provided in the survey, students list their current top three considered majors. A student who lists an IT major among his or her top three alternatives is already highly likely to apply to an IT major, and this should not be interpreted as the result of treatment. In Table 5 below, we see the proportion of students who mention an IT major at the start of the survey. There are no statistical differences between the control and treatment groups. We observe that male students are far more likely than female students to report an IT major among their top three considered college majors. Note that the tables presented in this section evaluate differences in means compared to the control group; differences in means comparing the two treatment groups are displayed in Appendix Tables 7, 14 and 15.

Table 5: Proportion of students with IT Major as Top 3 Alternative

	Control	Treatment 1	Treatment 2
All	0.174	0.179	0.172
	(0.24)	(0.024)	(0.024)
Males	0.258	0.254	0.275
	(0.038)	(0.038)	(0.039)
Females	0.075	0.095	0.046
	(0.026)	(0.027)	(0.020)

Note: Standard errors are displayed in parentheses. Asterisks indicate a significant difference in means compared to control, where ***$p < 0.01$, **p< 0.05 and *$p < 0.1$.

6.3 Gender Differences in Control Variables

Through the survey we obtain three different measures of how students value and relate to the ten factors of college major characteristics. Students both value and rank the factors according to how important they are in their choice of college major, and furthermore indicate which, if any, of the ten factors they associate with an IT major. Summary statistics for these variables are displayed in Appendix Table 16, which reports means both across groups and between genders. Looking at the factors across groups, we see few differences that are statistically significant. Instead, the majority of significant differences can be observed when focusing on differences between the genders.

Beginning with the importance given to each factor on a scale from one to ten, five out of the ten factors show statistically significant differences between the genders; *money, interest, ability, helping others/make a difference, work with people.* The largest difference appears for the factor *helping others/make a difference*, where female students give an average weight of 7.6, and males 6.2. This, and the fact that "earning a lot of money" was also more important to the men, is in line with findings of previous research (Eccles, 2011; Marini et al., 1996; Morgan et al., 2001; Reuben et al., 2015; Wiswall & Zafar, 2015). Contrasting previous findings and what we have hypothesized, however, is that there are no significant differences between the genders when it comes to the importance of job security, defined as easy to find a job after graduation. Moreover, the men have given this factor a significantly higher ranking than the women. This could suggest that the effects of treating students with information on job security will not differ depending on the gender, or perhaps even work better for men. When the students were asked to rank the ten factors instead, where a rank of one indicates the most important factor, the pattern is almost identical to that of the importance weights given to the factors, apart from the job security variable. This implies that the general quality of the answers is satisfactory, which we will analyze further in the next section.

Turning to how students associate the factors with IT, we see that the most frequently associated factor by male students is *job security*; 72% of male students, and 69% of female students, indicate associating this with an IT major. The most frequently associated factor by female students is *uneven gender balance* (81% compared to 64% among males). Overall, for eight out of ten IT association factors, we observe statistically significant gender differences. The only factors that do not display significant differences are *money* and *job security.* For seven out of the ten factors, more men associated the factor with IT than did women. Having more associations with IT majors may be an indication in itself that IT is a more plausible option for the men. Looking at what women associate and do not associate with IT, we see that only 5.8% thought that the people studying IT are similar to them, and the same share stated that they are good at it. In contrast, 27% of men associated IT with *I am good at it.* Helping others, which was valued highly in terms of importance weights and ranks among the females, only 11.9% of the women associate IT with. The factor least frequently associated by both genders is *work with people* (3.9% for females, 7.1% for males).

When lastly analyzing our three ability measures, we see that all three variables show gender differences significant at the 5% level or less. Whereas female students report higher current GPAs (16.63 compared to 16.28 for males, where 20 is the maximum), male students report higher estimated abilities relative to their current class. This difference is even greater when looking at the estimated ability relative to a hypothetical IT class; while the difference in the general ability variable is approximately 0.4, this difference is over 1.6 for the IT variable. Thus, on a one to ten scale, where ten implies that the student views themselves as "well above average," a man rates their IT skills on average 1.6 increments higher than a woman.

6.4 Quality of Answers

Throughout the process of the information experiment, a number of measures were taken to minimize different types of bias that could arise during data collection. The pilot study was very helpful in this regard, for example in increasing the face validity of the questions. Standardizing the instructions given to the students before taking part in the survey was equally helpful for reasons described above. In spite of these measures, issues negatively affecting the quality of the data may still remain, some of which are discussed below.

In the survey methodology research, the term *statisficing* refers to when respondents give answers they believe are reasonable, instead of dedicating effort to decide what they really think themselves (Krosnick, 1991). This may result in an increased number of non-responses to questions, or the same answer given to several questions with different meanings (Ornstein, 2013). In our sample, the number of non-responses is quite low. In total, 87% (686 students) answered all questions, and 95% had five or fewer non-responses. The two variables with the most missing values are the ranking of studying arts and humanities (relative to other fields of study), with 27 missing values among the 793 respondents, and the students' own GPA, with 26 missing values. The majority of the missing values for GPA were, not surprisingly, among second year students. Furthermore, potential non-differentiation of answers may appear in the importance weights the students gave to the ten different factors. A lazy respondent may put equal weight of importance on all factors, although it is not possible to rule out that they really do find all factors equally important. The students in our sample, however, generally applied different weights to different factors. Two students did report an importance of ten (maximum value) to all factors, but dropping these two individuals from our estimations does not change any conclusions.

Any potential agree response bias–the tendency to give positive answers to questions, regardless of their content–may also be present in the data. For instance, the students mostly gave high weights to the factors; seven on average. However, since the majority of factors were deliberately chosen due to their likely importance to the students, this result is reasonable. Still, agree response bias cannot be ruled out completely. Such bias could also impact the dependent variables. This is, however, not the case given the generally low probabilities given for IT. We manage to at least mitigate the issue of overstating the importance of a factor, or not answering the question properly, by also asking the students to rank the factors relative to each other. The downside of the ranking approach is that it may overstate the true importance of a factor relative to another, since equal importance of two or more factors is quite reasonable. For this reason, we report our results in Section 7 using the importance and not the ranking variable for the factors. Nonetheless, when performing the same estimations with the ranking variables instead, it does not change any of our conclusions. This supports the notion that the data do not exhibit substantial agree response bias.

A further issue common in survey data is measurement errors. As we primarily measure individual preferences in our survey, measurement error does not pose a major problem for estimation. It is reasonable to expect that the answer does at least reflect the preference the student had in the moment of answering the question. Thus, for many of the variables, it may rather be a matter of preferences and perceptions changing over time that could be problematic–not for consistency, but for establishing whether our results hold over time. For this reason, we analyze the differences in treatment effects between the two grades surveyed, and control for short-term changes in treatment effects due to all students not answering the survey on the same date.

Since several of the questions are quite specific regarding preferences for higher education and preferred majors, the quality of the answers is likely increasing in the time the students have spent contemplating their education plans beforehand. A first year student is probably not as far along in their thought process as second and third year students. Neither does the first year student's GPA add as much predictive value since it is based on fewer courses, and they might not even be aware of their GPA themselves. This is an additional reason for why we chose to target the second and third years only.

7 Results

Before drawing any inference from our data, we first confirm that randomization was successful by comparing differences in means of variables on the individual, class, program, and school levels between the control and two treatment groups. This is displayed in Table 7 on the next page, and by gender in Appendix Tables 14-15. As there are no systematic differences between the control and treatment groups in terms of their baseline characteristics, the sample appears to be balanced and random.

As a first step, it is helpful to get an overview of what IT probabilities the students have reported. We do this by inspecting differences in mean stated probabilities with no control variables. Recall that in addition to reporting their own probability of applying to an IT major, the students also estimated the average probability of their classmates, for each gender separately. Differences in means of the three IT probability variables (own probability, female classmates' probability, and male classmates' probability) compared to the control group are shown in Table 6. Differences in means between the two treatment groups can be seen in Table 7 on the next page, and Appendix Tables 14-15. All students report the lowest probabilities in the control group. Among the women in the sample, those subject to the student loan treatment (Treatment 1) have reported a significantly higher own IT probability than women in the control group. Similarly, when the women make estimations about their female classmates, the average estimated probability is significantly higher among women who learned about the student loan proposal, compared to those in the control group. However, there is no significant difference between females' probabilities between the two treatment groups. In contrast to the women, male students in Treatment 1 do not report higher probabilities for their female classmates. This may perhaps be due to the student loan proposal revealing to them that there is a significant problem in getting women to apply for IT programs.

For the men, learning about the student loan proposal did not lead to a personal probability, or estimation of male classmates' average probability, significantly different from not learning about it. In contrast, the job security treatment (Treatment 2) seems to have had some effect on the men in the sample, but not the women. The job security treatment yields higher mean probabilities for men both compared to the control group, and compared to the other treatment. However, this does not hold true for what the men, or the women, think about their male classmates.

Table 6: Difference in Means of Reported IT Probabilities

	All			Males			Females		
	C	T1	T2	C	T1	T2	C	T1	T2
Own IT Probability	0.291	0.325	0.338*	0.341	0.349	0.407*	0.222	0.295**	0.259
	(0.018)	(0.018)	(0.018)	(0.025)	(0.026)	(0.027)	(0.0230)	(0.023)	(0.022)
Male Classmates	0.507	0.505	0.528	0.466	0.446	0.495	0.554	0.567	0.565
	(0.013)	(0.013)	(0.014)	(0.018)	(0.018)	(0.019)	(0.019)	(1.758)	(1.957)
Female Classmates	0.243	0.278**	0.267	0.241	0.260	0.271	0.240	0.298**	0.262
	(0.011)	(0.013)	(0.012)	(0.016)	(0.019)	(0.017)	(0.016)	(0.017)	(0.015)

Note: The table displays differences in means between the following groups: C=control group, T1=Treatment 1, T2=Treatment 2. Probabilities are displayed for students' own stated preferences and the estimated preferences of their classmates (male and female). Standard errors are displayed in parentheses. Asterisks indicate a significant difference in means compared to control, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 7: Baseline Characteristics by Treatment Group

	Control	Treatment 1	Treatment 2	T1-C	T2-C	T1-T2
IT Probability	0.291	0.325	0.338	0.033	0.047*	-0.014
	(0.285)	(0.288)	(0.296)	(0.025)	(0.025)	(0.025)
Male classmates IT Prob	0.507	0.505	0.528	-0.002	0.021	-0.023
	(0.215)	(0.212)	(0.221)	(0.019)	(0.019)	(0.019)
Female classmates IT Prob	0.243	0.278	0.267	0.035**	0.024	0.011
	(0.181)	(0.203)	(0.190)	(0.017)	(0.016)	(0.017)
Female	0.447	0.481	0.458	0.034	0.011	0.023
	(0.498)	(0.501)	(0.499)	(0.022)	(0.044)	(0.031)
Age	17.712	17.730	17.754	0.018	0.042	-0.024
	(0.756)	(0.731)	(0.757)	(0.065)	(0.066)	(0.065)
Prob Study	90.406	89.582	89.914	-0.825	-0.492	-0.333
	(15.320)	(16.333)	(16.329)	(1.376)	(1.378)	(1.421)
GPA	16.553	16.369	16.411	-0.184	-0.142	-0.042
	(2.132)	(2.094)	(2.053)	(0.186)	(0.186)	(0.183)
IT Top 3 Alternative	0.174	0.179	0.172	0.005	-0.002	0.007
	(0.384)	(0.380)	(0.378)	(0.035)	(0.035)	(0.035)
Change rank prob	5.770	5.455	6.081	-0.315	0.312	-0.626*
	(2.835)	(2.704)	(2.869)	(0.248)	(0.257)	(0.249)
Ability	6.418	6.489	6.410	0.070	-0.008	0.079
	(1.674)	(1.844)	(1.764)	(0.154)	(0.150)	(0.158)
Ability IT	4.562	4.790	4.712	0.228	0.150	0.078
	(2.205)	(2.326)	(2.130)	(0.200)	(0.190)	(0.196)
No IT relation	0.310	0.285	0.267	-0.025	-0.043	0.018
	(0.463)	(0.452)	(0.443)	(0.040)	(0.040)	(0.039)
No Parent Higher Educ	0.171	0.139	0.125	-0.032	-0.046	0.014
	(0.347)	(0.377)	(0.331)	(0.032)	(0.031)	(0.030)
Advice No One	0.216	0.227	0.237	0.012	0.021	-0.010
	(0.412)	(0.420)	(0.426)	(0.037)	(0.037)	(0.037)
Proposal Awareness	0.179	0.192	0.121	0.013	-0.058*	0.072**
	(0.384)	(0.395)	(0.326)	(0.034)	(0.031)	(0.032)
IT Job Security Belief	7.574	7.669	7.724	0.095	0.150	-0.054
	(1.704)	(1.823)	(1.678)	(0.156)	(0.149)	(0.155)
Yes Apply	0.510	0.454	0.406	-0.056	-0.104	0.048
	(0.412)	(0.500)	(0.494)	(0.069)	(0.070)	(0.069)
Undecided Apply 16	0.173	0.231	0.277	0.058	0.104*	-0.046
	(0.424)	(0.380)	(0.450)	(0.055)	(0.058)	(0.060)
Class size	24.894	25.158	24.913	0.264	0.018	0.246
	(4.341)	(4.174)	(4.284)	(0.370)	(0.375)	(0.368)
Class female share	0.402	0.402	0.395	-0.005	-0.004	0.007
Median GPA	290.932	291.026	290.070	0.094	-0.863	0.957
	(29.828)	(30.141)	(30.645)	(2.605)	(2.645)	(2.632)
Program Foreign-Born	0.230	0.295	0.295	-0.005	-0.004	-0.001
	(0.172)	(0.172)	(0.169)	(0.015)	(0.015)	(0.014)
Program Higher Educ	0.793	0.794	0.793	0.001	-0.001	0.002
	(0.088)	(0.087)	(0.088)	(0.008)	(0.008)	(0.008)
Program Female share	0.457	0.453	0.449	-0.004	-0.007	0.004
	(0.142)	(0.146)	(0.145)	(0.013)	(0.012)	(0.013)
School Share Start College	0.701	0.700	0.695	-0.001	-0.006	0.005
	(0.081)	(0.082)	(0.081)	(0.007)	(0.007)	(0.007)
Technology	0.177	0.192	0.198	0.015	0.020	-0.005
	(0.382)	(0.395)	(0.399)	(0.034)	(0.034)	(0.035)
Grade 3	0.411	0.415	0.403	0.004	-0.008	0.012
	(0.493)	(0.493)	(0.491)	(0.043)	(0.043)	(0.043)
School size	1149.125	1157.321	1153.110	8.196	3.986	4.210
	(138.111)	(135.063)	(137.987)	(11.867)	(12.016)	(11.883)
Private School	0.034	0.030	0.030	-0.004	-0.004	-0.000
	(0.171)	(0.181)	(0.172)	(0.015)	(0.015)	(0.015)
N	265	265	263			

Note: The table displays descriptive statistics for the outcome and control variables separately over treatment and control groups. 9 Columns (1)-(3) display standard deviations in parentheses, columns (4)-(6) display standard errors in parentheses. Asterisks indicate a significant difference in means, where *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$.

In order to determine with certainty if the two treatments have any significant impacts on either gender, further analysis is required. When drawing inference from the data, both control variables and the sub-sample considered are varied. In the tables below, as well as in Appendix A.7-A.9, we choose to report six different specifications, columns (1)-(6) in the tables, although numerous versions were tested for robustness. We keep these specifications and their versions of controls constant as we vary sub-samples. This is done in order to see the effect on, for example, third year students compared to second year students. The first step of our analysis is to estimate the outcomes on the students' self-reported IT application probabilities.

7.1 Treatment Impact on Own IT Probability

First, we run regressions for the sample as a whole, which includes both genders and grades, in Table 8 below. For space considerations, the estimands of all control variables are not reported here, but in Appendix Table 17.

In all tables showing the results, specifications (1)-(4) use individual level controls only. Specification (5) adds class level controls and specification (6) includes program and school level controls. Fixed effects estimation on the school level are performed in all cases except for in (6). Each specification includes the same controls as the preceding one, and adds additional covariates according to the following list:

(1) Individual level: treatment dummies, female dummy, interactions between treatments and female.

(2) Individual level, corresponding to utility function: ability variables (GPA, ability relative to current class, IT ability), 1-10 rated importance values of each of the ten factors.

(3) Individual level, including controls of "special interest:" having IT as a pre-treatment top three choice of major, prior proposal awareness, scale 1-10 job security belief about IT.

(4) Individual level, additional controls: having a low rank for technology and science majors, not having asked anyone for college advice, having no parent with higher education, having no acquaintance in IT.

(5) Individual & class level: class size, class female share, technology program dummy, third grade dummy, class median GPA from ninth grade, day surveyed.

(6) Individual, class, program & school level: program female share, program share of students who have parent(s) with higher education, program share foreign-born students, school size, school share of students who continue on to college level studies.

Table 8: Impact on IT Probability: All Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.00512	-0.0119	-0.0104	-0.0107	-0.0109	-0.00931
	(0.0334)	(0.0296)	(0.0236)	(0.0224)	(0.0226)	(0.0219)
Treatment 2	0.0595*	0.0586**	0.0507*	0.0475*	0.0494*	0.0457
	(0.0318)	(0.0283)	(0.0275)	(0.0266)	(0.0270)	(0.0272)
Female	-0.114**	0.00967	0.0425	0.0439	0.0516	0.0420
	(0.0440)	(0.0417)	(0.0374)	(0.0371)	(0.0378)	(0.0381)
Female*t1	0.0681	0.0653	0.0423	0.0477	0.0472	0.0547
	(0.0421)	(0.0428)	(0.0408)	(0.0418)	(0.0423)	(0.0419)
Female*t2	-0.0195	-0.0382	-0.0205	-0.0149	-0.0180	-0.00161
	(0.0537)	(0.0493)	(0.0495)	(0.0483)	(0.0482)	(0.0491)
Ability IT		0.0569***	0.0418***	0.0374***	0.0376***	0.0371***
		(0.00498)	(0.00415)	(0.00395)	(0.00383)	(0.00380)
Utility Function Controls		yes	yes	yes	yes	yes
"Special Controls"			yes	yes	yes	yes
Further Individual Controls				yes	yes	yes
Class Level Controls					yes	yes
Program & School Controls						yes
Constant	0.340***	-0.0904	-0.214	-0.0478	0.604	-0.435
	(0.0293)	(0.142)	(0.130)	(0.129)	(0.462)	(1.027)
R^2	0.036	0.236	0.449	0.479	0.485	0.501
Observations	786	737	669	664	664	646

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Evidently, none of the treatments are statistically significant for the pooled sample across all specifications. Although initially significant around the 10% level, the job security treatment (Treatment 2) is not robust to adding program and school level controls in column (6). Hence, we find no support for any of our hypotheses. An important difference between the specifications in (1)-(5) and (6) is that the latter does not use fixed effects on the school level, but instead school-level variables are included. In other words, looking at the within-school variation of the data makes us observe a stronger treatment effect in terms of statistical significance (although the 10% level is not strong in the first place) than looking at variations in the data both within and between schools. The differences on the school level in propensity to respond to Treatment 2 is, thus, not controlled away by the observed program and school level variables that are added in regression (6). This implies that there are likely to be unobserved systematic differences between the schools in our sample, and that it matters for the treatment response which school a student comes from.

Important to note is that in column (1), with no control variables, being female has a significant negative impact on the IT probability. This significance disappears as control variables are added, which means that we are able to control for gender differences in the probability of studying IT. Testing different specifications where we combine the control variables in different ways allows us to conclude that the variables that make *female* insignificant are the following: whether the student has listed IT as one of their top three pre-treatment choices of majors, whether they associate IT with being interesting or with them being good at it, whether they are planning to start studying at the university the upcoming fall semester of 2016 (if they are in their third year), and their estimated ability for IT. This confirms that females are less interested in IT and do not think they are good at it (as noted in Section 6.3), and that the third year women who have decided what to apply for did not plan on studying IT, and were not willing to change their minds. 6.6% of the female third years planning on continuing with university studies right away listed IT as one of their top choices, whereas 12.4% of the males did. Interestingly, the only variable out of these five that does not only make the female variable insignificant, but also makes it switch signs from negative to positive, is the self-perceived IT ability. That is, controlling for women's low perceptions of their IT skills, the women in our sample are actually more interested in IT than the men, holding all other factors constant. We emphasize, however, that this positive effect of being female is not statistically significant.

Some of the control variables have robust and statistically significant effects on the pooled sample, which Appendix Table 17 displays. Perhaps not very surprising, especially given the simultaneity issue described previously, the reported IT probability is increasing in the student's self-perceived ability for IT. Also expected is that a student who has reported an IT major among their top three alternatives reports a higher IT probability. Since the students were asked to rank six fields of education (including not studying at all), we are able to control for the rank of "technology and natural science". The variable is named *low rank tech-science* in the tables. A rank of one means that it is the most preferred alternative, and a rank of six is given if it is the least preferred alternative. The results show that the lower the rank for technology and science (i.e., the less interesting), the lower is the stated IT probability. A further interesting finding is that not knowing someone who works in IT, or who has or is currently studying IT, significantly lowers the IT probability, which implies that there is a positive peer effect at work for the other students. However, having asked someone for advice does not have a significant impact on the IT probability, nor does being in the technology program when all other variables are held constant. None of the variables proxying socioeconomic background have significant effects either.

Recognizing that prior awareness of the student loan proposal by the Digitalization Commission may confound our estimates, we run the same regressions only on those students who did not know of the proposal. Table 9 below shows that dropping those with prior proposal awareness increases the size and statistical significance of the job security treatment (Appendix Table 20 reports all controls). This could be due to that those who have heard of the affirmative action previously may have created more negative associations with IT. The student loan treatment still shows no statistical significance. Since the interaction between the *female* variable and the job security treatment is insignificant, we do not find support for *Hypothesis II*, that female students are more affected by such a treatment than male students. The effects of the control variables are largely the same as for the pooled sample in Table 8; that is, having indicated an interest in IT or in the science and technology field, and having a relation to someone active in IT, positively affects the student's own interest in IT. Furthermore, ceteris paribus, being in the technology program seems not to matter, nor do the socioeconomic variables.

Table 9: Impact on IT Probability: All Students, No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0125	-0.00500	-0.0000994	-0.00400	-0.00372	-0.00916
	(0.0337)	(0.0291)	(0.0267)	(0.0260)	(0.0264)	(0.0257)
Treatment 2	0.0610*	0.0637**	0.0702**	0.0659**	0.0681**	0.0620**
	(0.0358)	(0.0306)	(0.0307)	(0.0292)	(0.0292)	(0.0292)
Female	-0.121***	-0.00208	0.0395	0.0413	0.0477	0.0467
	(0.0434)	(0.0415)	(0.0342)	(0.0356)	(0.0366)	(0.0373)
Female*t1	0.0651	0.0598	0.0414	0.0491	0.0479	0.0537
	(0.0442)	(0.0424)	(0.0386)	(0.0421)	(0.0435)	(0.0436)
Female*t2	0.00446	-0.0214	-0.0121	-0.00891	-0.0112	-0.000561
	(0.0540)	(0.0485)	(0.0474)	(0.0463)	(0.0466)	(0.0478)
Ability IT		0.0563***	0.0435***	0.0396***	0.0397***	0.0396***
		(0.00526)	(0.00449)	(0.00417)	(0.00414)	(0.00413)
Utility Function Controls		yes	yes	yes	yes	yes
"Special Controls"			yes	yes	yes	yes
Further Individual Controls				yes	yes	yes
Class Level Controls					yes	yes
Program & School Controls						yes
Constant	0.341***	-0.298	-0.388**	-0.260	0.110	1.837
	(0.0303)	(0.199)	(0.189)	(0.199)	(0.697)	(1.363)
R^2	0.008	0.258	0.509	0.526	0.533	0.552
Observations	355	335	300	296	296	291

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Looking separately at the results for the men in the sub-sample with no prior proposal awareness (Appendix Table 21), we see that the job security treatment is significant at the 5% level. For this sub-sample, *Hypothesis III* receives support, although statistically insignificant. In other words, learning about the student loan repayment benefiting women has a negative, but statistically insignificant effect on the men's IT probabilities. This implies that the men in our specific sample previously unaware of the proposal were thrown off by it and felt less like studying IT than the others.

Turning to the women who were unaware of the proposal (Appendix Table 22), no significant treatment effects appear. The student loan treatment has a positive effect unlike for the male sample, but it is not robust across specifications. As class level controls are added in (5), the student loan treatment becomes statistically insignificant. Adding the class level controls one by one, we find that using the dummy variable for whether the student is in the third grade alone makes the student loan treatment insignificant. This suggests that the third grade women are not affected by the treatment, which we will shortly investigate further. The control variables have effects on the female sub-sample very similar to those of the male sample, with one exception. None of the ten factors had any effect on the men, but the importance of studying what one is interested in is statistically significant for the women. Ceteris paribus, the reported IT probability is decreasing in the importance of the interest factor for women. This implies that females are not sufficiently interested in IT, which is supported by the fact that less than 27% of the women indicated in the survey that they found IT to be an interesting subject. We also note that when holding all other factors constant, women in the technology program are no more likely to study IT than women in the natural science program, since the *technology* dummy has no significant impact on the IT probability.

To determine whether second and third year students differ in their propensity to be affected by the treatments, Appendix Tables 24-29 divide the sample according to which year the students are in. The treatments have no statistically significant impacts on third year students; neither on the whole sample nor divided by gender. Turning instead to second year students, we see that Treatment 2 of job security has some effect both on the whole sample and on the male students. However, this effect is not robust across all specifications. On the other hand, what was implied already when we analyzed both years of females together, is confirmed by Appendix Table 29; the table shows that Treatment 1 of student loan repayment has an impact on second year female students, and this effect is robust across all specifications at the 5% level of statistical significance. This means that women in their second year are positively affected by the free student loan proposal. On average, this incentive increases the stated IT probability of these students by between six and nine percentage points, holding all other factors constant. In contrast, the second year women are just like the third years not affected by the job security treatment. Thus, results for second year women rejects and are the opposite of *Hypothesis I*, which states that females will be more affected by job security treatment than affirmative action. Since the interaction term between female gender and the job security treatment is insignificant for both second and third year students, women are not more affected by this treatment than are men. Hence, *Hypothesis II* gains no support either. Furthermore, none of the men in any of the grades, or any other sub sample for that matter, are significantly negatively impacted by the student loan proposal, thus rejecting that *Hypothesis III* holds for the population as a whole. However, the sign of the coefficient on this treatment is negative across all specifications in all sub-samples of males.

Throughout most of our regressions, we find that not having a peer within IT has a significant, negative impact on the stated IT probability. This is especially evident for second year women, where not having an acquaintance in IT is translated into a 12-13 percentage point lower IT probability, holding all other factors constant (Appendix Table 29). For the sample as a whole, no IT relations implies a seven percentage point lower stated IT probability (Appendix Table 17). Both estimates are significant on the 1% level. While we can only speculate as to the reason for this peer effect, it seems reasonable that knowing someone in IT leads to revised beliefs about the sector. The peer effect is less strong on men (and insignificant in both second and third year sub-samples; Appendix Tables 25 and 28). Male students may have less negative opinions about IT in general and, thus, may not suffer as much from having no IT peer to revise these. Furthermore, it is interesting that the relations with the strongest impact is having a mother, father or sibling in the field. Hence, students are more influenced by their family than their friends and other acquaintances. We further note that the peer effect seems not to be gender-specific, since sons are positively affected by their mothers in IT and daughters by their fathers.

Below, we summarize the most important results from the analysis of the students' own reported IT application probabilities.

Main Results from Own IT Probability

- The student loan proposal only has a significant impact on second year women.
- The job security treatment only works on men with no prior proposal awareness.
- Although the coefficient remains negative throughout specifications, men are not significantly impacted by the student loan proposal benefiting women.
- Controlling for self-perceived IT abilities, gender differences in the reported IT application probability disappear.

7.2 Beliefs About IT Probabilities of Classmates

In addition to analyzing whether the two treatments have any effects on the students' own probabilities, we also investigate if the students report a higher application probability for their classmates. Appendix Tables 33-38 show the results for what each gender believes about their own gender, and about the opposite gender, for the whole sample and for students with no prior proposal awareness. The only sub-sample exhibiting a positive treatment effect, however small in magnitude, consists of women with no prior proposal awareness subject to the student loan treatment (Treatment 1). They have reported, on average, six percentage points higher IT probabilities for their female classmates. These results support the aforementioned finding in Appendix Table 29, where second year female students were shown to be positively affected by the student loan incentive, as they increased their own reported probability by about six to nine percentage points. However, the positive treatment effect of job security on the males students' own probabilities, seen in Appendix Table 21, is not confirmed by the probabilities the men have reported for their classmates of the same gender, neither is it confirmed by what the women believe about the men. This adds some ambiguity to how effective an informational campaign on job security would be among men. In accordance with findings on the insignificant results on the females students' own IT probabilities, job security treatment does not affect the females' beliefs about other females, nor does it affect the beliefs of males regarding females.

While not robust across all specifications, male students in the student loan treatment group show some indication of believing that their fellow male classmates will report lower IT probabilities (Appendix Table 34). This suggests a possibility of men believing that other men will be negatively impacted by affirmative action targeting women. Furthermore, men show no sign of believing that their female classmates will be positively impacted by the affirmative action proposal.

An interesting finding from comparing Appendix Tables 33-38 is that for the pooled sample, females think that their male classmates are more likely to apply for an IT major than the males think about their male peers, by as much as around 13 percentage points more, and it is highly statistically significant. This implies that females perceive IT studies as being male dominated, and it gives some indication that a male stereotype could exist for the women. Recall that 81% of the female students associated IT majors with having an uneven gender balance, compared to 64% of the males. Both genders, however, significantly overestimate male students' preference for IT. There is no significant difference between the genders for what they believe about their female classmates' IT probabilities.

When analyzing the students' perceived gender differences, one must bear in mind how the questions were framed in the survey. Since the same student was asked to estimate the probabilities for the male and female classmates separately, the framing of these two questions may have exaggerated the students' perceptions of gender differences. An alternative could have been to ask the students to estimate only the average probability of all of their classmates, without mentioning gender at all. This alternative would, however, likely have led to the students answering an average of what they think the men responded and what the women responded, which means that we would not have been able to capture the gender differences in the same way as we do now. Hence, neither solution is perfect but we arrived at the decision to divide the probability estimation question into two depending on the gender of the classmates, since the overstating effect this type of framing could cause may affect all students more or less equally. In other words, the relative differences between the stated estimated probabilities of each gender should be largely the same, regardless of whether we managed to elicit true or somewhat overstated perceptions the students have about gender differences. Bearing this in mind, we note that the women have, on average, reported a 29 percentage point higher probability for their male peers than their female peers. The men have reported an average 21 percentage point higher estimated probability for their male classmates. This further supports the notion that women perceive a male IT norm more strongly than do the men themselves. Finally, we note that those who estimated the smallest gender difference were those subject to the student loan proposal. Then, the women estimated a higher probability for men of 27 percentage points and the males estimated a higher probability of 18 percentage points.

We can now summarize the results for what the students believe about their fellow classmates.

Main Results from Beliefs About Classmates

- Female students believe their female classmates will be significantly influenced by the student loan treatment.
- Women may perceive a male IT norm since they believe that men are more interested in studying IT than they actually are.

7.3 Sources of Gender Differences

In Section 7.1, we noted that controlling for either measures of IT ability or measures of interest in IT (captured by five different variables) made the variable *female* insignificant when analyzing the IT probability. We further noted that controlling for the self-perceived IT ability relative to one's future hypothetical IT class even made the female variable switch signs to have a positive impact on the stated IT probability in the pooled sample, although not statistically significant. A vast body of literature on the reasons for why women shy away from STEM careers already exists, and some of its findings are covered in Section 2.1.2.[8] The aim of our research is to evaluate whether the two treatments provide women with strong enough incentives to adjust their application behavior, and thereby overcome some of the underlying gender differences in attitudes for IT. Our findings above show that neither information on free student loans, nor appealing to the importance of job security is effective at overcoming the application barriers for women. For robustness, we also tested whether the treatments significantly nudged the women above the 50% threshold of reported IT application probability, by defining a dependent dummy variable taking on the value of one if the probability was 50% or higher. This was not the case; none of the two treatments made more women exceed this threshold when analyzing outcomes using OLS, Logit, or Probit. Treatment 2 of job security did, however, make more men report a probability of 50% or more.

Since we do not have access to a measure of actual IT abilities, when self-perceived abilities and the preferences one has for a major are interdependent, a way to handle the simultaneity in the regressions would be to instrument the stated ability measure. In the dataset at hand, there are no variables that could serve as valid instruments. In particular, finding a relevant instrument that only enters the structural equation through the IT ability variable

[8] However, one should bear in mind that the women in our sample have already selected into STEM studies by choosing such a program on the high school level, although they are not forced to stay within the field for their university studies. Thus, our analysis focuses on how to attract women with the required prerequisites for the IT field.

is difficult. For example, the current GPA variable is neither likely to be fully exogenous, nor is it relevant as it produces a very weak first stage. Current GPA could otherwise have been considered an objective measure of abilities, and instrumenting IT abilities with it would make use of the variation in IT abilities due to actual abilities only. Thus, under the current circumstances, where IT ability is likely to be an endogenous variable in all our regressions, its estimate may be upward biased, as found by Wiswall and Zafar (2015) . An upward bias is certainly reasonable since the higher the preferences for a major, the higher a student may think about their abilities for that major. However, we would assume the link running from abilities to preferences to be the stronger one–the better the student is in the area, the more likely they will choose it. For this reason, we keep the ability variable in the regressions. Nevertheless, the potential upward bias leads us to refrain from commenting on the exact size of its coefficient in any of our estimations.

Using self-perceived IT ability as dependent variable, instead of IT probability, and running the exact same specifications as for those in our standard regressions (1)-(6), the female variable is still negative and statistically significant. This holds regardless of whether IT probability and other IT-related control variables are included in the regressions. Thus, we do not manage to control away the gender differences in the IT ability in the same way as we do for IT probability. In other words, the two variables IT ability and IT probability are not interchangeable, supported by the fact that their correlation is not perfect (it is 0.37 for the women and 0.46 for the men). This adds further support to including stated IT ability in our main specifications. Furthermore, none of the two treatments have significant impacts on reported IT abilities, confirming what we had expected a priori; interventions aiming to have quick effects on application rates can only influence preferences, not ability perceptions.

Similarly, in addition to IT abilities, trying to analyze the gender differences in stated overall abilities in a regression framework brings no further insights, neither does analyzing the probability of reporting that IT is interesting. That is, the covariates available from the survey do not “control away” the negative and statistically significant impact of being of female gender on the interest for IT, IT abilities, or abilities relative to the current class. Since the survey was not designed to map the determinants of the students’ self-perceived abilities, we conclude that we do not have the tools needed to determine with certainty where the lower stated abilities among women stem from. For example, we cannot distinguish whether men are overconfident or realistic, or whether women exhibit too low levels of confidence. In principle, it could be justified to give yourself a high ability rating relative to the current class despite low grades. Ruling out that the differences in the confidence variable do not simply depend on men being smart but spending less time doing homework and, for this or some other reason, have lower GPAs, would require measures of abilities from an IQ test or similar. Nonetheless, the gender differences in ability perceptions are disheartening and deserve attention from schools, policy makers, and researchers alike.

An extension of the analysis of the level of confidence among the students, and differences between the genders, is to create a proxy variable for confidence. We do this by first assigning each student a rank between one and ten based on their GPA performance relative to their current class. For example, a student in the bottom 10% in their class in terms of GPA is given a rank of one. In a second step, we compare the GPA ranking to the student’s own ranking and create the following variable: *confidence = self-perceived ability - GPA percentile rank*. A positive outcome indicates confidence, whereas a negative value indicates a lack of it. In general, the students rank themselves slightly higher than their GPA rank, and the men more so than the women. The outcomes among the female students are in the range [-6,7], and for male students [-4,8]. The average level of confidence among women is 1.48, compared to 1.55 among men. Including the *confidence* variable in our regressions where the IT probability is the outcome variable does not change our results. We choose to report specifications using self-perceived ability and GPA as control variables, since it is more relevant to interpret them separately than combined in the *confidence* variable. Next, we summarize our findings regarding gender differences.

Main Results on Gender Differences

- The women show indication of being less confident than the men, which may impact their reported IT abilities.

7.4 Robustness

Performing our estimations, a number of robustness checks were made to ensure that we do not arrive at faulty conclusions. One such robustness check was to run multiple specifications on all sub-samples. The version of control variables we have decided to display in our tables generates the most restrictive results, ensuring that we do not overstate the significance of our findings. Most notable is the change from including the importance values for the ten college major factors (scale 1-10), to instead including dummies for which of the ten factors the students associate with IT. This leads to some increased statistical significance for our treatments in certain sub-samples. However, the change to using ranks of the factors instead does not lead to any increased, or decreased, significance.

The data collection process spanned a total of 28 days and the control variable counting day of survey participation is significantly negative in some sub-samples and specifications, indicating that the closer we got to April 15, when college applications closed, the less able we were to influence the students with the treatments. The variable is, however, not statistically significant across specifications. Furthermore, we also explored the possibility of a time dimension being included in the error term in our econometric model (Equation 4) by using fixed effects on this time variable, but it did not lead to any different findings than those we present above and in the Appendix. This indicates that the timing of the treatments did not make a substantial difference for outcomes in the short-term. However, since second year women responded to one of the treatments, that of student loans, and third year women were not affected by any treatment, longer-term timing in terms of years apart seems to have implications for the treatment effects. We will discuss in the upcoming Section 8 why we think this is the case.

Although students are randomly assigned to control and treatment groups within each class, there may still exist class, program and school level correlations in the error terms in Equation 4, as indicated by its subscript *ikps*. However, since most of the covariates we use vary on the individual level, the grouped error structure should not be a substantial problem (Angrist & Pischke, 2008). Nevertheless, for prudence, we estimate cluster-robust standard errors on the class level to account for any remaining intra-cluster correlation in all our estimations presented above, and in the Appendix. We note that with a relatively low number of clusters (33 classes), standard error estimates may be biased when clustered (Angrist & Pischke, 2008; Wooldridge, 2010). However, each of the classes in the sample make up less than 5% of the total sample (the largest class makes up 3.9%), which, according to Rogers (1994), implies that the potential bias should not be large. On the school level, however, there are only eight clusters, and these therefore each constitute a large portion of the sample. The same is true when defining a cluster on the program level, where each program at each school makes up a cluster, generating ten program clusters. As a result of few school level clusters, we choose to use school fixed effects rather than clustering on this level. When the explanatory variables vary within each group, which our treatments and most control variables do, this is the approach recommended by Wooldridge (2010). Moreover, we expect respondents within each class to be even more similar than respondents within the same school but across classes, simply due to them spending more time together during the school day and being influenced by the same teachers. However, we can confirm that our inference does not change depending on which alternative we use. All results that we present are robust to the inclusion and removal of class, program and school level clusters, and fixed effects on the same levels.

In Appendix Tables 30-32, Tobit results equivalent to tables above are shown. The results presented in all OLS tables in Appendix A.7 hold for Tobit estimation too, however the inclusion of corresponding Tobit tables would contribute to an unreasonably long list of tables. In addition to Tobit, CLAD was also run on our main specifications to relax the assumptions of normality and heteroskedasticity. When running CLAD, we note that our estimates do not change significantly. Those variables that are significant under OLS and Tobit estimation are equally significant under CLAD. When this is the case, Wooldridge (2010) recommends using Tobit instead. Furthermore, since the results of OLS, in turn, do not differ significantly from Tobit, and since OLS allows us to draw asymptotic inference, we choose to primarily report the OLS estimates. In Section 4 Method, we evaluated cross-sectional estimation against an alternative of constructing panel data by letting the same student state their IT probability twice, pre and post treatment, in the spirit of Wiswall and Zafar (2015). A priori, we expected the bias of using OLS to be relatively small, and smaller than the bias associated with the construction of a panel. While we cannot make any statement regarding the bias from constructing a panel, the fact that a semi-parametric option relaxing the most questionable assumptions of OLS and Tobit (normality and homoscedasticity) does not produce very different results supports our chosen method.

8 Discussion

The results from our information experiment show that both types of policies we evaluate have limited impact on students' stated IT application probabilities. The estimated treatment effects vary greatly both by gender and grade of the student, indicating that neither treatment will have a robust effect on the population as a whole.

While second year female students are influenced by information on the free student loan proposal, the finding does not hold for third year students. It seems that female third years have already formed such strong preferences for other majors that they cannot be influenced through either treatment. This explanation seems especially plausible considering that neither of the treatments shows any effect on either gender of the third years. The fact that we are not able to impact the third year students through our treatments indicates that any potential intervention needs to be put in place at an earlier stage. Only targeting those who are right on the cusp of making their college major decision does not appear to be effective. Furthermore, women in their third year may find it unlikely that the student loan proposal will be put into effect in time to impact them, and would thus not be influenced by learning about it. If implementing the proposal would have any effect at all, it is therefore likely to be of a lagged nature. Then, the costs of the proposal would be even greater than anticipated.

Had the proposal been put into effect already, we cannot rule out that the third year women would have shown a treatment effect. If we would play with this idea, and assume that it was the pooled sample of women that exhibited a positive treatment effect of six to nine percentage points, the economic significance of this increase must be evaluated. The average IT probability of the control group in the sub-sample of second year women is 21%. Increasing this probability by nine percentage points or less is unlikely to translate into a sufficiently higher proportion of females in IT majors. In our opinion, the treatment would need to show a much higher impact on reported probabilities to be worthy of consideration, particularly in view of its estimated cost. Even if the second year women in our experiment would have responded even more, had the proposal been established and well-known, the baseline application probability is still too low.

While the student loan treatment directed at female students only positively impacts second year women, it is important to note that it does not significantly impact the men negatively, thus rejecting *Hypothesis III*. That is, the results do not support that men learning of the affirmative action policy targeted at women respond by lowering their own IT probability. Nevertheless, the coefficient on this treatment does have a negative sign throughout all sub-samples and specifications for the men. The negative reactions we experienced from some of the male students in the classrooms tell us that an affirmative action proposal like the one currently put forward would need to be implemented with caution. While these reactions are not statistically significant, they indicate that a negative environment surrounding IT majors may be created. The IT sector at large suffers from a shortage of professionals, and even if the negative reactions do not translate into immediately lowered application rates, the negativity may have a long-term impact.

Moving on to the job security treatment, we find some limited support that treating students with information on employability for IT graduates could raise application rates, although the impact is restricted to certain sub-samples of males. This finding contrasts both *Hypothesis I*, that the job security treatment will affect women more than will the student loan incentive, and *Hypothesis II*, that women will have a larger treatment effect from job security information than will men. It may simply be the case that IT is more of a viable option for male students, which increases the propensity to respond to the job security information. For females, on the other hand, IT may be such a considerably less prospective option, that simply receiving job security information is not enough to adjust their preferences. Furthermore, the fact that all students seem to believe that finding employment upon graduation from IT studies is relatively easy reduces the potential impact information on the matter may have in the first place. Nevertheless, given that the baseline interest in IT and self-assessed IT abilities are low, the two treatments may still have had some effects, had funding aspects and job security been of even greater importance among Swedish students. While these factors did not turn out to be important enough when it comes to shifting IT preferences, we note that performing the same study in other countries may very well generate different conclusions. For instance, in a country where students need to pay high tuition fees, monetary incentives may have a larger impact.

If neither treatment has economic significance, what then can be done to raise IT application rates among women? We turn instead to consideration of the control variables in our dataset. The students' estimated IT ability is the variable most significantly associated with a higher stated IT probability throughout all specifications and sub-samples. The fact that including IT ability makes the female dummy variable insignificant is of particular interest. Why do female students believe so little in their own IT abilities?

While we cannot answer this question with certainty with the data collected for this study, we believe it to be the next step for future research. The literature has shown a correlation between abilities and preferences (Wiswall & Zafar, 2015). We would like to add to this the notion that both of these aspects of the choice of college major may be correlated with confidence. The women in our sample report lower overall level of abilities than the men, unjustified given the reported grades, and an even lower IT ability. Given the fact that the women, just like the men, attend either of the two STEM programs in the Swedish high school system, and that all students are provided with a personal laptop by their schools, there are no obvious reasons for why the women should have lower *actual* IT abilities than the men. Testing the IT abilities in a formal exam setting would allow future research to determine whether it is purely a matter of confidence. It is noteworthy that the females estimated their male classmates' IT probabilities to be much higher than they actually were. Viewing IT as such a male dominated field may be accompanied by certain stereotypes and perceptions of the skills necessary for success.

Lastly, we would like to point out that increasing the share of female students applying for IT majors is not perfectly correlated with an increased share of females who obtain IT degrees. Students who have applied to and initiated a major may switch university programs entirely if they are not satisfied with their choice. Although we do not model this, it could serve as an interesting extension of our research. For example, Dickson (2010) models the probability of switching majors and finds that women are more likely than men to discontinue an engineering major. A policy intervention that raises female IT application rates may, therefore, encounter the problem of an increasing share of women dropping out of the major if they experience the culture or stereotypes negatively. If this would prove to be a substantial problem for women pursuing IT majors, it may be necessary to evaluate measures that could prevent it.

8.1 Generalizability of Results

Through our approach of within-class randomization, we circumvent several types of bias that may threaten the internal validity of results, including omitted variable bias and selection bias. However, the experimental nature of the study does bring with it some potential problems for external validity. First of all, Stockholm may not be representative of all of Sweden, implying that students in other areas of the country may respond differently to the treatments. Women in Stockholm may be more interested in IT than the average Swedish female high school student, as shown in the survey conducted by Insight Intelligence (2015). However, that survey found a higher IT interest than we did in ours (36%, compared to 22% in our female control group). Would the IT interest nevertheless be greater in Stockholm, sampling schools also outside this area may generate weaker treatment effects. Since neither treatment seems to have a strong effect in Stockholm, however, a more widely defined sample would probably not change the main results of this study. It could be that the indicated positive effect of the student loan incentive among second year women in our sample would not be present in the population as a whole.

Furthermore, as discussed in Section 5.1, teachers of some schools declined to participate, which may have resulted in a sample systematically different from the population as a whole. Randomization within classes ensures internal validity, but an unrepresentative sample calls the generalizability of the results into question. While this is not something we are able to control for, we observe that participating schools represent both the lower- and higher-performing end of the spectrum (see Appendix Table 10). However, we do note an under-representation of private schools in our sample. To our knowledge, private senior high schools in Sweden do not vary systematically from public ones in a way that would have implications for the students' IT probabilities, but more classes from such schools would nonetheless have been preferable.

9 Conclusions

Men and women should have equal opportunities to take on transformative, leading roles in society. An important step in the right direction would be to even out the gender distribution in key industries, such as IT. However, in a population where the general interest for IT is low, the implementation of policies that are intended to work instantaneously is not effective. Our results show that these types of policies only have the potential to affect preferences at the margin. Those who are affected by an informational campaign on job security are primarily male students who show a relatively high pre-treatment preference for IT. Female students barely exhibit any treatment effects at all. The female students affected by a free student loan incentive belong to the younger sub-sample, which has not yet formed as strong preferences. However, the small treatment effect these women exhibit is not sufficient to noticeably increase the share of female IT applicants. The objective of our two evaluated treatments, to encourage women to select into an influential sector, is therefore not achieved.

It appears that there are no quick fixes to the underlying gender differences in the probability of pursuing an IT major. At least partially solving the problem quickly would indeed be desirable considering the current skill shortage in IT. In order for policies intended to have an instantaneous, rather than lagged, effect to work, a sufficient interest in IT is required among female students at baseline. If women do not think highly of their IT abilities, their preference for the field will remain low, and vice versa. In order to achieve a substantial shift in preferences as well as self-perceived abilities among young women in Sweden today, we believe that thorough work needs to be done–work in the form of policies with a longer time horizon in terms of their effects. We recommend such interventions to attack attitudes and stereotypes, and to aim at increasing confidence and ability perceptions. Not until reaping the benefits from these types of policy measures, if they prove efficient, could policies like the ones examined in this thesis be effective.

We recommend future research to explore which would be the most suitable way to permanently shift preferences and perceived abilities for IT in the entire population. Getting at the share of female graduates in IT is one important way to lessen the power gap between men and women. Another way worthy of attention is strengthening the position of females active in the industry today, which could have positive spillover effects on the number of female applicants for IT majors. Given the substantial peer effect on female students from having a relation in IT, a positive spiral could result from students encountering more females in the industry. Inclusive employers and successful women today could pave the way for the female leaders of tomorrow.

Finally, we would like to emphasize that diversity has many dimensions. Increasing the share of women in male-dominated sectors is only one step among many that need to be taken. It would be interesting to test the equivalent form of treatments but targeted at other underrepresented groups, not least males in female-dominated sectors. Utilization of the whole population's skills is desirable for the progress of society and businesses alike.

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A Appendix

A.1 Further Details on the Swedish Education System

Gymnasium

Students apply for senior high school by ranking schools and programs of their choice anywhere in the municipality in which they live. A student does not receive an offer from several schools; if they are admitted to their first choice, this is the only offer they will get. Some schools accept applicants from neighboring municipalities, or from anywhere in the country. Whether the student gets admitted to a specific school and program depends on their GPA from the ninth grade.

The programs preparing the students for university are:

- Arts Programme
- Business Management and Economics Programme
- Humanities Programme
- Natural Science Programme
- Social Science Programme
- Technology Programme

All of these programs contain core courses in the following subjects: English, history, physical education and health, mathematics, religion, social studies, and Swedish or Swedish as a second language. In the Natural Science Programme, the students take further courses in biology, physics, chemistry, and modern languages (a third language in addition to Swedish and English). In the Technology Programme, the students take further courses in physics, chemistry, and technology (Utbildningsinfo, 2016a).

All programs come with different specializations, or so called *orientations*, which further deepen the knowledge in one specific field. For the Natural Science Programme, the students choose between *Natural sciences*, and *Natural sciences and society.* The students in the technical program choose between *Design and product development, Information and media technology, Production technology, Community building and environment*, and *Technology sciences* (Utbildningsinfo, 2016b). In general, the choice of orientation has little impact on the eligibility for higher studies. It could, however, have an effect on the eligibility for some specific university programs, such as medical studies or engineering (Utbildningsinfo, 2016b).

University and College: The Application Process

The majority of students are admitted to college using their gymnasium GPA. It is also possible to improve one's grades after graduating from high school, via Municipal Adult Education, *Komvux–Kommunal Vuxenutbildning*, and apply with these. Furthermore, if a student is not eligible to apply for a certain program, they can take the courses they need to fulfill the eligibility criteria after high school graduation. *Komvux*, and some universities offer such courses. In other words, someone who has studied social sciences in high school will still be able to become, for example, an engineer, however with some delay (typically a year).

When applying for a university program, students compete in different groups; i.e., the students who have completed the University Test *Högskoleprovet* compete against each other, students who apply with their gymnasium GPA compete in another group, and those who have improved their grades after graduation in yet another group. The same student can compete in multiple groups simultaneously. The three aforementioned application groups are the main ones, but depending on the university and the specific program, further groups may be included. For instance, a temporary group for recent high school graduates has been used in the past few years for all programs due to the implementation of a new grading scale in senior high school, with more steps than the previous one. This group will be removed in 2017 (Universitets- och Högskolerådet, 2016).

A.2 School Descriptive Statistics

Table 10 below displays descriptive statistics on program level for each of the surveyed schools. Data is obtained from the database SIRIS (Skolverket, 2016b). The following schools are included:

1=Blackebergs Gymnasium
2=Bromma Gymnasium
3=Kungsholmens Gymnasium
4=Kärrtoprs Gymnasium
5=Norra Real
6=Thorén Business School
7=Thorildsplans Gymnasium natural science
8=Thorildsplans Gymnasium technology
9=Värmdö Gymnasium natural science
10=Värmdö Gymnasium technology

Table 10: Summary Statistics for Program at Each School

	1	2	3	4	5	6	7	8	9	10
School size	1159	1050	1199	928	996	747	1299	1299	1221	1221
Private	No	No	No	No	No	Yes	No	No	No	No
Foreign-Born	0.24	0.35	0.32	0.72	0.18	0.40	0.59	0.25	0.17	0.11
Higher Educ	0.84	0.76	0.86	0.60	0.89	0.73	0.65	0.75	0.85	0.79
Female share	0.54	0.45	0.63	0.38	0.56	0.54	0.39	0.21	0.53	0.11
Share Start College	0.81	0.60	0.77	0.66	0.76		0.71	0.71	0.60	0.60
N (Surveyed)	164	23	56	67	93	25	60	119	155	31

Note: the table displays mean values for each program (natural science or technology) for the surveyed schools. Program-level variables are *foreign-born* (share of students who are foreign-born or have parents who are foreign-born), *higher educ* (share of students with parents who have attended higher education), and *female share* (share of female students in the program). School-level variables are: *school size*, *private* and *share start college*. A missing value is observed for Thorén Business School for *share start college*, as data on this variable is from 2011 and Thorén Business School did not exist then.

A.3 The Surveys

Original Swedish versions of the survey questions can be found below. See Section 5.2 for treatment versions of question 4.

Ålder
Kön (frivilligt)
Program & Inriktning
1. Vad är sannolikheten att du kommer att skaffa en examen från högskola/universitet i framtiden? (%)
2. Om du skulle söka till högskolan idag, vilka tre utbildningar är det mest troligt att du skulle söka till?
3. Hur sannolikt är det att du kommer att ändra denna rangordning i framtiden? (Skala 1-10)
4. Vad är sannolikheten att du skulle söka till en IT utbildning? Exempel på IT-utbildningar är dataingenjör, systemvetare, programmerare och app- eller webbutvecklare. (%)
5. Vad tror du att dina manliga klasskamrater anger för sannolikhet på föregående fråga, i genomsnitt? (%)
6. Vad tror du att dina kvinnliga klasskamrater anger för sannolikhet på fråga 4, i genomsnitt? (%)
7. Hur attraktiv tror du att en IT-utbildning är bland dina klasskamrater? (Skala 1-10)
8. Rangordna följande utbildningsalternativ utifrån hur troligt det är att du skulle studera inom respektive område: Samhällsvetenskap, Teknik/Naturvetenskap, Vård/Omsorg, Pedagogik/Lärarutbildning, Humaniora/Språk/Konst/Estetik, Inte studera på högskolan.
9. Hur viktiga anser du följande faktorer vara i ditt val av högskoleutbildning? (Skala 1-10):

- Att tjäna mycket pengar
- Utbildningens status
- Att få plugga det jag är intresserad av
- Att få plugga det jag är duktig på
- Att få hjälpa andra/göra skillnad
- Att få möjlighet till balans mellan jobb och fritid
- Att få studera med likasinnade personer
- Andelen kvinnor (om du är kvinna)/män (om du är man) på utbildningen
- Att få jobba med människor efter examen
- Att lätt få jobb efter examen

10. Rangordna följande faktorer utifrån vad som är viktigast för dig i valet av högskoleutbildning: [samma faktorer som ovan]
11. Vilka av följande faktorer associerar du med en IT-utbildning: [samma faktorer som ovan]
12. Hur skulle du uppskatta dina färdigheter i skolan i förhållande till din gymnasieklass? (Skala 1-10)
13. Om du skulle studera på en IT-utbildning, hur skulle du uppskatta dina färdiheter inom ämnet i förhållande till din IT klass? (Skala 1-10)
14. Uppskatta ditt meritvärde. [Alla A=20, B=17.5, C=15, D=12.5, E=10]
15. Har du rådfrågat någon annan om ditt högskoleval? (Alternativ: förälder, syskon, lärare, studievägledare, vänner, ingen.)
16. Har någon av dina föräldrar eftergymnasial utbildning? (Alternativ: ja – en, ja – båda, nej – ingen.)
17. Har någon i din närhet pluggat och/eller arbetar med IT? (Alternativ: mamma, pappa, syskon, vän, annan (ange relation), ingen.)
18. Hur lätt tror du det är för en person att få jobb efter avslutad IT-utbildning? (Skala 1-10)
19. Den 1 december 2015 lämnade Digitaliseringskommisionen ett betänkande till regeringen med förslaget att kvinnor som tar en kandidatexamen (3 år) inom IT inte ska behöva betala tillbaka sina studielån till CSN. Kände du till detta förslag sedan innan? (Alternativ: ja, nej.)
20. Om du går i tredje klass: Har du eller kommer du att söka till högskola/universitet för att börja studera hösten 2016? (Alternativ: ja, nej, har inte bestämt mig.)

Translated English versions of the survey questions can be found below. See Section 5.2 for treatment versions of question 4.

Age
Gender (voluntary)
Programme & Specialization
1. What is the probability that you will obtain a college degree in the future? (%)
2. If you were to apply today, which three majors would you apply to?
3. How likely is it that you will change this ranking in the future? (Scale 1-10)
4. What is the probability that you would apply to an IT major? (%)
5. What probability do you estimate that your male classmates answered on average for the previous question? (%)
6. What probability do you estimate that your female classmates answered? (%)
7. How attractive do you think IT is among your classmates? (Scale 1-10)
8. Rank the following areas of education according to which you would most likely study: Social sciences, Technology/Natural Sciences, Health Care, Pedagogy/Teaching, Humanities/Languages/Art, Not study at university.
9. How important do you consider the following factors to be in your choice of higher education (Scale 1-10):

- Earning a lot of money
- Status of the major
- Studying what I am interested in
- Studying what I am good at
- To be able to help others/make a difference
- To be able to have work-life balance
- Studying with like-minded people
- Share of women (if you are a woman)/men (if you are a man) in the major
- Getting a job working with people
- Easily getting a job after your studies

10. Rank the following factors according to what is most important to you in your choice of higher education (Rank 1-10) [same factors as above]
11. Which of the following factors do you associate with an IT major: [same factors as above]
12. How would you estimate your abilities relative to your current class? (Scale 1-10)
13. How would you estimate your abilities relative to a hypothetical future IT class? (Scale 1-10)
14. What is your current GPA? [All A's=20, B's=17.5, C's=15, D's=12.5, E's=10]
15. Have you consulted anyone about your choice of higher education? (Alternatives: parent, sibling, teacher, guidance counselor, friend(s), no one.)
16. Do any of your parents have a higher education? (Alternatives: Yes – one, yes – both, no – neither.)
17. Has anyone close to you studied and/or worked with IT? (Alternatives: Mother, father, sibling, friend, other (state relation), no one.)
18. How easy do you think it is to get a job after having studied IT? (Scale 1-10)
19. According to a suggestion from the Digitalization Commission (SOU 2015:91), women who choose to study IT will not have to repay their student loans after graduation. Were you previously aware of this proposal? (Alternatives: yes, no.)
20. If you are currently in third grade, have you or will you apply to continue studying this coming fall semester? (Alternatives: yes, no, undecided.)

A.4 List of Variables

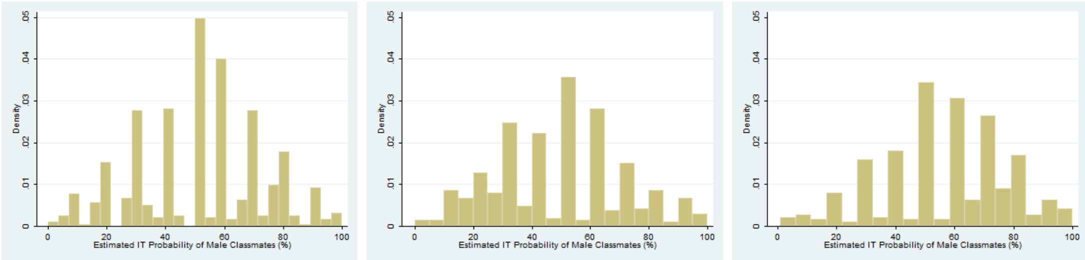
Table 11: List of Variables Part 1

Variable	**Description**
Age	Age in years
Female	Gender dummy; value 0 indicates male, value 1 indicates female.
Prob Study	Student's stated probability of continuing on to university level studies.
IT Top 3 Alternative	Dummy variable; 1 if one of the student's top three reported choices is IT (asked prior to treatment information).
Change Rank Prob	Scale 1-10 how likely it is that the top three listed major alternatives will change in the future; 10 indicates highly likely.
Treatment 1	Dummy variable; 1 if in treatment group 1 (receives information on student loan proposal).
Treatment 2	Dummy variable; 1 if in treatment group 2 (receives information on IT job security).
IT Probability	Stated probability of applying to an IT major (0-100).
Male Classmates IT Prob	Student's estimated average IT probability for male classmates (0-100).
Female Classmates IT Prob	Student's estimated average IT probability for female classmates (0-100).
Low Rank Tech-Science	Rank variable 1-6, where a value of 6 indicates Tech-Science is least preferred study option.
Importance Money	Importance given to factor money, scale 1-10 where 10 indicates maximum importance.
Importance Status	Importance given to factor status, scale 1-10 where 10 indicates maximum importance.
Importance Interest	Importance given to factor interesting topic, scale 1-10 where 10 indicates maximum importance.
Importance Ability	Importance given to factor ability (being good at chosen major), scale 1-10 where 10 indicates maximum importance.
Importance Helping	Importance given to factor helping others/make a difference, scale 1-10 where 10 indicates maximum importance.
Importance Balance	Importance given to factor work-life balance, scale 1-10 where 10 indicates maximum importance.
Importance Like-minded	Importance given to factor like-minded (getting to study with like-minded people), scale 1-10 where 10 indicates maximum importance.
Importance Gender Share	Importance given to factor gender share of major, scale 1-10 where 10 indicates maximum importance.
Importance People	Importance given to factor people (getting to work with people), scale 1-10 where 10 indicates maximum importance.
Importance Job Security	Importance given to factor job security, scale 1-10 where 10 indicates maximum importance.
Rank Money	Rank given to factor money, range 1-10 where 1 indicates most important factor.
Rank Status	Rank given to factor status, range 1-10 where 1 indicates most important factor.
Rank Interest	Rank given to factor interesting topic, range 1-10 where 1 indicates most important factor.
Rank Ability	Rank given to factor ability (being good at chosen major), range 1-10 where 1 indicates most important factor.
Rank Helping	Rank given to factor helping others/make a difference, range 1-10 where 1 indicates most important factor.
Rank Balance	Rank given to factor work-life balance, range 1-10 where 1 indicates most important factor.
Rank Like-minded	Rank given to factor like-minded (getting to study with like-minded people), range 1-10 where 1 indicates most important factor.
Rank Gender Share	Rank given to factor gender share of major, range 1-10 where 1 indicates most important factor.
Rank People	Rank given to factor people (getting to work with people), range 1-10 where 1 indicates most important factor.
Rank Job Security	Rank given to factor job security, range 1-10 where 1 indicates most important factor.
IT Money	Dummy variable where 1 indicates associating IT with money.
IT Status	Dummy variable where 1 indicates associating IT with status.
IT Interest	Dummy variable where 1 indicates associating IT with an interesting topic.
IT Ability	Dummy variable where 1 indicates associating IT with "I am good at it".

Table 12: List of Variables Part 2

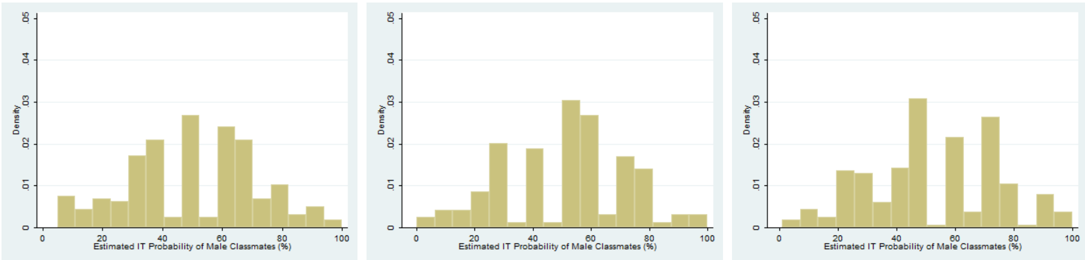
Variable	**Description**
IT Helping	Dummy variable where 1 indicates associating IT with helping others/make a difference.
IT Balance	Dummy variable where 1 indicates associating IT with work-life balance.
IT Like-minded	Dummy variable where 1 indicates associating IT with like-minded people.
IT Uneven Gender Share	Dummy variable where 1 indicates associating IT with uneven gender share.
IT People	Dummy variable where 1 indicates associating IT with getting to work with people.
IT Job Security	Dummy variable where 1 indicates associating IT with job security.
Ability	Estimated ability compared to current class, scale 1-10 where 10 indicates highest ability.
Ability IT	Estimated ability compared to hypothetical IT class, scale 1-10 where 10 indicates highest ability.
GPA	Current GPA, range 0-20 where a value of 20 indicates all A's.
One Parent Higher Educ	Dummy variable; 1 indicates having one parent who has a higher education.
Two Parents Higher Educ	Dummy variable; 1 indicates having two parents who have higher education.
No Parent Higher Educ	Dummy variable; 1 indicates having no parent who has a higher education.
Advice Parent	Dummy variable; 1 indicates having consulted a parent about the choice of college major.
Advice Sibling	Dummy variable; 1 indicates having consulted a sibling about the choice of college major.
Advice Teacher	Dummy variable; 1 indicates having consulted a teacher about the choice of college major.
Advice Counselor	Dummy variable; 1 indicates having consulted a guidance counselor about the choice of college major.
Advice Friend	Dummy variable; 1 indicates having consulted a friend about the choice of college major.
Advice No One	Dummy variable; 1 indicates not having consulted anyone about the choice of college major.
No IT Relation	Dummy variable; 1 indicates having no acquaintance working with or having studied IT.
Mother IT	Dummy variable; 1 indicates having a mother who has studied/works with IT.
Father IT	Dummy variable; 1 indicates having a father who has studied/works with IT.
Sibling IT	Dummy variable; 1 indicates having a sibling who has studied/works with IT.
Friend IT	Dummy variable; 1 indicates having a friend who has studied/works with IT.
Other IT	Dummy variable; 1 indicates having another relation who has studied/works with IT.
IT Job Security Belief	Estimated job security for an IT graduate, scale 1-10 where 10 indicates maximum job security.
Proposal Awareness	Dummy variable; 1 indicates being aware of student loan proposal prior to survey participation.
Yes Apply	Dummy variable for third year students; 1 indicates applying to start studying fall semester 2016.
No Apply	Dummy variable for third year students; 1 indicates not applying to start studying fall semester 2016.
Undecided Apply	Dummy variable for third year students; 1 indicates being undecided on applying to start studying fall semester 2016.
Grade 3	Dummy variable; 1 indicates third grade students.
Class Size	Number of students in the class at time of survey.
Class female share	Proportion of female students in the class at time of survey.
Technology	Program dummy; value 0 indicates natural science, value 1 indicates technology.
Median GPA	Ninth grade median GPA of class.
Day Surveyed	Range 1-28, value 1 indicates first day of survey, value 28 indicates last day of survey.
Program Female Share	Proportion of female students, in program (natural science or technology) at school.
Program Higher Educ	Proportion of students with parent(s) with higher education, in program (natural science or technology) at school.
Program Foreign-Born	Proportion of students who are foreign-born or have parents who are foreign-born, in program (natural science or technology) at school.
School size	Number of students in school.
School Share Start College	Proportion of students who continue on to university level studies, in school.
Private	Dummy variable; 1 indicates private school.

A.5 Histograms



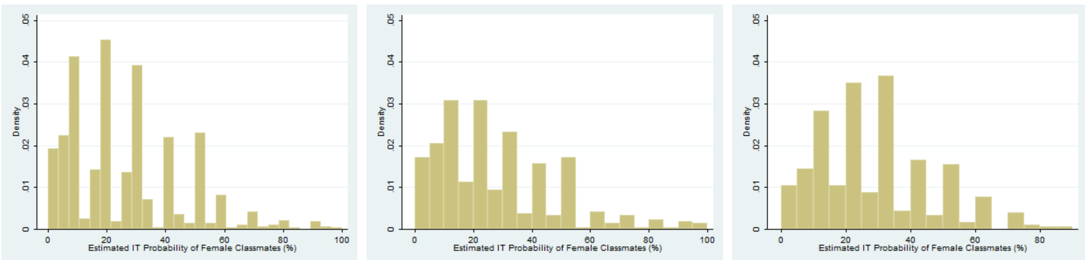
(a) By All students (b) By Males (c) By Females

Figure 3: Estimated IT Probability for Male Classmates, by Gender



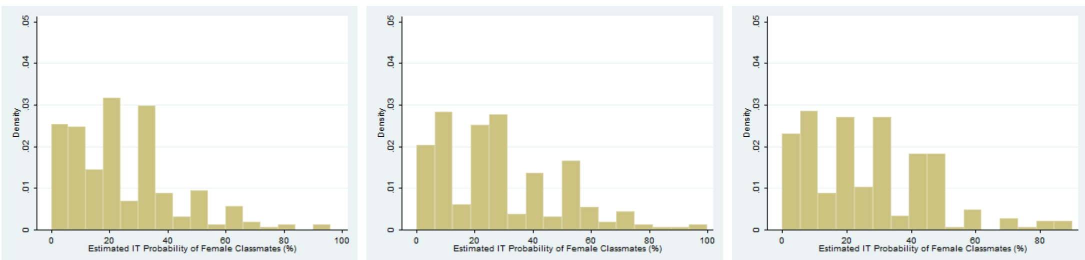
(a) By Control (b) By Treatment 1 (c) By Treatment 2

Figure 4: Estimated IT Probability for Male Classmates, by Treatment



(a) By All Students (b) By Males (c) By Females

Figure 5: Estimated IT Probability for Female Classmates, by Gender



(a) By Control (b) By Treatment 1 (c) By Treatment 2

Figure 6: Estimated IT Probability for Female Classmates, by Treatment

A.6 Summary Statistics

Table 13: Summary Statistics by Program

	Natural Science			Technology		
	All	Males	Females	All	Males	Females
IT Probability	0.290	0.332	0.247	0.442***	0.463***	0.366***
	(0.271)	(0.294)	(0.243)	(0.334)	(0.338)	(0.319)
Male Classmates IT Prob	0.497	0.429	0.560	0.587***	0.586***	0.579
	(0.208)	(0.192)	(0.202)	(0.238)	(0.242)	(0.231)
Female Classmates IT Prob	0.243	0.225	0.259	0.350***	0.351***	0.340***
	(0.167)	(0.161)	(0.172)	(0.258)	(0.278)	(0.197)
GPA	16.755	16.701	16.795	15.076***	15.068***	15.131***
	(1.929)	(2.068)	(1.792)	(2.237)	(2.209)	(2.377)
Ability	6.471	6.716	6.225	6.302	6.418	5.946
	(1.727)	(1.767)	(1.660)	(1.728)	(1.767)	(1.660)
Ability IT	4.521	5.304	3.769	5.414***	5.769*	4.200
	(2.200)	(2.287)	(1.838)	(2.169)	(2.067)	(2.041)
Prob Study	91.659	90.515	92.702	82.719***	82.328***	84.258***
	(14.116)	(14.888)	(13.317)	(20.838)	(21.320)	(19.779)
IT Top 3 Alternative	0.145	0.223	0.070	0.306***	0.376**	0.094
	(0.352)	(0.417)	(0.255)	(0.262)	(0.487)	(0.296)
No IT Relation	0.299	0.318	0.285	0.233	0.224*	0.270
	(0.459)	(0.466)	(0.452)	(0.424)	(0.419)	(0.450)
No Parent Higher Educ	0.135	0.168	0.103	0.186	0.189	0.189
	(0.342)	(0.374)	(0.304)	(0.390)	(0.393)	(0.397)
Advice No One	0.213	0.226	0.199	0.286*	0.333**	0.162
	(0.409)	(0.419)	(0.400)	(0.453)	(0.473)	(0.373)
Proposal Awareness	0.161	0.164	0.153	0.177	0.176	0.189
	(0.368)	(0.371)	(0.361)	(0.283)	(0.383)	(0.397)
IT Job Security Belief	7.735	7.727	7.734	7.313	7.561	6.800
	(1.674)	(1.824)	(1.524)	(1.949)	(1.738)	(2.180)
Yes Apply	0.465	0.461	0.469	0.415	0.378	0.500
	(0.500)	(0.500)	(0.501)	(0.497)	(0.492)	(0.519)
Class female share	0.506	0.467	0.546	0.253***	0.208***	0.375***
	(0.141)	(0.139)	(0.132)	(0.176)	(0.169)	(0.127)
Class Size	25.406	25.029	25.816	23.200***	23.800**	21.421***
	(0.011)	(3.794)	(3.597)	(6.073)	(6.350)	(5.038)
Program Female Share	0.514	0.501	0.527	0.189***	0.183***	0.207***
	(0.072)	(0.076)	(0.652)	(0.041)	(0.045)	(0.016)
Program Foreign-Born	0.314	0.342	0.288	0.221***	0.212***	0.246
	(0.183)	(0.202)	(0.160)	(0.057)	(0.062)	(0.023)
Program Higher Educ	0.802	0.786	0.816	0.758***	0.761**	0.751***
	(0.095)	(0.104)	(0.084)	(0.016)	(0.018)	(0.006)
Median GPA	299.288	295.613	302.851	253.767***	255.977***	247.829***
	(24.898)	(26.324)	(23.048)	(21.813)	(23.905)	(13.332)

Note: The table displays descriptive statistics for the outcome and control variables across programs. Standard deviations are reported in parentheses. Asterisks indicate a significant difference in means compared Natural Science, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 14: Baseline Characteristics by Treatment Group: Males

	Control	Treatment 1	Treatment 2	T1-C	T2-C	T1-T2
IT Probability	0.341	0.349	0.407	0.008	0.065*	-0.057
	(0.302)	(0.307)	(0.320)	(0.036)	(0.037)	(0.038)
Male Classmates IT Prob	0.466	0.446	0.495	-0.020	0.030	-0.050*
	(0.217)	(0.210)	(0.222)	(0.026)	(0.026)	(0.026)
Female Classmates IT Prob	0.241	0.260	0.271	0.019	0.030	-0.012
	(0.188)	(0.218)	(0.208)	(0.024)	(0.024)	(0.026)
Age	17.694	17.699	17.787	0.004	0.093	-0.089
	(0.732)	(0.703)	(0.782)	(0.086)	(0.090)	(0.089)
Prob Study	88.264	87.766	89.123	-0.498	0.859	-1.357
	(17.953)	(17.168)	(16.364)	(2.094)	(2.029)	(2.008)
GPA	16.387	16.299	16.154	-0.089	-0.233	0.145
	(2.255)	(2.199)	(2.218)	(0.270)	(0.269)	(0.268)
IT Top 3 Alternative	0.258	0.254	0.275	-0.004	0.017	-0.021
	(0.437)	(0.439)	(0.448)	(0.054)	(0.055)	(0.055)
Change rank prob	5.500	5.023	5.818	-0.477	0.318	-0.795
	(2.705)	(2.975)	(2.865)	(0.350)	(0.358)	(0.344)**
Ability	6.490	6.794	6.638	0.305	0.149	0.156
	(1.788)	(1.826)	(1.762)	(0.216)	(0.211)	(0.216)
Ability IT	5.5255	5.737	5.300	0.482*	0.045	0.437
	(2.260)	(2.286)	(2.154)	(0.275)	(0.263)	(0.269)
No IT relation	0.295	0.306	0.281	0.011	-0.014	0.025
	(0.462)	(0.458)	(0.458)	(0.056)	(0.054)	(0.055)
No Parent Higher Educ	0.187	0.173	0.159	-0.014	-0.028	0.014
	(0.391)	(0.380)	(0.367)	(0.047)	(0.046)	(0.045)
Advice No One	0.229	0.269	0.266	0.040	0.038	0.002
	(0.421)	(0.445)	(0.444)	(0.052)	(0.052)	(0.054)
Proposal Awareness	0.151	0.216	0.137	0.065	-0.014	0.080*
	(0.359)	(0.413)	(0.345)	(0.047)	(0.042)	(0.046)
IT Job Security Belief	7.4644	7.754	7.835*	0.290	0.371	-0.081
	(1.772)	(1.960)	(1.658)	(0.226)	(0.206)	(0.219)
Yes Apply	0.473	0.462	0.397	-0.011	-0.076	0.065
	(0.503)	(0.504)	(0.493)	(0.097)	(0.094)	(0.095)
Undecided Apply 16	0.236	0.250	0.310	0.058	0.104	-0.060
	(0.380)	(0.424)	(0.450)	(0.055)	(0.058)	(0.087)
Class size	24.628	24.978	24.535	0.351	-0.092	0.443
	(4.729)	(4.515)	(4.624)	(0.551)	(0.552)	(0.547)
Class female share	0.402	0.402	0.395	0.001	-0.007	0.007
	(0.182)	(0.193)	(0.185)	(0.022)	(0.022)	(0.023)
Median GPA	286.667	286.354	282.978	-0.313	-2.689	3.376
	(31.309)	(30.231)	(31.570)	(3.669)	(3.712)	(3.703)
Program Foreign-Born	0.314	0.3086	0.302	-0.006	-0.013	0.007
	(0.188)	(0.189)	(0.181)	(0.022)	(0.022)	(0.022)
Program Higher Educ	0.780	0.780	0.779	0.000	-0.001	0.001
	(0.092)	(0.092)	(0.088)	(0.011)	(0.011)	(0.011)
Program Female Share	0.426	0.422	0.408	-0.003	-0.018	0.014
	(0.158)	(0.154)	(0.158)	(0.019)	(0.018)	(0.019)
School Share Start College	0.696	0.689	0.680	-0.007	-0.016*	0.009
	(0.080)	(0.078)	(0.076)	(0.010)	(0.010)	(0.009)
Technology	0.234	0.248	0.296	0.014	0.061	-0.048
	(0.425)	(0.434)	(0.458)	(0.051)	(0.052)	(0.053)
Grade 3	0.393	0.380	0.430	-0.014	0.036	-0.050
	(0.490)	(0.487)	(0.497)	(0.058)	(0.058)	(0.059)
School size	1155.028	1153.277	1175.021	-1.750	19.994	-21.744
	(132.633)	(145.622)	(132.144)	(16.573)	(15.631)	(16.637)
Private School	0.014	0.036	0.014	0.023	0.000	0.022
	(0.118)	(0.117)	(0.188)	(0.014)	(0.019)	(0.187)
N	145	137	142			

Note: The table displays descriptive statistics for the outcome and control variables separately over treatment and control groups. Columns (1)-(3) display standard deviations in parentheses, columns (4)-(6) display standard errors in parentheses. Asterisks indicate a significant difference in means, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 15: Baseline Characteristics by Treatment Group: Females

	Control	Treatment 1	Treatment 2	T1-C	T2-C	T1-T2
IT Probability	0.222	0.295	0.259	0.073**	0.037	0.036
	(0.248)	(0.263)	(0.244)	(0.033)	(0.032)	(0.032)
Male Classmates IT Prob	0.554	0.567	0.565	0.014	0.011	0.002
	(0.204)	(0.197)	(0.214)	(0.026)	(0.027)	(0.026)
Female Classmates IT Prob	0.240	0.298	0.262	0.058**	0.022	0.036
	(0.170)	(0.185)	(0.168)	(0.023)	(0.022)	(0.023)
Age	17.718	17.762	17.720	0.044	0.002	0.042
	(0.786)	(0.763)	(0.727)	(0.099)	(0.099)	(0.096)
Prob Study	93.200	91.537	90.775	-1.663	-2.425	0.762
	(10.557)	(15.277)	(16.357)	(1.694)	(1.793)	(2.013)
GPA	16.727	16.464	16.712	-0.263	-0.015	-0.248
	(1.974)	(1.978)	(1.803)	(0.246)	(0.250)	(0.246)
IT Top 3 Alternative	0.075	0.095	0.046	0.020	-0.028	0.049
	(0.264)	(0.294)	(0.211)	(0.038)	(0.033)	(0.034)
Change rank prob	6.082	5.893	6.351	-0.189	0.269	-0.458
	(2.665)	(2.632)	(2.847)	(0.349)	(0.369)	(0.357)
Ability	6.316	6.144	6.134	-0.172	-0.182	0.010
	(1.813)	(1.529)	(1.741)	(0.216)	(0.213)	(0.228)
Ability IT	3.6586	3.756	4.017	0.098	0.359	-0.261
	(1.905)	(1.769)	(1.896)	(0.239)	(0.240)	(0.244)
No IT relation	0.336	0.264	0.252	-0.072	-0.084	0.012
	(0.474)	(0.442)	(0.436)	(0.059)	(0.060)	(0.057)
No Parent Higher Educ	0.155	0.104	0.077	-0.051	-0.078*	0.027
	(0.363)	(0.306)	(0.268)	(0.043)	(0.042)	(0.037)
Advice No One	0.207	0.184	0.197	-0.023	-0.010	-0.013
	(0.389)	(0.407)	(0.399)	(0.051)	(0.053)	(0.051)
Proposal Awareness	0.200	0.168	0.103	-0.032	-0.097**	0.065
	(0.402)	(0.375)	(0.305)	(0.050)	(0.047)	(0.044)
IT Job Security Belief	7.739	7.598	7.590	-0.141	-0.149	0.009
	(1.499)	(1.655)	(1.708)	(0.206)	(0.211)	(0.218)
Yes Apply	0.543	0.545	0.419	-0.089	-0.125	0.0356
	(0.503)	(0.504)	(0.499)	(0.101)	(0.106)	(0.102)
Undecided Apply 16	0.087	0.200	0.233	0.113	0.146*	-0.033
	(0.285)	(0.404)	(0.427)	(0.071)	(0.077)	(0.084)
Class size	25.333	25.362	25.375	0.029	0.042	-0.013
	(3.774)	(3.796)	(3.828)	(0.485)	(0.494)	(0.485)
Class female share	0.537	0.514	0.533	-0.023	-0.005	-0.019
	(0.143)	(0.137)	(0.145)	(0.018)	(0.018)	(0.018)
Median GPA	296.562	296.429	298.357	-0.132	1.795	-1.928
	(28.420)	(27.888)	(27.498)	(3.609)	(3.598)	(3.562)
Program Foreign-Born	0.284	0.280	0.287	-0.004	0.003	-0.007
	(0.150)	(0.146)	(0.161)	(0.019)	(0.020)	(0.020)
Program Higher Educ	0.808	0.810	0.810	0.001	0.001	0.001
	(0.079)	(0.081)	(0.086)	(0.010)	(0.011)	(0.010)
Program female share	0.495	0.488	0.498	-0.008	0.003	-0.010
	(0.115)	(0.122)	(0.110)	(0.015)	(0.015)	(0.015)
School Share Start College	0.708	0.712	0.715	0.005	0.007	-0.002
	(0.084)	(0.084)	(0.083)	(0.011)	(0.011)	(0.011)
Technology	0.103	0.126	0.083	0.023	-0.019	0.043
	(0.305)	(0.333)	(0.277)	(0.041)	(0.038)	(0.039)
Grade 3	0.419	0.449	0.375	0.030	-0.043	0.074
	(0.495)	(0.499)	(0.486)	(0.064)	(0.064)	(0.063)
School size	1143.145	1160.567	1128.042	17.421	-15.104	32.525*
	(144.555)	(123.065)	(141.190)	(17.145)	(18.561)	(16.828)
Private School	0.060	0.024	0.050	-0.036	-0.010	-0.026
	(0.238)	(0.152)	(0.219)	(0.025)	(0.029)	(0.024)
N	117	127	120			

Note: The table displays descriptive statistics for the outcome and control variables separately over treatment and control groups. Columns (1)-(3) display standard deviations in parentheses, columns (4)-(6) display standard errors in parentheses. Asterisks indicate a significant difference in means, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 16: Differences in Abilities and the Ten Factors

	Control	Treatment 1	Treatment 2	T1-T2	Males	Females
GPA	16.553	16.369	16.411	-0.042	16.280	16.630**
	(0.133)	(0.130)	(0.129)	(0.183)	(0.110)	(0.102)
Ability	6.418	6.489	6.410	0.079	6.638	6.197***
	(0.103)	(0.114)	(0.110)	(0.158)	(0.087)	(0.089)
Ability IT	4.562	4.790	4.712	0.078	5.425	3.812***
	(0.137)	(0.145)	(0.132)	(0.196)	(0.110	(0.099)
Importance Money	7.156	7.257	7.260	-0.003	7.343	7.093*
	(0.118)	(0.120)	(0.114)	(0.166)	(0.098)	(0.091)
Importance Status	5.820	5.633	5.897	-0.264	5.893	5.678
	(0.151)	(0.157)	(0.147)	(0.215)	(0.123)	(0.124)
Importance Interest	9.297	9.249	9.145	0.104	9.050	9.437***
	(0.065)	(0.078)	(0.079)	(0.111)	(0.065)	(0.053)
Importance Ability	8.118	7.807**	7.775**	0.032	7.769	8.050**
	(0.102)	(0.116)	(0.114)	(0.163)	(0.096)	(0.083)
Importance Helping	6.981	6.857	6.786	0.070	6.240	7.623***
	(0.153)	(0.154)	(0.152)	(0.216)	(0.124)	(0.114)
Importance Balance	7.458	7.356	7.538	-0.182	7.343	7.589
	(0.122)	(0.142)	(0.129)	(0.192)	(0.106)	(0.108)
Importance Like-minded	6.977	6.977	7.069	-0.092	6.898	7.141
	(0.132)	(0.146)	(0.131)	(0.197)	(0.113)	(0.109)
Importance Gender Share	3.575	3.528	3.985*	-0.456**	3.616	3.821
	(0.158)	(0.151)	(0.157)	(0.218)	(0.129)	(0.125)
Importance People	6.686	6.390	6.698	-0.308	6.181	7.091***
	(0.161)	(0.164)	(0.160)	(0.229)	(0.130)	(0.129)
Importance Job Security	8.303	8.030*	8.237	-0.206	8.205	8.180
	(0.112)	(0.120)	(0.113)	(0.165)	(0.093)	(0.096)
Rank Money	4.335	4.064	4.188	-0.123	3.852	4.593***
	(0.150)	(0.150)	(0.151)	(0.213)	(0.124)	(0.118)
Rank Status	6.422	6.129	5.996*	0.133	5.829	6.577***
	(0.159)	(0.161)	(0.161)	(0.228)	(0.126)	(0.134)
Rank Interest	1.977	2.148	2.034	0.113	2.137	1.958
	(0.121)	(0.129)	(0.120)	(0.176)	(0.097)	(0.107)
Rank Ability	4.035	4.316	4.096	0.220	4.062	4.252
	(0.132)	(0.131)	(0.127)	(0.183)	(0.097)	(0.118)
Rank Helping	5.523	5.525	5.747	-0.222	6.235	4.869***
	(0.160)	(0.159)	(0.158)	(0.225)	(0.122)	(0.130)
Rank Balance	5.450	5.399	5.379	0.020	5.370	5.452
	(0.139)	(0.131)	(0.135)	(0.188)	(0.108)	(0.114)
Rank Like-minded	6.287	6.308	6.574	-0.267	6.358	6.440
	(0.137)	(0.136)	(0.136)	(0.192)	(0.107)	(0.117)
Rank Gender Share	8.775	8.894	8.866	0.028	8.772	8.922
	(0.128)	(0.113)	(0.114)	(0.160)	(0.092)	(0.103)
Rank People	7.070	7.254	7.080	0.174	7.495	6.715***
	(0.140)	(0.140)	(0.141)	(0.199)	(0.100)	(0.129)
Rank Job Security	4.907	4.913	4.862	0.050	4.651	5.177**
	(0.146)	(0.143)	(0.150)	(0.207)	(0.113)	(0.125)
IT Money	0.496	0.489	0.494	-0.006	0.482	0.510
	(0.031)	(0.031)	(0.031)	(0.044)	(0.024)	(0.026)
IT Status	0.261	0.270	0.253	0.016	0.231	0.299**
	(0.027)	(0.027)	(0.027)	(0.038)	(0.021)	(0.024)
IT Interest	0.379	0.413	0.368	0.045	0.486	0.266***
	(0.030)	(0.030)	(0.030)	(0.043)	(0.024)	(0.023)
IT Ability	0.157	0.193	0.172	0.021	0.274	0.058***
	(0.023)	(0.024)	(0.023)	(0.034)	(0.022)	(0.012)
IT Helping	0.115	0.182**	0.134	0.048	0.162	0.119*
	(0.020)	(0.024)	(0.021)	(0.032)	(0.018)	(0.017)
IT Balance	0.173	0.217	0.238*	-0.021	0.243	0.172**
	(0.024)	(0.025)	(0.026)	(0.037)	(0.021)	(0.020)
IT Like-minded	0.103	0.148	0.107	0.040	0.169	0.058***
	(0.019)	(0.022)	(0.019)	(0.029)	(0.018)	(0.012)
IT Uneven Gender Share	0.720	0.697	0.732	-0.035	0.640	0.809***
	(0.028)	(0.028)	(0.027)	(0.039)	(0.023)	(0.021)
IT People	0.034	0.049	0.085**	-0.035	0.071	0.039**
	(0.011)	(0.013)	(0.017)	(0.022)	(0.013)	(0.010)
IT Job Security	0.659	0.705	0.747**	-0.043	0.717	0.690
	(0.029)	(0.028)	(0.027)	(0.039)	(0.022)	(0.024)
N	265	265	263		424	364

Note: The table displays descriptive statistics for ability variables and three versions of the ten factors; first, importance of each factor (scale 1-10; 10 indicates maximum importance), second, rank of each factor (1-10; 1 indicates ranked most important), and third, association of factor with IT (binary; 1 indicates association). Standard errors are displayed in parentheses. Asterisks indicate a significant difference in means, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Column (2) and (3) are compared to control, column (4) shows difference between treatment groups, and finally column 6 shows significance between genders.

A.7 OLS Estimated Impact on IT Probability

Table 17: Impact on IT Probability: All Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.00512	-0.0119	-0.0104	-0.0107	-0.0109	-0.00931
	(0.0334)	(0.0296)	(0.0236)	(0.0224)	(0.0226)	(0.0219)
Treatment 2	0.0595*	0.0586**	0.0507*	0.0475*	0.0494*	0.0457
	(0.0318)	(0.0283)	(0.0275)	(0.0266)	(0.0270)	(0.0272)
Female	-0.114**	0.00967	0.0425	0.0439	0.0516	0.0420
	(0.0440)	(0.0417)	(0.0374)	(0.0371)	(0.0378)	(0.0381)
Female*t1	0.0681	0.0653	0.0423	0.0477	0.0472	0.0547
	(0.0421)	(0.0428)	(0.0408)	(0.0418)	(0.0423)	(0.0419)
Female*t2	-0.0195	-0.0382	-0.0205	-0.0149	-0.0180	-0.00161
	(0.0537)	(0.0493)	(0.0495)	(0.0483)	(0.0482)	(0.0491)
Ability IT		0.0569***	0.0418***	0.0374***	0.0376***	0.0371***
		(0.00498)	(0.00415)	(0.00395)	(0.00383)	(0.00380)
GPA		0.00800	0.0109*	0.00955	0.00982**	0.0113**
		(0.00759)	(0.00602)	(0.00581)	(0.00465)	(0.00481)
Ability		-0.00350	-0.00485	-0.00576	-0.00582	-0.00641
		(0.00696)	(0.00547)	(0.00508)	(0.00492)	(0.00504)
Importance Money		-0.000782	0.00881	0.00745	0.00833	0.00774
		(0.00646)	(0.00578)	(0.00613)	(0.00600)	(0.00623)
Importance Status		0.00356	0.00330	0.00287	0.00225	0.00329
		(0.00497)	(0.00369)	(0.00405)	(0.00412)	(0.00421)
Importance Interest		-0.00917	-0.0170	-0.0201**	-0.0212**	-0.0170*
		(0.0106)	(0.0101)	(0.00961)	(0.00930)	(0.00890)
Importance Ability		-0.00524	0.00201	-0.000238	0.000491	0.000216
		(0.00647)	(0.00558)	(0.00559)	(0.00571)	(0.00603)
Importance Helping		-0.0113**	-0.00633	-0.00507	-0.00411	-0.00339
		(0.00551)	(0.00489)	(0.00460)	(0.00480)	(0.00485)
Importance Balance		0.00820*	0.00688*	0.00952**	0.00974**	0.0107***
		(0.00461)	(0.00352)	(0.00363)	(0.00370)	(0.00342)
Importance Like-minded		0.00962*	0.00531	0.00367	0.00402	0.00252
		(0.00501)	(0.00466)	(0.00467)	(0.00471)	(0.00486)
Importance Gender Share		-0.00481	-0.000767	-0.000202	-0.00106	-0.000443
		(0.00471)	(0.00407)	(0.00427)	(0.00429)	(0.00441)
Importance People		-0.00550	-0.00473	-0.00446	-0.00519	-0.00610
		(0.00454)	(0.00412)	(0.00375)	(0.00386)	(0.00362)
Importance Job Security		0.0151***	0.00945	0.00966*	0.00926*	0.00938
		(0.00529)	(0.00590)	(0.00548)	(0.00538)	(0.00556)
IT Top 3 Alternative			0.350***	0.330***	0.319***	0.325***
			(0.0325)	(0.0329)	(0.0346)	(0.0348)
Proposal Awareness			-0.00461	-0.00367	-0.00939	-0.0200
			(0.0218)	(0.0206)	(0.0219)	(0.0211)
IT Job Security Belief			0.00799*	0.00801*	0.00842*	0.00866*
			(0.00464)	(0.00460)	(0.00485)	(0.00506)
Low Rank Tech-Science				-0.0371***	-0.0377***	-0.0351***
				(0.00811)	(0.00777)	(0.00778)
Advice No One				-0.00362	-0.00501	0.00196
				(0.0254)	(0.0257)	(0.0248)
No Parent Higher Educ				0.0147	0.0162	0.0220
				(0.0290)	(0.0285)	(0.0278)
No IT Relation				-0.0718***	-0.0710***	-0.0683***
				(0.0216)	(0.0216)	(0.0223)
Class Size					0.00431	0.00535
					(0.00422)	(0.00409)
Class Female Share					0.0117	-0.0682
					(0.0839)	(0.105)
Technology					0.00321	-0.0150
					(0.0531)	(0.127)
Grade 3					-0.0115	-0.00179
					(0.0297)	(0.0384)
Median GPA					-0.00237	-0.00175
					(0.00154)	(0.00196)
Day Surveyed					-0.00562*	-0.00384
					(0.00282)	(0.00232)
Program Female Share						-0.134
						(0.550)
Program Higher Educ						1.202
						(1.625)
Program Foreign-Born						0.430
						(0.610)
School Size						0.000110
						(0.000113)
School Share Start College						-0.537
						(0.354)
Constant	0.340***	-0.0904	-0.214	-0.0478	0.604	-0.435
	(0.0293)	(0.142)	(0.130)	(0.129)	(0.462)	(1.027)
R^2	0.036	0.236	0.449	0.479	0.485	0.501
Observations	786	737	669	664	664	646

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 18: Impact on IT Probability: Males

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.00502	-0.00917	-0.00293	-0.00502	-0.00395	-0.00297
	(0.0336)	(0.0305)	(0.0245)	(0.0241)	(0.0248)	(0.0244)
Treatment 2	0.0591*	0.0603*	0.0547*	0.0510*	0.0550*	0.0499*
	(0.0325)	(0.0296)	(0.0282)	(0.0277)	(0.0282)	(0.0285)
Ability IT		0.0615***	0.0410***	0.0365***	0.0357***	0.0345***
		(0.00720)	(0.00573)	(0.00573)	(0.00576)	(0.00593)
GPA		0.0122	0.0127	0.0106	0.0122	0.0127
		(0.00855)	(0.00906)	(0.00902)	(0.00794)	(0.00783)
Ability		-0.0115	-0.00841	-0.00764	-0.00644	-0.00566
		(0.00856)	(0.00772)	(0.00757)	(0.00740)	(0.00732)
Importance Money		-0.00536	0.00523	0.00286	0.00214	0.00141
		(0.00929)	(0.00741)	(0.00785)	(0.00770)	(0.00781)
Importance Status		0.00452	0.00425	0.00481	0.00585	0.00593
		(0.00584)	(0.00475)	(0.00494)	(0.00502)	(0.00524)
Importance Interest		0.00373	-0.0000980	-0.00225	-0.00320	-0.00358
		(0.0136)	(0.0116)	(0.0109)	(0.0110)	(0.0109)
Importance Ability		-0.00187	0.00119	-0.00113	-0.000953	-0.00107
		(0.00696)	(0.00660)	(0.00658)	(0.00579)	(0.00617)
Importance Helping		-0.0162**	-0.00903	-0.00857	-0.00777	-0.00832
		(0.00759)	(0.00658)	(0.00682)	(0.00749)	(0.00769)
Importance Balance		0.0108	0.0106*	0.0125*	0.0135**	0.0141**
		(0.00683)	(0.00611)	(0.00647)	(0.00651)	(0.00662)
Importance Like-minded		0.0117*	0.00474	0.00293	0.00285	0.00202
		(0.00576)	(0.00582)	(0.00581)	(0.00588)	(0.00629)
Importance Gender Share		-0.00715	-0.00348	-0.00268	-0.00407	-0.00353
		(0.00596)	(0.00514)	(0.00511)	(0.00531)	(0.00559)
Importance People		-0.00547	-0.00582	-0.00589	-0.00700	-0.00594
		(0.00638)	(0.00536)	(0.00538)	(0.00550)	(0.00541)
Importance Job Security		0.0192**	0.0132*	0.0149**	0.0143**	0.0156**
		(0.00767)	(0.00702)	(0.00650)	(0.00672)	(0.00677)
IT Top 3 Alternative			0.352***	0.335***	0.320***	0.327***
			(0.0360)	(0.0354)	(0.0375)	(0.0383)
Proposal Awareness			-0.00129	0.00418	-0.0100	-0.00327
			(0.0343)	(0.0364)	(0.0382)	(0.0393)
IT Job Security Belief			0.00555	0.00527	0.00601	0.00632
			(0.00628)	(0.00622)	(0.00637)	(0.00648)
Low Rank Tech-Science				-0.0325**	-0.0324***	-0.0305**
				(0.0120)	(0.0117)	(0.0123)
Advice No One				0.0108	0.0116	0.0117
				(0.0315)	(0.0339)	(0.0325)
No Parent Higher Educ				0.0364	0.0428	0.0423
				(0.0344)	(0.0352)	(0.0351)
No IT Relation				-0.0587**	-0.0594**	-0.0598**
				(0.0285)	(0.0286)	(0.0283)
Class Size					0.00437	0.00661
					(0.00463)	(0.00461)
Class Female Share					-0.139	-0.192
					(0.105)	(0.140)
Technology					-0.0826	-0.0984
					(0.0547)	(0.127)
Grade 3					-0.0495	-0.0425
					(0.0314)	(0.0466)
Median GPA					-0.00299	-0.00274
					(0.00184)	(0.00229)
Day Surveyed					-0.00387	-0.00316
					(0.00356)	(0.00263)
Program Female Share						0.416
						(0.657)
Program Higher Educ						-1.387
						(2.073)
Program Foreign-Born						-0.727
						(0.784)
School Size						0.0000939
						(0.000138)
School Share Start College						0.0159
						(0.439)
Constant	0.344***	-0.271	-0.345*	-0.197	0.677	1.553
	(0.0296)	(0.178)	(0.171)	(0.178)	(0.545)	(1.286)
R^2	0.008	0.259	0.512	0.528	0.537	0.555
Observations	423	398	362	358	358	352

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 19: Impact on IT Probability: Females

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0727**	0.0545	0.0442	0.0431	0.0447	0.0515
	(0.0303)	(0.0322)	(0.0313)	(0.0313)	(0.0311)	(0.0317)
Treatment 2	0.0430	0.0209	0.0326	0.0241	0.0243	0.0362
	(0.0359)	(0.0382)	(0.0357)	(0.0340)	(0.0339)	(0.0356)
Ability IT		0.0478***	0.0427***	0.0372***	0.0379***	0.0369***
		(0.00784)	(0.00641)	(0.00699)	(0.00698)	(0.00724)
GPA		0.00365	0.0114	0.0125	0.0126	0.0173*
		(0.0141)	(0.0107)	(0.00879)	(0.00885)	(0.00879)
Ability		0.00641	-0.00222	-0.00695	-0.00934	-0.0120
		(0.0135)	(0.0120)	(0.00941)	(0.00903)	(0.00981)
Importance Money		0.0118	0.0194**	0.0194**	0.0247***	0.0209**
		(0.00976)	(0.00905)	(0.00863)	(0.00894)	(0.00949)
Importance Status		0.000281	0.000197	-0.00221	-0.00322	-0.00142
		(0.00921)	(0.00752)	(0.00785)	(0.00821)	(0.00837)
Importance Interest		-0.0324*	-0.0417***	-0.0515***	-0.0491***	-0.0424***
		(0.0182)	(0.0144)	(0.0154)	(0.0152)	(0.0138)
Importance Ability		-0.0153	0.00148	-0.000347	0.000126	0.000940
		(0.0160)	(0.0133)	(0.0126)	(0.0122)	(0.0130)
Importance Helping		-0.00476	-0.00571	-0.00317	-0.00330	-0.00125
		(0.00899)	(0.00824)	(0.00700)	(0.00718)	(0.00713)
Importance Balance		0.00981	0.00826	0.0127**	0.0114*	0.0148**
		(0.00727)	(0.00674)	(0.00618)	(0.00599)	(0.00591)
Importance Like-minded		0.00528	0.00434	0.00319	0.00278	0.000685
		(0.00842)	(0.00749)	(0.00722)	(0.00764)	(0.00756)
Importance Gender Share		-0.00108	0.00279	0.00402	0.00459	0.00513
		(0.00563)	(0.00555)	(0.00630)	(0.00615)	(0.00615)
Importance People		-0.00725	-0.00430	-0.00427	-0.00456	-0.00721
		(0.00716)	(0.00622)	(0.00470)	(0.00492)	(0.00447)
Importance Job Security		0.0103	0.00473	0.00384	0.00229	0.00233
		(0.00704)	(0.00882)	(0.00837)	(0.00873)	(0.00890)
IT Top 3 Alternative			0.313***	0.290***	0.292***	0.293***
			(0.0653)	(0.0663)	(0.0695)	(0.0712)
Proposal Awareness			0.0115	-0.000433	0.00258	-0.0253
			(0.0470)	(0.0423)	(0.0428)	(0.0407)
IT Job Security Belief			0.0138**	0.0120*	0.0122	0.0121
			(0.00623)	(0.00689)	(0.00741)	(0.00754)
Low Rank Tech-Science				-0.0396***	-0.0417***	-0.0407***
				(0.0116)	(0.0106)	(0.0114)
Advice No One				-0.0186	-0.0129	-0.00641
				(0.0371)	(0.0350)	(0.0358)
No Parent Higher Educ				-0.0545	-0.0529	-0.0371
				(0.0409)	(0.0374)	(0.0353)
No IT Relation				-0.0949***	-0.0966***	-0.0912***
				(0.0245)	(0.0244)	(0.0264)
Class Size					0.00435	0.000929
					(0.00639)	(0.00581)
Class Female Share					0.162	0.0565
					(0.118)	(0.117)
Technology					0.124	0.124
					(0.0736)	(0.221)
Grade 3					0.0300	0.0550
					(0.0346)	(0.0363)
Median GPA					-0.00165	0.000401
					(0.00173)	(0.00201)
Day Surveyed					-0.0115***	-0.00688*
					(0.00349)	(0.00372)
Program Female Share						-0.609
						(1.119)
Program Higher Educ						3.435
						(2.729)
Program Foreign-Born						1.527
						(1.037)
School Size						0.000239
						(0.000193)
School Share Start College						-1.257**
						(0.501)
Constant	0.220***	0.194	-0.0638	0.178	0.580	-2.398
	(0.0248)	(0.260)	(0.220)	(0.215)	(0.584)	(1.855)
R^2	0.014	0.199	0.327	0.394	0.419	0.426
Observations	363	339	307	306	306	294

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $***p < 0.01$, $**p < 0.05$ and $*p < 0.1$.

Table 20: Impact on IT Probability: Excluding Students With Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0125	-0.00500	-0.0000994	-0.00400	-0.00372	-0.00916
	(0.0337)	(0.0291)	(0.0267)	(0.0260)	(0.0264)	(0.0257)
Treatment 2	0.0610*	0.0637**	0.0702**	0.0659**	0.0681**	0.0620**
	(0.0358)	(0.0306)	(0.0307)	(0.0292)	(0.0292)	(0.0292)
Female	-0.121***	-0.00208	0.0395	0.0413	0.0477	0.0467
	(0.0434)	(0.0415)	(0.0342)	(0.0356)	(0.0366)	(0.0373)
Female*t1	0.0651	0.0598	0.0414	0.0491	0.0479	0.0537
	(0.0442)	(0.0424)	(0.0386)	(0.0421)	(0.0435)	(0.0436)
Female*t2	0.00446	-0.0214	-0.0121	-0.00891	-0.0112	-0.000561
	(0.0540)	(0.0485)	(0.0474)	(0.0463)	(0.0466)	(0.0478)
Ability IT		0.0563***	0.0435***	0.0396***	0.0397***	0.0396***
		(0.00526)	(0.00449)	(0.00417)	(0.00414)	(0.00413)
GPA		0.00888	0.0131*	0.0117*	0.0114*	0.0123*
		(0.00889)	(0.00719)	(0.00691)	(0.00604)	(0.00614)
Ability		-0.00418	-0.00731	-0.00715	-0.00653	-0.00683
		(0.00838)	(0.00602)	(0.00607)	(0.00585)	(0.00591)
Importance Money		0.000782	0.00840	0.00677	0.00715	0.00719
		(0.00682)	(0.00608)	(0.00631)	(0.00615)	(0.00630)
Importance Status		0.00469	0.00591	0.00571	0.00552	0.00574
		(0.00487)	(0.00381)	(0.00409)	(0.00409)	(0.00411)
Importance Interest		-0.00966	-0.0138	-0.0180*	-0.0189*	-0.0175
		(0.0114)	(0.0109)	(0.0105)	(0.0103)	(0.0105)
Importance Ability		-0.00375	0.00499	0.00410	0.00409	0.00303
		(0.00729)	(0.00658)	(0.00677)	(0.00687)	(0.00716)
Importance Helping		-0.0102*	-0.00663	-0.00550	-0.00467	-0.00482
		(0.00520)	(0.00484)	(0.00473)	(0.00491)	(0.00491)
Importance Balance		0.00632	0.00439	0.00696	0.00668	0.00697
		(0.00554)	(0.00391)	(0.00415)	(0.00427)	(0.00425)
Importance Like-minded		0.00988**	0.00521	0.00393	0.00429	0.00430
		(0.00440)	(0.00421)	(0.00420)	(0.00431)	(0.00460)
Importance Gender Share		-0.00285	0.00107	0.000926	0.0000988	0.000497
		(0.00511)	(0.00437)	(0.00453)	(0.00456)	(0.00461)
Importance People		-0.00642	-0.00623	-0.00645	-0.00684	-0.00643
		(0.00486)	(0.00477)	(0.00444)	(0.00442)	(0.00443)
Importance Job Security		0.00960*	0.00495	0.00639	0.00615	0.00660
		(0.00541)	(0.00638)	(0.00600)	(0.00593)	(0.00610)
IT Top 3 Alternative			0.349***	0.331***	0.320***	0.328***
			(0.0380)	(0.0389)	(0.0404)	(0.0414)
IT Job Security Belief			0.00501	0.00497	0.00527	0.00500
			(0.00499)	(0.00471)	(0.00528)	(0.00562)
Low Rank Tech-Science				-0.0285***	-0.0288***	-0.0275***
				(0.00803)	(0.00738)	(0.00767)
Advice No One				0.00318	0.00217	0.00771
				(0.0295)	(0.0293)	(0.0284)
No Parent Higher Educ				0.0148	0.0138	0.0168
				(0.0303)	(0.0296)	(0.0290)
No IT Relation				-0.0641***	-0.0633***	-0.0631**
				(0.0224)	(0.0225)	(0.0230)
Class Size					0.00358	0.00515
					(0.00497)	(0.00462)
Class Female Share					-0.00645	-0.114
					(0.0834)	(0.0976)
Technology					-0.00160	0.0357
					(0.0567)	(0.134)
Grade 3					-0.0112	-0.0105
					(0.0301)	(0.0371)
Median GPA					-0.00217	-0.00195
					(0.00176)	(0.00192)
Day Surveyed					-0.00559*	-0.00446*
					(0.00277)	(0.00221)
Program Female Share						0.248
						(0.557)
Program Higher Educ						0.698
						(1.719)
Program Foreign-Born						0.245
						(0.626)
School Size						0.0000900
						(0.000102)
School Share Start College						-0.612*
						(0.342)
Constant	0.333***	-0.0752	-0.233	-0.0964	0.534	0.0122
	(0.0305)	(0.151)	(0.141)	(0.135)	(0.522)	(1.045)
R^2	0.038	0.236	0.451	0.472	0.478	0.494
Observations	662	621	558	554	554	540

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $***p < 0.01$, $**p < 0.05$ and $*p < 0.1$.

Table 21: Impact on IT Probability: Males, No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.00709	-0.0111	-0.00121	-0.00668	-0.00394	-0.00501
	(0.0343)	(0.0309)	(0.0271)	(0.0268)	(0.0285)	(0.0279)
Treatment 2	0.0589	0.0640**	0.0702**	0.0660**	0.0686**	0.0649**
	(0.0363)	(0.0313)	(0.0311)	(0.0300)	(0.0307)	(0.0307)
Ability IT		0.0606***	0.0424***	0.0377***	0.0371***	0.0364***
		(0.00811)	(0.00625)	(0.00612)	(0.00618)	(0.00626)
GPA		0.0145	0.0165*	0.0145	0.0141*	0.0137*
		(0.00970)	(0.00903)	(0.00876)	(0.00817)	(0.00772)
Ability		-0.0107	-0.00839	-0.00693	-0.00541	-0.00360
		(0.0107)	(0.00880)	(0.00897)	(0.00889)	(0.00903)
Importance Money		-0.00180	0.00729	0.00340	0.00262	0.00170
		(0.00948)	(0.00755)	(0.00772)	(0.00761)	(0.00771)
Importance Status		0.00419	0.00513	0.00574	0.00674	0.00648
		(0.00543)	(0.00474)	(0.00490)	(0.00511)	(0.00526)
Importance Interest		-0.000814	-0.00132	-0.00435	-0.00444	-0.00414
		(0.0150)	(0.0138)	(0.0138)	(0.0140)	(0.0140)
Importance Ability		0.00161	0.00420	0.00303	0.00265	0.00181
		(0.00697)	(0.00721)	(0.00718)	(0.00655)	(0.00676)
Importance Helping		-0.0158**	-0.00940	-0.00845	-0.00773	-0.00838
		(0.00743)	(0.00689)	(0.00723)	(0.00778)	(0.00808)
Importance Work-Life Balance		0.00986	0.00870	0.0113	0.0117	0.0116
		(0.00892)	(0.00695)	(0.00709)	(0.00720)	(0.00741)
Importance Like-Minded People		0.0131**	0.00606	0.00355	0.00351	0.00238
		(0.00596)	(0.00561)	(0.00555)	(0.00567)	(0.00617)
Importance Gender Share		-0.00633	-0.00204	-0.00121	-0.00205	-0.00170
		(0.00696)	(0.00532)	(0.00513)	(0.00525)	(0.00558)
Importance Work With People		-0.00520	-0.00673	-0.00750	-0.00805	-0.00689
		(0.00718)	(0.00665)	(0.00655)	(0.00683)	(0.00665)
Importance Job Security		0.0156*	0.00935	0.0136	0.0129	0.0131
		(0.00839)	(0.00865)	(0.00830)	(0.00863)	(0.00858)
IT Top 3 Alternative			0.343***	0.326***	0.317***	0.325***
			(0.0434)	(0.0426)	(0.0447)	(0.0463)
IT Job Security Belief			0.00302	0.00253	0.00336	0.00360
			(0.00739)	(0.00705)	(0.00746)	(0.00784)
Low Rank Tech-Science				-0.0288**	-0.0274**	-0.0255*
				(0.0133)	(0.0133)	(0.0143)
Advice No One				0.0275	0.0288	0.0226
				(0.0365)	(0.0386)	(0.0365)
No Parent Higher Educ				0.0301	0.0304	0.0297
				(0.0413)	(0.0407)	(0.0399)
No IT Relation				-0.0643*	-0.0619*	-0.0617*
				(0.0320)	(0.0323)	(0.0325)
Class Size					0.00188	0.00588
					(0.00560)	(0.00541)
Class Female Share					-0.156	-0.223
					(0.117)	(0.153)
Technology					-0.0479	-0.0705
					(0.0648)	(0.143)
Grade 3					-0.0401	-0.0746
					(0.0403)	(0.0459)
Median School GPA					-0.00106	-0.00318
					(0.00230)	(0.00236)
Day Surveyed					-0.00183	-0.00497*
					(0.00398)	(0.00260)
Program Female Share						0.640
						(0.707)
Program Higher Educ						-1.244
						(2.178)
Program Foreign-Born						-0.729
						(0.821)
School Size						-0.00000938
						(0.000152)
School Share Start College						-0.270
						(0.435)
Constant	0.341***	-0.298	-0.388**	-0.260	0.110	1.837
	(0.0303)	(0.199)	(0.189)	(0.199)	(0.697)	(1.363)
R^2	0.008	0.258	0.509	0.526	0.533	0.552
Observations	355	335	300	296	296	291

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $***p < 0.01$, $**p < 0.05$ and $*p < 0.1$.

Table 22: Impact on IT Probability: Females, No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0786**	0.0528*	0.0544*	0.0534*	0.0501	0.0522
	(0.0297)	(0.0295)	(0.0286)	(0.0306)	(0.0310)	(0.0328)
Treatment 2	0.0746**	0.0498	0.0644**	0.0524*	0.0493	0.0559*
	(0.0302)	(0.0312)	(0.0295)	(0.0301)	(0.0300)	(0.0326)
Ability IT		0.0438***	0.0420***	0.0378***	0.0383***	0.0381***
		(0.00822)	(0.00647)	(0.00724)	(0.00743)	(0.00723)
GPA		0.00496	0.0121	0.0129	0.0123	0.0177*
		(0.0142)	(0.0120)	(0.0103)	(0.0103)	(0.0103)
Ability		0.00331	-0.00836	-0.0115	-0.0129	-0.0170
		(0.0140)	(0.0120)	(0.0101)	(0.0103)	(0.0109)
Importance Money		0.0107	0.0146	0.0154	0.0200*	0.0174
		(0.0114)	(0.00996)	(0.0101)	(0.0105)	(0.0110)
Importance Status		0.00397	0.00547	0.00377	0.00355	0.00332
		(0.00969)	(0.00857)	(0.00919)	(0.00953)	(0.00945)
Importance Interest		-0.0212	-0.0304*	-0.0419***	-0.0382**	-0.0408**
		(0.0190)	(0.0150)	(0.0151)	(0.0151)	(0.0154)
Importance Ability		-0.0195	0.00471	0.00377	0.00260	0.00301
		(0.0172)	(0.0128)	(0.0126)	(0.0122)	(0.0135)
Importance Helping		-0.00713	-0.00961	-0.00682	-0.00766	-0.00631
		(0.00878)	(0.00872)	(0.00831)	(0.00821)	(0.00816)
Importance Balance		0.00861	0.00607	0.00966	0.00771	0.0109*
		(0.00761)	(0.00674)	(0.00626)	(0.00581)	(0.00625)
Importance Like-minded		0.00601	0.00286	0.00275	0.00224	0.00234
		(0.00833)	(0.00759)	(0.00747)	(0.00790)	(0.00786)
Importance Gender Share		0.00117	0.00299	0.00279	0.00314	0.00378
		(0.00639)	(0.00642)	(0.00705)	(0.00678)	(0.00662)
Importance People		-0.00869	-0.00415	-0.00564	-0.00582	-0.00648
		(0.00785)	(0.00677)	(0.00607)	(0.00581)	(0.00591)
Importance Job Security		0.00383	0.000601	0.000668	0.000604	0.00108
		(0.00697)	(0.00873)	(0.00838)	(0.00877)	(0.00891)
IT Top 3 Alternative			0.344***	0.317***	0.308***	0.308***
			(0.0736)	(0.0777)	(0.0790)	(0.0815)
IT Job Security Belief			0.0109	0.00952	0.00960	0.00798
			(0.00748)	(0.00802)	(0.00839)	(0.00865)
Low Rank Tech-Science				-0.0251**	-0.0263***	-0.0271**
				(0.0110)	(0.00954)	(0.0104)
Advice No One				-0.0200	-0.00853	-0.00861
				(0.0389)	(0.0356)	(0.0367)
No Parent Higher Educ				-0.0384	-0.0400	-0.0367
				(0.0416)	(0.0348)	(0.0365)
No IT Relation				-0.0848***	-0.0885***	-0.0844***
				(0.0250)	(0.0246)	(0.0265)
Class Size					0.00554	0.000589
					(0.00678)	(0.00662)
Class Female Share					0.144	0.00293
					(0.102)	(0.117)
Technology					0.0774	0.184
					(0.0816)	(0.229)
Grade 3					0.0190	0.0401
					(0.0380)	(0.0409)
Median GPA					-0.00302	-0.000491
					(0.00192)	(0.00238)
Day Surveyed					-0.0121***	-0.00626
					(0.00357)	(0.00425)
Program Female Share						0.0741
						(1.097)
Program Higher Educ						2.270
						(2.791)
Program Foreign-Born						1.095
						(1.065)
School Size						0.000353
						(0.000218)
School Share Start College						-1.097*
						(0.562)
Constant	0.202***	0.183	-0.0654	0.137	0.958	-1.566
	(0.0208)	(0.267)	(0.226)	(0.209)	(0.624)	(1.883)
R^2	0.021	0.196	0.321	0.366	0.395	0.414
Observations	307	286	258	258	258	249

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 23: Impact on IT Probability: Only Students With Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.0621	-0.0502	-0.0734	-0.0491	-0.0389	0.00367
	(0.0783)	(0.0875)	(0.0719)	(0.0766)	(0.0853)	(0.0783)
Treatment 2	0.0353	0.0232	-0.0668	-0.0334	-0.0434	-0.0397
	(0.0883)	(0.0947)	(0.0636)	(0.0730)	(0.0705)	(0.0685)
Female	-0.117	0.0645	0.0306	0.0467	0.0762	0.0179
	(0.122)	(0.128)	(0.118)	(0.116)	(0.126)	(0.112)
Female*t1	0.138	0.111	0.0690	0.0230	0.0111	0.0162
	(0.110)	(0.114)	(0.119)	(0.114)	(0.119)	(0.116)
Female*t2	-0.113	-0.115	-0.145	-0.148	-0.144	-0.0650
	(0.121)	(0.128)	(0.112)	(0.107)	(0.115)	(0.113)
Ability IT		0.0619***	0.0380***	0.0332**	0.0310**	0.0257**
		(0.0119)	(0.0109)	(0.0121)	(0.0131)	(0.0109)
GPA		-0.00700	-0.0109	-0.00640	0.00149	0.00883
		(0.0175)	(0.0124)	(0.0127)	(0.0138)	(0.0103)
Ability		0.00495	0.0115	0.000314	-0.00212	-0.00482
		(0.0158)	(0.0161)	(0.0175)	(0.0197)	(0.0180)
Importance Money		-0.00522	0.00391	0.00601	0.0109	0.00795
		(0.0144)	(0.0113)	(0.0121)	(0.0116)	(0.0117)
Importance Status		0.00448	0.00986	0.00205	-0.0000836	-0.00121
		(0.0150)	(0.0115)	(0.0103)	(0.0110)	(0.0123)
Importance Interest		0.00353	-0.00855	-0.00663	0.000351	0.00707
		(0.0233)	(0.0225)	(0.0233)	(0.0275)	(0.0273)
Importance Ability		-0.0232	-0.0101	-0.0252	-0.0185	-0.0111
		(0.0268)	(0.0249)	(0.0208)	(0.0227)	(0.0246)
Importance Helping		-0.0204	-0.0115	-0.00598	-0.00587	-0.00238
		(0.0135)	(0.0151)	(0.0169)	(0.0177)	(0.0170)
Importance Balance		0.0154	0.0196	0.0170	0.0188	0.0253
		(0.0164)	(0.0171)	(0.0173)	(0.0183)	(0.0188)
Importance Like-minded		0.0123	0.00407	0.00333	0.00487	-0.00462
		(0.0116)	(0.0125)	(0.0142)	(0.0153)	(0.0128)
Importance Gender Share		-0.0177	-0.0124	-0.00270	-0.00401	-0.00230
		(0.0121)	(0.00768)	(0.00961)	(0.0105)	(0.0102)
Importance People		-0.00560	0.00229	0.00252	0.00156	-0.000318
		(0.0152)	(0.0142)	(0.0124)	(0.0128)	(0.0132)
Importance Job Security		0.0448**	0.0231	0.0205	0.0172	0.0140
		(0.0164)	(0.0185)	(0.0170)	(0.0173)	(0.0186)
IT Top 3 Alternative			0.371***	0.354***	0.336***	0.335***
			(0.0556)	(0.0530)	(0.0594)	(0.0565)
IT Job Security Belief			0.0179	0.0228*	0.0225	0.0219
			(0.0120)	(0.0128)	(0.0138)	(0.0132)
Low Rank Tech-Science				-0.0744***	-0.0811***	-0.0827***
				(0.0189)	(0.0250)	(0.0265)
Advice No One				-0.0629	-0.0453	-0.0235
				(0.0471)	(0.0507)	(0.0463)
No Parent Higher Educ				-0.00508	0.0333	0.0595
				(0.0948)	(0.0987)	(0.0782)
No IT Relation				-0.0670	-0.0760	-0.0915
				(0.0707)	(0.0703)	(0.0642)
Class Size					0.0138	0.0148
					(0.0110)	(0.0111)
Class Female Share					0.0215	0.0618
					(0.223)	(0.200)
Technology					-0.111	-0.473
					(0.148)	(0.393)
Grade 3					-0.0677	-0.0200
					(0.0817)	(0.0804)
Median GPA					-0.00783	-0.00631
					(0.00477)	(0.00515)
Day Surveyed					-0.00834	-0.00722
					(0.00763)	(0.00706)
Program Female Share						-2.987
						(1.929)
Program Higher Educ						9.685
						(6.059)
Program Foreign-Born						3.502
						(2.338)
School Size						0.000652
						(0.000408)
School Share Start College						-0.799
						(1.129)
Constant	0.375***	-0.0941	-0.128	0.0952	1.970	-6.251
	(0.0738)	(0.389)	(0.377)	(0.410)	(1.284)	(3.738)
R^2	0.046	0.304	0.547	0.607	0.626	0.652
Observations	143	132	111	110	110	106

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 24: Impact on IT Probability: Grade 3 Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.0204	-0.0295	-0.0135	0.00108	-0.0178	-0.0178
	(0.0614)	(0.0560)	(0.0416)	(0.0472)	(0.0459)	(0.0459)
Treatment 2	0.0504	0.0350	-0.0124	-0.00510	-0.0131	-0.0131
	(0.0461)	(0.0488)	(0.0374)	(0.0427)	(0.0416)	(0.0416)
Female	-0.0847	0.0793	0.0562	0.0583	0.0619	0.0619
	(0.0879)	(0.0818)	(0.0733)	(0.0783)	(0.0776)	(0.0776)
Female*t1	0.0676	0.0446	0.0288	0.0293	0.0464	0.0464
	(0.0783)	(0.0843)	(0.0801)	(0.0882)	(0.0844)	(0.0844)
Female*t2	0.0110	-0.0414	0.0431	0.0421	0.0439	0.0439
	(0.0994)	(0.0959)	(0.0884)	(0.0937)	(0.0932)	(0.0932)
Ability IT		0.0580***	0.0424***	0.0420***	0.0389***	0.0389***
		(0.00946)	(0.00848)	(0.00748)	(0.00695)	(0.00695)
GPA		0.00989	0.0171*	0.0160*	0.0209**	0.0209**
		(0.0109)	(0.00806)	(0.00882)	(0.00764)	(0.00764)
Ability		0.00410	-0.00997	-0.0117	-0.0126	-0.0126
		(0.0115)	(0.00924)	(0.00847)	(0.00861)	(0.00861)
Importance Money		-0.00502	0.00726	0.00393	0.00292	0.00292
		(0.00892)	(0.00920)	(0.0102)	(0.00979)	(0.00979)
Importance Status		0.00623	0.00521	0.00417	0.00340	0.00340
		(0.00878)	(0.00606)	(0.00720)	(0.00749)	(0.00749)
Importance Interest		-0.0148	-0.0195*	-0.0197*	-0.0139	-0.0139
		(0.0150)	(0.0104)	(0.00991)	(0.0114)	(0.0114)
Importance Ability		-0.00809	0.00732	0.00392	-0.000800	-0.000800
		(0.0102)	(0.00850)	(0.00907)	(0.0101)	(0.0101)
Importance Helping		-0.0145	-0.00303	-0.00238	-0.000608	-0.000608
		(0.0111)	(0.00776)	(0.00729)	(0.00712)	(0.00712)
Importance Balance		0.0166**	0.00761	0.00773	0.00601	0.00601
		(0.00688)	(0.00635)	(0.00620)	(0.00669)	(0.00669)
Importance Like-minded		-0.00423	0.000425	-0.00124	-0.00185	-0.00185
		(0.00819)	(0.00832)	(0.00870)	(0.00843)	(0.00843)
Importance Gender Share		0.00687	0.00804	0.00986	0.0109*	0.0109*
		(0.00528)	(0.00521)	(0.00568)	(0.00535)	(0.00535)
Importance People		-0.00637	-0.00700	-0.00556	-0.00904	-0.00904
		(0.0112)	(0.00795)	(0.00679)	(0.00691)	(0.00691)
Importance Job Security		0.0165*	0.00135	0.00144	0.00292	0.00292
		(0.00840)	(0.00704)	(0.00761)	(0.00797)	(0.00797)
IT Top 3 Alternative			0.418***	0.403***	0.381***	0.381***
			(0.0551)	(0.0612)	(0.0625)	(0.0625)
Proposal Awareness			-0.00884	-0.0129	-0.00376	-0.00376
			(0.0336)	(0.0327)	(0.0333)	(0.0333)
IT Job Security Belief			0.0112	0.0104	0.00721	0.00721
			(0.00855)	(0.00968)	(0.00952)	(0.00952)
Low Rank Tech-Science				-0.0206*	-0.0233*	-0.0233*
				(0.0108)	(0.0115)	(0.0115)
Advice No One				-0.0502	-0.0544	-0.0544
				(0.0338)	(0.0333)	(0.0333)
No Parent Higher Educ				0.0345	0.0271	0.0271
				(0.0462)	(0.0446)	(0.0446)
No IT Relation				-0.0632	-0.0529	-0.0529
				(0.0416)	(0.0391)	(0.0391)
Yes_apply				0.0164	0.0161	0.0161
				(0.0275)	(0.0244)	(0.0244)
Undecided_apply				-0.0187	-0.00690	-0.00690
				(0.0432)	(0.0477)	(0.0477)
Class Size					-0.00672	-0.00672
					(0.00662)	(0.00662)
Class Female Share					0.853***	0.853***
					(0.223)	(0.223)
Technology					-0.0338	1.854***
					(0.0361)	(0.380)
Median GPA					-0.0215***	-0.0215***
					(0.00435)	(0.00435)
Day Surveyed					-0.00266	-0.00266
					(0.00455)	(0.00455)
Program Female Share						13.60***
						(2.602)
Program Higher Educ						-19.59***
						(4.277)
Program Foreign-Born						-7.385***
						(1.585)
School Size						-0.000943***
						(0.000212)
School Share Start College						-0.116
						(0.681)
Constant	0.330***	-0.0914	-0.284*	-0.151	5.724***	18.04***
	(0.0554)	(0.189)	(0.141)	(0.140)	(1.184)	(3.452)
R^2	0.017	0.248	0.521	0.542	0.570	0.580
Observations	321	303	280	276	276	276

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 25: Impact on IT Probability: Male Grade 3 Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.0175	-0.0158	-0.000716	0.0133	-0.00279	-0.00279
	(0.0626)	(0.0572)	(0.0460)	(0.0548)	(0.0512)	(0.0512)
Treatment 2	0.0525	0.0394	-0.0141	-0.0198	-0.0251	-0.0251
	(0.0479)	(0.0551)	(0.0382)	(0.0433)	(0.0432)	(0.0432)
Ability IT		0.0681***	0.0406***	0.0358***	0.0286**	0.0286**
		(0.0137)	(0.0108)	(0.0102)	(0.00968)	(0.00968)
GPA		0.0272*	0.0227	0.0237	0.0314**	0.0314**
		(0.0134)	(0.0136)	(0.0162)	(0.0135)	(0.0135)
Ability		-0.0133	-0.0190	-0.0186	-0.0101	-0.0101
		(0.0176)	(0.0144)	(0.0146)	(0.0143)	(0.0143)
Importance Money		-0.0152	-0.00349	-0.00846	-0.00911	-0.00911
		(0.0144)	(0.0137)	(0.0157)	(0.0140)	(0.0140)
Importance Status		0.0102	0.00507	0.00459	0.00503	0.00503
		(0.00925)	(0.00907)	(0.0103)	(0.00952)	(0.00952)
Importance Interest		-0.00813	-0.00812	-0.00880	-0.00154	-0.00154
		(0.0187)	(0.0141)	(0.0141)	(0.0150)	(0.0150)
Importance Ability		0.00669	0.0119	0.00403	-0.00135	-0.00135
		(0.00832)	(0.00939)	(0.0107)	(0.0122)	(0.0122)
Importance Helping		-0.0318*	-0.0169	-0.0198**	-0.0174*	-0.0174*
		(0.0154)	(0.00967)	(0.00840)	(0.00839)	(0.00839)
Importance Balance		0.0216	0.0136	0.0132	0.00982	0.00982
		(0.0129)	(0.00903)	(0.00770)	(0.00898)	(0.00898)
Importance Like-minded		-0.00565	-0.00294	-0.00548	-0.00641	-0.00641
		(0.00926)	(0.00994)	(0.00943)	(0.00862)	(0.00862)
Importance Gender Share		0.00563	0.00714	0.00860	0.00611	0.00611
		(0.00963)	(0.00780)	(0.00775)	(0.00784)	(0.00784)
Importance People		-0.00203	-0.00817	-0.00642	-0.00914	-0.00914
		(0.0128)	(0.00860)	(0.00877)	(0.00809)	(0.00809)
Importance Job Security		0.0181	0.0113	0.0171	0.0223**	0.0223**
		(0.0115)	(0.00892)	(0.00981)	(0.0100)	(0.0100)
IT Top 3 Alternative			0.399***	0.395***	0.367***	0.367***
			(0.0583)	(0.0635)	(0.0680)	(0.0680)
Proposal Awareness			0.0726	0.0773	0.0754	0.0754
			(0.0525)	(0.0481)	(0.0483)	(0.0483)
IT Job Security Belief			0.0191	0.0288*	0.0270	0.0270
			(0.0128)	(0.0152)	(0.0160)	(0.0160)
Low Rank Tech-Science				-0.00807	-0.0118	-0.0118
				(0.0164)	(0.0161)	(0.0161)
Advice No One				-0.0865*	-0.0794*	-0.0794*
				(0.0478)	(0.0409)	(0.0409)
No Parent Higher Educ				0.0811	0.0686	0.0686
				(0.0672)	(0.0583)	(0.0583)
No IT Relation				-0.0983	-0.0884	-0.0884
				(0.0558)	(0.0530)	(0.0530)
Yes Apply				0.0172	-0.0130	-0.0130
				(0.0472)	(0.0449)	(0.0449)
Undecided Apply				0.00749	0.0250	0.0250
				(0.0730)	(0.0702)	(0.0702)
Class Size					0.0103*	0.0103*
					(0.00578)	(0.00578)
Class Female Share					-0.134	-0.134
					(0.356)	(0.356)
Technology					-0.152**	0.653
					(0.0581)	(0.477)
Median GPA					-0.0123**	-0.0123**
					(0.00506)	(0.00506)
Day Surveyed					-0.00264	-0.00264
					(0.00487)	(0.00487)
Program Female Share						6.056*
						(3.132)
Program Higher Educ						-9.998*
						(4.809)
Program Foreign-Born						-3.833*
						(1.810)
School Size						-0.000620**
						(0.000282)
School Share Start College						0.276
						(0.677)
Constant	0.335***	-0.387	-0.442	-0.406	2.777*	9.478**
	(0.0583)	(0.300)	(0.258)	(0.273)	(1.304)	(4.093)
R^2	0.008	0.331	0.604	0.637	0.682	0.709
Observations	170	160	150	147	147	147

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 26: Impact on IT Probability: Female Grade 3 Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0457	-0.00300	0.00927	0.0362	0.0465	0.0465
	(0.0539)	(0.0491)	(0.0556)	(0.0641)	(0.0616)	(0.0616)
Treatment 2	0.0650	-0.00350	0.0216	0.0306	0.0356	0.0356
	(0.0755)	(0.0796)	(0.0729)	(0.0797)	(0.0808)	(0.0808)
Ability IT		0.0389**	0.0381**	0.0409**	0.0418**	0.0418**
		(0.0180)	(0.0143)	(0.0150)	(0.0156)	(0.0156)
GPA		-0.0114	0.0109	0.0145	0.0115	0.0115
		(0.0231)	(0.0173)	(0.0154)	(0.0180)	(0.0180)
Ability		0.0223	-0.00690	-0.00914	-0.00832	-0.00832
		(0.0193)	(0.0181)	(0.0156)	(0.0143)	(0.0143)
Importance Money		0.0199	0.0311**	0.0329**	0.0286*	0.0286*
		(0.0151)	(0.0131)	(0.0127)	(0.0138)	(0.0138)
Importance Status		0.00335	0.00176	-0.00729	-0.00309	-0.00309
		(0.0188)	(0.0136)	(0.0168)	(0.0183)	(0.0183)
Importance Interest		-0.0256	-0.0342	-0.0398	-0.0419	-0.0419
		(0.0322)	(0.0220)	(0.0259)	(0.0240)	(0.0240)
Importance Ability		-0.0392	-0.00478	-0.00796	-0.00737	-0.00737
		(0.0258)	(0.0223)	(0.0214)	(0.0233)	(0.0233)
Importance Helping		0.0103	0.00873	0.0147	0.0183	0.0183
		(0.0157)	(0.0111)	(0.00917)	(0.0112)	(0.0112)
Importance Balance		0.0145	0.00794	0.0101	0.0117	0.0117
		(0.0107)	(0.0122)	(0.0130)	(0.0140)	(0.0140)
Importance Like-minded		-0.00232	0.00978	0.0103	0.00795	0.00795
		(0.0137)	(0.0139)	(0.0130)	(0.0121)	(0.0121)
Importance Gender Share		0.00716	0.00913	0.0169	0.0158	0.0158
		(0.00765)	(0.00910)	(0.0102)	(0.0109)	(0.0109)
Importance People		-0.0243	-0.0132	-0.0152	-0.0192	-0.0192
		(0.0144)	(0.0137)	(0.0111)	(0.0121)	(0.0121)
Importance Job Security		0.0162	-0.0118	-0.0188	-0.0215	-0.0215
		(0.0115)	(0.0111)	(0.0145)	(0.0214)	(0.0214)
IT Top 3 Alternative			0.385***	0.364***	0.395***	0.395***
			(0.0988)	(0.107)	(0.107)	(0.107)
Proposal Awareness			-0.0456	-0.0434	-0.0355	-0.0355
			(0.0621)	(0.0658)	(0.0699)	(0.0699)
IT Job Security Belief			0.0100	0.00273	0.00414	0.00414
			(0.0110)	(0.0156)	(0.0187)	(0.0187)
Low Rank Tech-Science				-0.0327	-0.0257	-0.0257
				(0.0191)	(0.0174)	(0.0174)
Advice No One				-0.0547	-0.0484	-0.0484
				(0.0771)	(0.0985)	(0.0985)
No Parent Higher Educ				-0.0265	-0.0236	-0.0236
				(0.0579)	(0.0519)	(0.0519)
No IT Relation				-0.0609*	-0.0658	-0.0658
				(0.0484)	(0.0503)	(0.0503)
Yes Apply				0.00586	0.0229	0.0229
				(0.0528)	(0.0660)	(0.0660)
Undecided Apply				-0.0960*	-0.0863	-0.0863
				(0.0538)	(0.0655)	(0.0655)
Class Size					-0.00971	-0.00971
					(0.0223)	(0.0223)
Class Female Share					1.024	1.024
					(0.987)	(0.987)
Technology					0.0618	1.864
					(0.133)	(2.349)
Median GPA					-0.0167	-0.0167
					(0.0281)	(0.0281)
Day Surveyed					-0.000484	-0.000484
					(0.00690)	(0.00690)
Program Female Share						12.61
						(16.98)
Program Higher Educ						-18.28
						(23.44)
Program Foreign-Born						-6.675
						(9.088)
School Size						-0.000718
						(0.00113)
School Share Start College						-0.402
						(0.930)
Constant	0.238***	0.438	-0.0331	0.158	4.726	16.16
	(0.0454)	(0.383)	(0.242)	(0.256)	(7.927)	(21.65)
R^2	0.010	0.225	0.425	0.473	0.492	0.514
Observations	151	143	130	129	129	129

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 27: Impact on IT Probability: Grade 2 Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0195	-0.0104	-0.00876	-0.0134	-0.0166	-0.0128
	(0.0407)	(0.0359)	(0.0298)	(0.0253)	(0.0269)	(0.0255)
Treatment 2	0.0679	0.0739*	0.0851**	0.0688*	0.0721**	0.0665*
	(0.0452)	(0.0385)	(0.0361)	(0.0334)	(0.0335)	(0.0348)
Female	-0.135***	-0.0418	0.0152	0.00956	0.0149	-0.000949
	(0.0455)	(0.0439)	(0.0407)	(0.0375)	(0.0377)	(0.0364)
Female*t1	0.0729	0.0953*	0.0692	0.0728	0.0744	0.0872*
	(0.0505)	(0.0483)	(0.0449)	(0.0454)	(0.0482)	(0.0454)
Female*t2	-0.0417	-0.0280	-0.0401	-0.00935	-0.0230	0.0102
	(0.0643)	(0.0596)	(0.0639)	(0.0620)	(0.0604)	(0.0615)
Ability IT		0.0556***	0.0425***	0.0357***	0.0366***	0.0356***
		(0.00613)	(0.00491)	(0.00510)	(0.00530)	(0.00506)
GPA		0.00597	0.00448	0.00517	0.00679	0.00733
		(0.00750)	(0.00755)	(0.00701)	(0.00633)	(0.00688)
Ability		-0.00800	-0.00252	-0.00511	-0.00704	-0.00649
		(0.00661)	(0.00592)	(0.00567)	(0.00560)	(0.00634)
Importance Money		0.00282	0.00784	0.00941	0.00593	0.00699
		(0.00908)	(0.00835)	(0.00859)	(0.00865)	(0.00877)
Importance Status		-0.0000502	0.00164	0.00229	0.00122	0.00245
		(0.00570)	(0.00469)	(0.00504)	(0.00538)	(0.00546)
Importance Interest		-0.00115	-0.0107	-0.0156	-0.0220	-0.0131
		(0.0140)	(0.0150)	(0.0146)	(0.0146)	(0.0134)
Importance Ability		-0.00322	-0.00134	-0.00217	-0.000804	-0.00163
		(0.00828)	(0.00669)	(0.00687)	(0.00670)	(0.00731)
Importance Helping		-0.00946*	-0.00803	-0.00476	-0.00157	-0.00176
		(0.00501)	(0.00518)	(0.00437)	(0.00584)	(0.00596)
Importance Balance		0.000560	0.00402	0.00792	0.00742	0.00970*
		(0.00631)	(0.00505)	(0.00541)	(0.00574)	(0.00538)
Importance Like-minded		0.0208***	0.0123**	0.00801	0.00773	0.00638
		(0.00547)	(0.00538)	(0.00560)	(0.00564)	(0.00615)
Importance Gender Share		-0.0129**	-0.00704	-0.00725	-0.00726	-0.00707
		(0.00571)	(0.00501)	(0.00520)	(0.00485)	(0.00510)
Importance People		-0.00599	-0.00393	-0.00288	-0.00340	-0.00576
		(0.00432)	(0.00511)	(0.00508)	(0.00540)	(0.00501)
Importance Job Security		0.0181**	0.0173*	0.0167**	0.0152*	0.0165*
		(0.00799)	(0.00870)	(0.00752)	(0.00745)	(0.00824)
IT Top 3 Alternative			0.295***	0.283***	0.259***	0.269***
			(0.0425)	(0.0429)	(0.0449)	(0.0423)
Proposal Awareness			0.00267	-0.00692	-0.00764	-0.0248
			(0.0292)	(0.0267)	(0.0286)	(0.0269)
IT Job Security Belief			0.00478	0.00380	0.00557	0.00416
			(0.00657)	(0.00616)	(0.00571)	(0.00591)
Low Rank Tech-Science				-0.0578***	-0.0608***	-0.0560***
				(0.0105)	(0.0105)	(0.0111)
Advice No One				0.0271	0.0147	0.0325
				(0.0305)	(0.0333)	(0.0293)
No Parent Higher Educ				-0.0104	0.00458	0.00647
				(0.0357)	(0.0341)	(0.0301)
No IT Relation				-0.0747***	-0.0721***	-0.0707**
				(0.0241)	(0.0243)	(0.0263)
Class Size					0.00416	0.00353
					(0.00297)	(0.00332)
Class Female Share					0.164**	0.112
					(0.0684)	(0.114)
Technology					0.117***	0.0747
					(0.0298)	(0.0944)
Median GPA					-0.00142*	0.000738
					(0.000747)	(0.00170)
Day Surveyed					-0.0165***	-0.00466*
					(0.00230)	(0.00225)
Program Female Share						-0.400
						(0.439)
Program Higher Educ						1.002
						(1.578)
Program Foreign-Born						0.548
						(0.619)
School Size						-0.0000447
						(0.000104)
School Share Start College						-0.643
						(0.380)
Constant	0.347***	-0.133	-0.169	-0.0000583	0.493	-0.651
	(0.0355)	(0.182)	(0.212)	(0.218)	(0.325)	(1.020)
R^2	0.064	0.270	0.419	0.461	0.480	0.497
Observations	465	434	389	387	387	369

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $***p < 0.01$, $**p < 0.05$ and $*p < 0.1$.

Table 28: Impact on IT Probability: Male Grade 2 Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0141	-0.0168	-0.00103	-0.0147	-0.0187	-0.0158
	(0.0412)	(0.0392)	(0.0289)	(0.0271)	(0.0274)	(0.0278)
Treatment 2	0.0638	0.0693	0.0834**	0.0681*	0.0721**	0.0698*
	(0.0468)	(0.0413)	(0.0340)	(0.0345)	(0.0337)	(0.0342)
Ability IT		0.0552***	0.0413***	0.0391***	0.0409***	0.0406***
		(0.00730)	(0.00600)	(0.00657)	(0.00634)	(0.00708)
GPA		0.00391	0.00317	0.00313	0.00546	0.00503
		(0.00900)	(0.00993)	(0.00959)	(0.00903)	(0.00864)
Ability		-0.00842	-0.00103	-0.00583	-0.00796	-0.00761
		(0.00877)	(0.00917)	(0.00887)	(0.00828)	(0.00884)
Importance Money		-0.00251	0.00870	0.0104	0.00665	0.00676
		(0.0138)	(0.0114)	(0.0113)	(0.0113)	(0.0108)
Importance Status		-0.000207	0.000793	-0.000316	-0.000460	-0.00193
		(0.00688)	(0.00676)	(0.00696)	(0.00733)	(0.00728)
Importance Interest		0.0130	0.00490	0.00347	-0.00319	-0.00231
		(0.0191)	(0.0171)	(0.0159)	(0.0167)	(0.0163)
Importance Ability		-0.00728	-0.00524	-0.00541	-0.00236	-0.00219
		(0.00954)	(0.00819)	(0.00760)	(0.00752)	(0.00767)
Importance Helping		-0.00548	-0.00202	0.00136	0.00580	0.00373
		(0.00873)	(0.00842)	(0.00838)	(0.0104)	(0.0102)
Importance Balance		0.00406	0.00636	0.00424	0.00490	0.00626
		(0.0110)	(0.00909)	(0.0101)	(0.0106)	(0.0107)
Importance Like-minded		0.0221***	0.0130*	0.0106	0.0113	0.0120
		(0.00650)	(0.00731)	(0.00713)	(0.00671)	(0.00752)
Importance Gender Share		-0.0148**	-0.0108*	-0.00929	-0.00948	-0.0100
		(0.00678)	(0.00607)	(0.00578)	(0.00587)	(0.00617)
Importance People		-0.00699	-0.00466	-0.00458	-0.00569	-0.00527
		(0.00796)	(0.00697)	(0.00711)	(0.00737)	(0.00763)
Importance Job Security		0.0242**	0.0188*	0.0202**	0.0199*	0.0222*
		(0.0109)	(0.0106)	(0.00953)	(0.0106)	(0.0112)
IT Top 3 Alternative			0.291***	0.276***	0.247***	0.252***
			(0.0440)	(0.0453)	(0.0518)	(0.0506)
Proposal Awareness			-0.0754	-0.0809	-0.0932	-0.0763
			(0.0451)	(0.0566)	(0.0603)	(0.0648)
IT Job Security Belief			0.00239	0.00111	0.00333	0.00130
			(0.00829)	(0.00746)	(0.00691)	(0.00654)
Low Rank Tech-Science				-0.0606**	-0.0657**	-0.0573*
				(0.0280)	(0.0277)	(0.0320)
Advice No One				0.0492	0.0536	0.0583
				(0.0405)	(0.0454)	(0.0421)
No Parent Higher Educ				0.0204	0.0326	0.0219
				(0.0464)	(0.0483)	(0.0467)
No IT Relation				-0.0256	-0.0156	-0.0204
				(0.0313)	(0.0327)	(0.0346)
Class Size					0.0107**	0.00928
					(0.00416)	(0.00595)
Class Female Share					-0.0450	0.132
					(0.0755)	(0.157)
Technology					-0.0231	-0.180
					(0.0714)	(0.153)
Median GPA					-0.00186	0.000458
					(0.00164)	(0.00249)
Day Surveyed					-0.00952**	-0.00553***
					(0.00391)	(0.00139)
Program Female Share						-1.204*
						(0.629)
Program Higher Educ						1.828
						(2.535)
Program Foreign-Born						0.776
						(0.913)
School Size						0.0000587
						(0.000183)
School Share Start College						-0.578
						(0.415)
Constant	0.352***	-0.241	-0.285	-0.146	0.259	-1.327
	(0.0293)	(0.273)	(0.259)	(0.281)	(0.568)	(1.469)
R^2	0.009	0.248	0.464	0.486	0.503	0.525
Observations	253	238	212	211	211	205

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $***p < 0.01$, $**p < 0.05$ and $*p < 0.1$.

Table 29: Impact on IT Probability: Female Grade 2 Students

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0858**	0.0906**	0.0788**	0.0667**	0.0647**	0.0792**
	(0.0372)	(0.0354)	(0.0299)	(0.0312)	(0.0294)	(0.0304)
Treatment 2	0.0259	0.0411	0.0460	0.0546	0.0312	0.0683
	(0.0346)	(0.0399)	(0.0427)	(0.0400)	(0.0354)	(0.0394)
Ability IT		0.0542***	0.0479***	0.0303***	0.0368***	0.0272**
		(0.00943)	(0.00898)	(0.00986)	(0.0101)	(0.00944)
GPA		0.0228*	0.0126	0.0145	0.00395	0.00885
		(0.0116)	(0.0135)	(0.0123)	(0.0123)	(0.0121)
Ability		-0.0147	-0.0113	-0.0120	-0.00565	-0.0127
		(0.0151)	(0.0154)	(0.0123)	(0.0120)	(0.0132)
Importance Money		0.0125	0.00772	0.00685	0.00514	0.0000619
		(0.0113)	(0.0117)	(0.00994)	(0.00928)	(0.0104)
Importance Status		-0.00365	0.00173	0.00895	0.00575	0.0124
		(0.00971)	(0.00882)	(0.00720)	(0.00806)	(0.00862)
Importance Interest		-0.0322	-0.0325*	-0.0474**	-0.0547***	-0.0463***
		(0.0191)	(0.0181)	(0.0167)	(0.0145)	(0.0137)
Importance Ability		0.00299	0.00378	-0.00215	0.00212	0.00733
		(0.0147)	(0.0150)	(0.0138)	(0.0124)	(0.0147)
Importance Helping		-0.0155	-0.0210*	-0.0160**	-0.0188**	-0.0159*
		(0.00895)	(0.0101)	(0.00756)	(0.00775)	(0.00902)
Importance Balance		0.00233	0.00173	0.0156**	0.0105*	0.0220**
		(0.00949)	(0.00833)	(0.00722)	(0.00581)	(0.00762)
Importance Like-minded		0.0157*	0.00909	0.00296	-0.00145	-0.00507
		(0.00787)	(0.00755)	(0.00814)	(0.00745)	(0.00885)
Importance Gender Share		-0.00656	-0.000318	0.000683	0.00168	0.0000676
		(0.00597)	(0.00666)	(0.00848)	(0.00724)	(0.00883)
Importance People		-0.00222	-0.000382	-0.00100	0.000709	-0.00146
		(0.00920)	(0.00794)	(0.00678)	(0.00623)	(0.00624)
Importance Job Security		0.00920	0.0134	0.0163	0.0154	0.0123
		(0.00990)	(0.0134)	(0.0104)	(0.0108)	(0.0113)
IT Top 3 Alternative			0.212**	0.217**	0.196**	0.197**
			(0.0877)	(0.0868)	(0.0921)	(0.0897)
Proposal Awareness			0.114*	0.0749	0.0788*	0.00762
			(0.0613)	(0.0495)	(0.0444)	(0.0389)
IT Job Security Belief			0.0109	0.00675	0.0106	0.00920
			(0.0116)	(0.0119)	(0.0119)	(0.0123)
Low Rank Tech-Science				-0.0573***	-0.0583***	-0.0618***
				(0.0131)	(0.0130)	(0.0142)
Advice No One				0.0286	0.00310	0.0360
				(0.0362)	(0.0347)	(0.0307)
No Parent Higher Educ				-0.0996*	-0.0565	-0.0586
				(0.0571)	(0.0419)	(0.0411)
No IT Relation				-0.131***	-0.122***	-0.120***
				(0.0270)	(0.0329)	(0.0331)
Class Size					0.0153**	0.00258
					(0.00682)	(0.00861)
Class Female Share					0.302**	-0.102
					(0.130)	(0.151)
Technology					0.325***	0.815**
					(0.0663)	(0.298)
Median GPA					-0.00354*	0.000696
					(0.00203)	(0.00336)
Day Surveyed					-0.0332***	-0.0106
					(0.00426)	(0.00632)
Program Female Share						2.166*
						(1.080)
Program Higher Educ						-0.460
						(2.980)
Program Foreign-Born						0.319
						(1.128)
School Size						-0.000182
						(0.000266)
School Share Start College						-1.510
						(0.882)
Constant	0.211***	-0.126	-0.0334	0.215	1.383**	0.605
	(0.0238)	(0.235)	(0.323)	(0.317)	(0.619)	(1.894)
R^2	0.023	0.246	0.290	0.402	0.485	0.487
Observations	212	196	177	176	176	164

Note: The table displays OLS estimates for treatment effect on stated IT Probability. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

A.8 Tobit Estimated Impact on IT Probability

Table 30: Impact on IT Probability, All Students (Tobit)

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.00252	-0.0187	-0.0155	-0.0173	-0.0181	-0.0152
	(0.0388)	(0.0328)	(0.0259)	(0.0241)	(0.0243)	(0.0236)
Treatment 2	0.0611*	0.0606**	0.0520*	0.0457*	0.0470*	0.0443*
	(0.0330)	(0.0288)	(0.0283)	(0.0261)	(0.0263)	(0.0264)
Female	-0.132***	0.00643	0.0427	0.0449	0.0512	0.0418
	(0.0473)	(0.0447)	(0.0405)	(0.0394)	(0.0401)	(0.0404)
Female*t1	0.0836*	0.0784	0.0505	0.0583	0.0586	0.0647
	(0.0502)	(0.0501)	(0.0479)	(0.0483)	(0.0484)	(0.0490)
Female*t2	-0.0127	-0.0299	-0.0132	-0.00563	-0.00853	0.00698
	(0.0576)	(0.0507)	(0.0508)	(0.0480)	(0.0478)	(0.0486)
Ability IT		0.0625***	0.0468***	0.0418***	0.0419***	0.0416***
		(0.00533)	(0.00440)	(0.00410)	(0.00397)	(0.00398)
GPA		0.0100	0.0133**	0.0118*	0.0121**	0.0128**
		(0.00820)	(0.00640)	(0.00629)	(0.00523)	(0.00530)
Ability		-0.00432	-0.00553	-0.00657	-0.00672	-0.00718
		(0.00718)	(0.00550)	(0.00515)	(0.00495)	(0.00513)
Importance Money		-0.00162	0.00866	0.00715	0.00809	0.00793
		(0.00687)	(0.00612)	(0.00671)	(0.00660)	(0.00686)
Importance Status		0.00609	0.00568	0.00529	0.00459	0.00526
		(0.00546)	(0.00426)	(0.00457)	(0.00469)	(0.00481)
Importance Interest		-0.0108	-0.0194*	-0.0231**	-0.0243**	-0.0198**
		(0.0115)	(0.0110)	(0.0103)	(0.00989)	(0.00963)
Importance Ability		-0.00435	0.00401	0.00151	0.00231	0.00180
		(0.00748)	(0.00636)	(0.00632)	(0.00639)	(0.00683)
Importance Helping		-0.0130**	-0.00778	-0.00631	-0.00532	-0.00485
		(0.00615)	(0.00544)	(0.00503)	(0.00516)	(0.00523)
Importance Balance		0.0101**	0.00855**	0.0120***	0.0122***	0.0132***
		(0.00486)	(0.00373)	(0.00393)	(0.00405)	(0.00386)
Importance Like-minded		0.00968*	0.00566	0.00369	0.00399	0.00237
		(0.00557)	(0.00504)	(0.00505)	(0.00511)	(0.00524)
Importance Gender Share		-0.00545	-0.00101	-0.000374	-0.00126	-0.000972
		(0.00488)	(0.00430)	(0.00456)	(0.00459)	(0.00471)
Importance People		-0.00861*	-0.00778*	-0.00729*	-0.00807**	-0.00934**
		(0.00503)	(0.00443)	(0.00406)	(0.00409)	(0.00387)
Importance Job Security		0.0170***	0.0114*	0.0117**	0.0112*	0.0113*
		(0.00598)	(0.00628)	(0.00583)	(0.00576)	(0.00610)
IT Top 3 Alternative			0.360***	0.336***	0.326***	0.331***
			(0.0323)	(0.0326)	(0.0343)	(0.0349)
Proposal Awareness			-0.0104	-0.0106	-0.0160	-0.0252
			(0.0231)	(0.0217)	(0.0231)	(0.0224)
IT Job Security Belief			0.00743	0.00758	0.00798	0.00818
			(0.00485)	(0.00490)	(0.00519)	(0.00544)
Low Rank Tech-Science				-0.0462***	-0.0467***	-0.0434***
				(0.00955)	(0.00931)	(0.00907)
Advice No One				-0.00199	-0.00386	0.0000197
				(0.0283)	(0.0282)	(0.0278)
No Parent Higher Educ				0.0163	0.0180	0.0252
				(0.0323)	(0.0312)	(0.0301)
No IT Relation				-0.0784***	-0.0779***	-0.0764***
				(0.0226)	(0.0225)	(0.0233)
Class Size					0.00438	0.00644
					(0.00453)	(0.00502)
Class Female Share					0.0258	-0.0253
					(0.0868)	(0.113)
Technology					0.00695	-0.0669
					(0.0582)	(0.146)
Grade 3					-0.0104	-0.0232
					(0.0325)	(0.0370)
Median GPA					-0.00235	-0.00320
					(0.00169)	(0.00202)
Day Surveyed					-0.00521*	-0.00566**
					(0.00294)	(0.00260)
Program Female Share						-1.111
						(0.923)
Program Higher Educ						5.731*
						(3.020)
Program Foreign-Born						2.384*
						(1.225)
School Size						0.0000373
						(0.000155)
School Share Start College						-1.874***
						(0.686)
Constant	0.344***	-0.142	-0.250*	-0.0412	0.629	-2.790
	(0.0299)	(0.164)	(0.151)	(0.146)	(0.457)	(1.868)
Sigma	0.309***	0.271***	0.232***	0.226***	0.225***	0.224***
	(0.0126)	(0.0110)	(0.00572)	(0.00603)	(0.00606)	(0.00614)
Observations	786	737	669	664	664	646

Note: The table displays Tobit estimates for marginal treatment effect on stated IT Probability, $E(y|X)$. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school dummies. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 31: Impact on IT Probability: Male Students No Proposal Awareness (Tobit)

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.00146	-0.0191	-0.00779	-0.0144	-0.0108	-0.0126
	(0.0395)	(0.0330)	(0.0291)	(0.0283)	(0.0300)	(0.0292)
Treatment 2	0.0603	0.0677**	0.0725**	0.0665**	0.0693**	0.0645**
	(0.0379)	(0.0315)	(0.0323)	(0.0303)	(0.0310)	(0.0311)
Ability IT		0.0651***	0.0457***	0.0406***	0.0399***	0.0395***
		(0.00836)	(0.00627)	(0.00613)	(0.00616)	(0.00628)
GPA		0.0170	0.0187**	0.0168*	0.0165**	0.0155*
		(0.0108)	(0.00921)	(0.00882)	(0.00831)	(0.00827)
Ability		-0.0122	-0.00985	-0.00842	-0.00713	-0.00478
		(0.0106)	(0.00827)	(0.00859)	(0.00831)	(0.00862)
Importance Money		-0.000878	0.00923	0.00493	0.00392	0.00357
		(0.00958)	(0.00762)	(0.00779)	(0.00762)	(0.00772)
Importance Status		0.00657	0.00705	0.00771	0.00884	0.00814
		(0.00612)	(0.00549)	(0.00566)	(0.00589)	(0.00593)
Importance Interest		-0.000638	-0.00256	-0.00607	-0.00533	-0.00447
		(0.0162)	(0.0146)	(0.0143)	(0.0145)	(0.0147)
Importance Ability		0.00493	0.00836	0.00690	0.00614	0.00404
		(0.00740)	(0.00743)	(0.00734)	(0.00647)	(0.00678)
Importance Helping		-0.0178**	-0.0107	-0.00954	-0.00915	-0.00889
		(0.00798)	(0.00747)	(0.00769)	(0.00803)	(0.00820)
Importance Balance		0.0112	0.0101	0.0129	0.0129	0.0119
		(0.00978)	(0.00758)	(0.00783)	(0.00787)	(0.00800)
Importance Like-minded		0.0149**	0.00785	0.00525	0.00506	0.00397
		(0.00638)	(0.00562)	(0.00546)	(0.00554)	(0.00606)
Importance Gender Share		-0.00823	-0.00323	-0.00237	-0.00316	-0.00294
		(0.00679)	(0.00540)	(0.00531)	(0.00549)	(0.00584)
Importance People		-0.00747	-0.00954	-0.0101	-0.0105	-0.00941
		(0.00746)	(0.00671)	(0.00651)	(0.00664)	(0.00653)
Importance Job Security		0.0157*	0.00893	0.0134	0.0132	0.0140
		(0.00929)	(0.00905)	(0.00856)	(0.00867)	(0.00861)
IT Top 3 Alternative			0.354***	0.336***	0.326***	0.339***
			(0.0424)	(0.0413)	(0.0433)	(0.0451)
IT Job Security Belief			0.00439	0.00388	0.00462	0.00516
			(0.00763)	(0.00723)	(0.00761)	(0.00804)
Low Rank Tech-Science				-0.0332**	-0.0319**	-0.0275*
				(0.0150)	(0.0147)	(0.0148)
Advice No One				0.0301	0.0309	0.0285
				(0.0371)	(0.0391)	(0.0378)
No Parent Higher Educ				0.0290	0.0298	0.0292
				(0.0400)	(0.0390)	(0.0378)
No IT Relation				-0.0664**	-0.0642**	-0.0645**
				(0.0308)	(0.0309)	(0.0316)
Class Size					0.00223	0.00534
					(0.00555)	(0.00599)
Class Female Share					-0.135	-0.247*
					(0.116)	(0.148)
Technology					-0.0579	-0.0776
					(0.0727)	(0.152)
Grade 3					-0.0473	-0.0881*
					(0.0458)	(0.0488)
Median GPA					-0.00134	-0.00316
					(0.00247)	(0.00266)
Day Surveyed					-0.00131	-0.00383
					(0.00412)	(0.00349)
Program Female Share						1.226
						(1.246)
Program Higher Educ						-3.563
						(5.047)
Program Foreign-Born						-1.885
						(2.117)
School Size						0.0000843
						(0.000208)
School Share Start College						0.383
						(1.242)
Constant	0.340***	-0.358	-0.483**	-0.288	0.144	3.113
	(0.0254)	(0.236)	(0.211)	(0.223)	(0.724)	(2.961)
Sigma	0.323***	0.276***	0.226***	0.223***	0.221***	0.222***
	(0.0172)	(0.0129)	(0.00952)	(0.00972)	(0.00953)	(0.00968)
Observations	355	335	300	296	296	291

Note: The table displays Tobit estimates for marginal treatment effect on stated IT Probability, $E(y|X)$. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school dummies. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 32: Impact on IT Probability: Female Students No Proposal Awareness (Tobit)

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0932***	0.0621*	0.0615*	0.0590*	0.0551	0.0556
	(0.0331)	(0.0331)	(0.0323)	(0.0345)	(0.0337)	(0.0349)
Treatment 2	0.0841**	0.0564*	0.0707**	0.0550*	0.0508	0.0550
	(0.0355)	(0.0327)	(0.0315)	(0.0322)	(0.0315)	(0.0335)
Ability IT		0.0499***	0.0480***	0.0432***	0.0437***	0.0457***
		(0.00865)	(0.00718)	(0.00787)	(0.00798)	(0.00795)
GPA		0.00776	0.0157	0.0161	0.0154	0.0177
		(0.0149)	(0.0132)	(0.0114)	(0.0115)	(0.0118)
Ability		0.00176	-0.00991	-0.0132	-0.0146	-0.0170
		(0.0147)	(0.0128)	(0.0102)	(0.0103)	(0.0112)
Importance Money		0.0101	0.0136	0.0150	0.0193*	0.0201*
		(0.0113)	(0.0102)	(0.0102)	(0.0103)	(0.0108)
Importance Status		0.00629	0.00853	0.00637	0.00584	0.00557
		(0.0101)	(0.00913)	(0.00978)	(0.0100)	(0.0101)
Importance Interest		-0.0239	-0.0327**	-0.0454***	-0.0416***	-0.0404**
		(0.0200)	(0.0158)	(0.0157)	(0.0154)	(0.0158)
Importance Ability		-0.0253	0.0000566	-0.000801	-0.00166	-0.00235
		(0.0191)	(0.0150)	(0.0146)	(0.0137)	(0.0152)
Importance Helping		-0.00622	-0.00906	-0.00613	-0.00698	-0.00719
		(0.00902)	(0.00909)	(0.00867)	(0.00846)	(0.00858)
Importance Balance		0.0119	0.00934	0.0138**	0.0119**	0.0136**
		(0.00771)	(0.00677)	(0.00625)	(0.00576)	(0.00583)
Importance Like-minded		0.00626	0.00330	0.00299	0.00260	0.00218
		(0.00943)	(0.00863)	(0.00827)	(0.00864)	(0.00896)
Importance Gender Share		0.00189	0.00408	0.00401	0.00429	0.00483
		(0.00623)	(0.00628)	(0.00711)	(0.00667)	(0.00670)
Importance People		-0.0133*	-0.00806	-0.00975	-0.0101*	-0.0114*
		(0.00791)	(0.00672)	(0.00617)	(0.00582)	(0.00594)
Importance Job Security		0.00413	0.00150	0.00198	0.00168	0.0000675
		(0.00830)	(0.00978)	(0.00923)	(0.00955)	(0.00994)
IT Top 3 Alternative			0.351***	0.321***	0.309***	0.309***
			(0.0727)	(0.0753)	(0.0762)	(0.0781)
IT Job Security Belief			0.00759	0.00614	0.00608	0.00546
			(0.00828)	(0.00868)	(0.00897)	(0.00944)
Low Rank Tech-Science				-0.0302**	-0.0319***	-0.0303***
				(0.0128)	(0.0112)	(0.0116)
Advice No One				-0.0257	-0.0138	-0.0110
				(0.0446)	(0.0401)	(0.0420)
No Parent Higher Educ				-0.0446	-0.0437	-0.0355
				(0.0455)	(0.0371)	(0.0370)
No IT Relation				-0.0945***	-0.0981***	-0.0983***
				(0.0262)	(0.0258)	(0.0267)
Class Size					0.00435	0.00480
					(0.00709)	(0.00730)
Class Female Share					0.152	0.149
					(0.105)	(0.123)
Technology					0.0782	-0.0181
					(0.0911)	(0.340)
Grade 3					0.0288	0.0301
					(0.0404)	(0.0380)
Median GPA					-0.00270	-0.00283
					(0.00214)	(0.00212)
Day Surveyed					-0.0112***	-0.0110***
					(0.00377)	(0.00379)
Program Female Share						-3.206*
						(1.857)
Program Higher Educ						14.80***
						(5.227)
Program Foreign-Born						6.676***
						(2.023)
School Size						0.0000104
						(0.000281)
School Share Start College						-4.699***
						(1.024)
Constant	0.120***	0.0611	-0.157	0.0983	0.940	-8.195***
	(0.0185)	(0.287)	(0.259)	(0.245)	(0.615)	(3.099)
Sigma	0.266***	0.238***	0.219***	0.211***	0.206***	0.207***
	(0.0125)	(0.0102)	(0.00919)	(0.00965)	(0.00990)	(0.0102)
Observations	307	286	258	258	258	249

Note: The table displays Tobit estimates for marginal treatment effect on stated IT Probability, $E(y|X)$. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school dummies. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

A.9 OLS Estimated Impact on Classmates' IT Probability

Table 33: Estimated IT Probability of Male Classmates

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.0218	-0.0305	-0.0312	-0.0306	-0.0346*	-0.0395**
	(0.0215)	(0.0201)	(0.0204)	(0.0198)	(0.0191)	(0.0186)
Treatment 2	0.0245	0.0131	-0.000793	-0.00415	-0.00432	-0.00369
	(0.0263)	(0.0259)	(0.0277)	(0.0271)	(0.0259)	(0.0258)
Female	0.0973***	0.132***	0.136***	0.135***	0.149***	0.146***
	(0.0348)	(0.0301)	(0.0311)	(0.0305)	(0.0281)	(0.0293)
Female*t1	0.0339	0.0397	0.0472	0.0486	0.0527	0.0640*
	(0.0323)	(0.0329)	(0.0377)	(0.0364)	(0.0355)	(0.0346)
Female*t2	-0.0141	-0.0153	-0.00618	-0.00338	-0.00627	0.00556
	(0.0367)	(0.0343)	(0.0390)	(0.0378)	(0.0374)	(0.0358)
Ability IT		0.0182***	0.0171***	0.0161***	0.0157***	0.0157***
		(0.00430)	(0.00450)	(0.00455)	(0.00429)	(0.00439)
GPA		0.00517	0.00806	0.00824	0.00838	0.00832
		(0.00710)	(0.00703)	(0.00739)	(0.00615)	(0.00609)
Ability		-0.00487	-0.00728	-0.00662	-0.00638	-0.00624
		(0.00503)	(0.00509)	(0.00523)	(0.00544)	(0.00552)
Importance Money		0.0161***	0.0197***	0.0182***	0.0175***	0.0175***
		(0.00389)	(0.00420)	(0.00434)	(0.00422)	(0.00435)
Importance Status		-0.00263	-0.00366	-0.00248	-0.00183	-0.00198
		(0.00382)	(0.00392)	(0.00397)	(0.00408)	(0.00426)
Importance Interest		0.000550	-0.00377	-0.00548	-0.00704	-0.00705
		(0.00912)	(0.00888)	(0.00899)	(0.00892)	(0.00923)
Importance Ability		-0.00407	0.00175	0.00146	0.00211	0.000842
		(0.00607)	(0.00552)	(0.00575)	(0.00568)	(0.00580)
Importance Helping		-0.00366	-0.00206	-0.00116	0.000895	0.00130
		(0.00398)	(0.00394)	(0.00388)	(0.00390)	(0.00387)
Importance Balance		0.00191	0.000824	0.00150	0.00141	0.00139
		(0.00332)	(0.00331)	(0.00344)	(0.00329)	(0.00337)
Importance Like-minded		0.01000***	0.00790**	0.00716*	0.00763*	0.00913**
		(0.00358)	(0.00383)	(0.00380)	(0.00377)	(0.00375)
Importance Gender Share		0.00541	0.00582	0.00601	0.00485	0.00368
		(0.00395)	(0.00360)	(0.00362)	(0.00362)	(0.00342)
Importance People		-0.000639	-0.000307	-0.000767	-0.00184	-0.00294
		(0.00333)	(0.00374)	(0.00386)	(0.00359)	(0.00366)
Importance Job Security		0.00433	0.00233	0.00337	0.00290	0.00390
		(0.00486)	(0.00527)	(0.00526)	(0.00489)	(0.00500)
IT Top 3 Alternative			0.0703***	0.0659***	0.0473**	0.0455**
			(0.0210)	(0.0214)	(0.0189)	(0.0191)
Proposal Awareness			-0.0161	-0.0170	-0.0282	-0.0291
			(0.0238)	(0.0236)	(0.0209)	(0.0220)
IT Job Security Belief			0.00584	0.00521	0.00874*	0.00796*
			(0.00439)	(0.00432)	(0.00429)	(0.00430)
Low Rank Tech-Science				-0.00534	-0.000609	0.000862
				(0.00820)	(0.00737)	(0.00781)
Advice No One				0.0179	0.00906	0.0161
				(0.0214)	(0.0206)	(0.0195)
No Parent Higher Educ				0.00683	0.0150	0.0197
				(0.0263)	(0.0246)	(0.0244)
No IT Relation				-0.0262*	-0.0233	-0.0271*
				(0.0153)	(0.0152)	(0.0150)
Class Size					0.00858**	0.00712**
					(0.00320)	(0.00288)
Class Female Share					-0.102	-0.0785
					(0.0732)	(0.0857)
Technology					0.0345	-0.271**
					(0.0430)	(0.103)
Grade 3					-0.0468	-0.0491
					(0.0317)	(0.0318)
Median GPA					-0.00241*	-0.00241*
					(0.00129)	(0.00119)
Day Surveyed					-0.00547*	-0.00563**
					(0.00308)	(0.00244)
Program Female Share						-1.543***
						(0.495)
Program Higher Educ						3.832**
						(1.470)
Program Foreign-Born						1.173*
						(0.598)
School Size						0.0000328
						(0.000117)
School Share Start College						-0.608*
						(0.352)
Constant	0.463***	0.128	0.0485	0.0745	0.667	-1.555
	(0.0282)	(0.129)	(0.130)	(0.143)	(0.413)	(1.018)
R^2	0.060	0.149	0.182	0.184	0.236	0.260
Observations	783	735	667	662	662	644

Note: The table displays OLS estimates for treatment effect on stated IT probability of male classmates. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 34: Estimated IT Probability of Male Classmates, by Males with No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	-0.0299	-0.0436*	-0.0428*	-0.0407	-0.0404	-0.0456*
	(0.0239)	(0.0232)	(0.0246)	(0.0253)	(0.0246)	(0.0245)
Treatment 2	0.0178	0.00587	-0.00406	-0.00458	-0.00577	-0.00279
	(0.0292)	(0.0305)	(0.0311)	(0.0303)	(0.0294)	(0.0292)
Ability IT		0.0160***	0.0141**	0.0132**	0.0121**	0.0143***
		(0.00564)	(0.00530)	(0.00552)	(0.00535)	(0.00515)
GPA		0.00000835	0.00346	0.00356	0.000344	0.000215
		(0.00947)	(0.00987)	(0.0114)	(0.0106)	(0.0103)
Ability		-0.000773	-0.000779	0.000542	0.00362	0.00463
		(0.00873)	(0.00940)	(0.00979)	(0.00981)	(0.00991)
Importance Money		0.0148**	0.0194***	0.0162**	0.0154**	0.0180**
		(0.00600)	(0.00611)	(0.00687)	(0.00723)	(0.00711)
Importance Status		-0.00183	-0.00299	-0.00151	-0.000360	-0.00137
		(0.00471)	(0.00516)	(0.00549)	(0.00552)	(0.00546)
Importance Interest		0.00508	0.00331	0.00103	-0.00371	-0.00284
		(0.0123)	(0.0122)	(0.0123)	(0.0125)	(0.0123)
Importance Ability		-0.00325	0.00319	0.00310	0.00344	0.000916
		(0.00727)	(0.00666)	(0.00701)	(0.00682)	(0.00654)
Importance Helping		-0.00632	-0.00420	-0.00277	0.00148	0.00263
		(0.00494)	(0.00501)	(0.00533)	(0.00539)	(0.00532)
Importance Balance		-0.00396	-0.00410	-0.00380	-0.00395	-0.00566
		(0.00620)	(0.00642)	(0.00669)	(0.00667)	(0.00678)
Importance Like-minded		0.0134**	0.0112*	0.00981	0.0102*	0.0127**
		(0.00563)	(0.00591)	(0.00588)	(0.00581)	(0.00572)
Importance Gender Share		0.00213	0.00162	0.00230	0.000500	-0.000951
		(0.00532)	(0.00471)	(0.00506)	(0.00512)	(0.00518)
Importance People		0.00114	0.00175	0.00138	-0.00115	-0.00136
		(0.00561)	(0.00578)	(0.00632)	(0.00498)	(0.00505)
Importance Job Security		-0.000402	-0.000417	0.00202	-0.0000899	-0.00118
		(0.00849)	(0.00836)	(0.00876)	(0.00811)	(0.00813)
IT Top 3 Alternative			0.0735***	0.0702**	0.0459	0.0502*
			(0.0248)	(0.0259)	(0.0272)	(0.0273)
IT Job Security Belief			0.000321	-0.000923	0.00465	0.00235
			(0.00698)	(0.00643)	(0.00695)	(0.00696)
Low Rank Tech-Science				-0.00331	0.00666	0.00794
				(0.0159)	(0.0152)	(0.0168)
Advice No One				0.0321	0.0222	0.0203
				(0.0323)	(0.0313)	(0.0302)
No Parent Higher Educ				0.00504	0.0107	0.00734
				(0.0421)	(0.0384)	(0.0384)
No IT Relation				-0.0195	-0.00985	-0.0119
				(0.0236)	(0.0226)	(0.0222)
Class Size					0.00593	0.00615
					(0.00485)	(0.00415)
Class Female Share					-0.278**	-0.293**
					(0.126)	(0.117)
Technology					0.0375	-0.0260
					(0.0498)	(0.142)
Grade 3					-0.0534	-0.0615
					(0.0397)	(0.0403)
Median GPA					-0.000829	-0.00121
					(0.00222)	(0.00160)
Day Surveyed					-0.00507	-0.00559**
					(0.00400)	(0.00272)
Program Female Share						-0.0522
						(0.699)
Program Higher Educ						0.0119
						(2.543)
Program Foreign-Born						-0.119
						(0.980)
School Size						-0.00000512
						(0.000130)
School Share Start College						-0.226
						(0.439)
Constant	0.468***	0.239	0.119	0.140	0.456	0.803
	(0.0261)	(0.175)	(0.183)	(0.214)	(0.680)	(1.623)
R^2	0.009	0.088	0.134	0.134	0.241	0.306
Observations	354	334	299	295	295	290

Note: The table displays OLS estimates for treatment effect on stated IT probability of male classmates. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 35: Estimated IT Probability of Male Classmates, by Females with No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0348	0.0489	0.0623*	0.0623*	0.0621*	0.0667*
	(0.0258)	(0.0294)	(0.0361)	(0.0351)	(0.0351)	(0.0360)
Treatment 2	0.0250	0.0196	0.0145	0.0121	0.0116	0.0173
	(0.0283)	(0.0248)	(0.0289)	(0.0260)	(0.0258)	(0.0268)
Ability IT		0.0145*	0.0150*	0.0135	0.0144*	0.0167*
		(0.00826)	(0.00854)	(0.00844)	(0.00845)	(0.00863)
GPA		0.0207**	0.0269**	0.0268**	0.0261**	0.0268**
		(0.00929)	(0.0113)	(0.0116)	(0.0126)	(0.0126)
Ability		-0.0135	-0.0223*	-0.0230*	-0.0230*	-0.0244*
		(0.0112)	(0.0118)	(0.0122)	(0.0128)	(0.0131)
Importance Money		0.0165	0.0167*	0.0168*	0.0167*	0.0168
		(0.00989)	(0.00923)	(0.00949)	(0.00979)	(0.00991)
Importance Status		-0.000885	-0.00110	-0.00171	-0.00184	-0.00245
		(0.00584)	(0.00635)	(0.00645)	(0.00658)	(0.00676)
Importance Interest		-0.0143	-0.0215	-0.0250	-0.0237	-0.0235
		(0.0130)	(0.0149)	(0.0165)	(0.0165)	(0.0168)
Importance Ability		0.00258	0.00670	0.00670	0.00688	0.00440
		(0.00949)	(0.00984)	(0.00986)	(0.00980)	(0.0108)
Importance Helping		-0.00495	-0.00967	-0.00895	-0.00853	-0.00873
		(0.00753)	(0.00836)	(0.00787)	(0.00825)	(0.00897)
Importance Balance		0.0108*	0.00822	0.00926	0.00920	0.00774
		(0.00542)	(0.00575)	(0.00593)	(0.00607)	(0.00607)
Importance Like-minded		0.00422	0.00370	0.00379	0.00327	0.00461
		(0.00509)	(0.00603)	(0.00595)	(0.00614)	(0.00624)
Importance Gender Share		0.0130**	0.0137**	0.0133**	0.0130*	0.0122*
		(0.00600)	(0.00629)	(0.00641)	(0.00671)	(0.00680)
Importance People		-0.00261	-0.00363	-0.00397	-0.00348	-0.00491
		(0.00661)	(0.00702)	(0.00682)	(0.00733)	(0.00779)
Importance Job Security		0.00738	0.00674	0.00635	0.00501	0.00485
		(0.00746)	(0.00795)	(0.00774)	(0.00763)	(0.00836)
IT Top 3 Alternative			-0.0278	-0.0373	-0.0380	-0.0405
			(0.0587)	(0.0607)	(0.0623)	(0.0640)
IT Job Security Belief			0.00665	0.00607	0.00695	0.00738
			(0.00992)	(0.00994)	(0.0102)	(0.0105)
Low Rank Tech-Science				-0.0101	-0.0107	-0.00615
				(0.0134)	(0.0132)	(0.0129)
Advice No One				-0.0104	-0.0128	-0.00487
				(0.0381)	(0.0392)	(0.0395)
No Parent Higher Educ				0.00746	0.0181	0.0277
				(0.0348)	(0.0352)	(0.0338)
No IT Relation				-0.0353	-0.0354	-0.0388*
				(0.0226)	(0.0230)	(0.0226)
Class Size					0.00524	0.00581
					(0.00478)	(0.00429)
Class Female Share					-0.0196	0.0419
					(0.0789)	(0.0836)
Technology					0.0563	-0.340*
					(0.0598)	(0.184)
Grade 3					-0.00567	-0.0107
					(0.0396)	(0.0388)
Median GPA					-0.00156	-0.00223
					(0.00207)	(0.00187)
Day Surveyed					-0.000392	-0.00206
					(0.00308)	(0.00260)
Program Female Share						-1.778**
						(0.806)
Program Higher Educ						3.362*
						(1.690)
Program Foreign-Born						0.868
						(0.607)
School Size						0.000113
						(0.000139)
School Share Start College						-0.439
						(0.397)
Constant	0.548***	0.0645	0.0683	0.146	0.495	-1.197
	(0.0198)	(0.183)	(0.198)	(0.216)	(0.614)	(1.216)
R^2	0.005	0.131	0.152	0.163	0.173	0.205
Observations	306	286	258	258	258	249

Note: The table displays OLS estimates for treatment effect on stated IT probability of male classmates. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $***p < 0.01$, $**p < 0.05$ and $*p < 0.1$.

Table 36: Estimated IT Probability of Female Classmates

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0156	0.0142	0.0205	0.0208	0.0180	0.0192
	(0.0226)	(0.0209)	(0.0208)	(0.0214)	(0.0223)	(0.0223)
Treatment 2	0.0234	0.0291	0.0284	0.0280	0.0272	0.0233
	(0.0236)	(0.0246)	(0.0250)	(0.0252)	(0.0251)	(0.0259)
Female	0.000702	0.0367	0.0415	0.0411	0.0448	0.0349
	(0.0256)	(0.0253)	(0.0287)	(0.0288)	(0.0279)	(0.0274)
Female*t1	0.0418	0.0383	0.0291	0.0274	0.0317	0.0400
	(0.0273)	(0.0268)	(0.0286)	(0.0293)	(0.0305)	(0.0302)
Female*t2	0.00160	-0.0131	-0.00731	-0.00742	-0.00824	0.00761
	(0.0335)	(0.0335)	(0.0345)	(0.0360)	(0.0349)	(0.0352)
Ability IT		0.0213***	0.0216***	0.0205***	0.0209***	0.0203***
		(0.00283)	(0.00294)	(0.00291)	(0.00283)	(0.00277)
GPA		0.00381	0.00851*	0.00824*	0.00729*	0.00761*
		(0.00536)	(0.00482)	(0.00462)	(0.00364)	(0.00395)
Ability		-0.00804	-0.0105*	-0.0107*	-0.0107*	-0.0115*
		(0.00636)	(0.00616)	(0.00599)	(0.00611)	(0.00618)
Importance Money		0.00378	0.00699	0.00707	0.00809	0.00797
		(0.00477)	(0.00495)	(0.00500)	(0.00509)	(0.00524)
Importance Status		0.000163	-0.00226	-0.00221	-0.00299	-0.00273
		(0.00405)	(0.00427)	(0.00433)	(0.00434)	(0.00449)
Importance Interest		-0.00449	-0.0100	-0.0114*	-0.0131**	-0.0102*
		(0.00652)	(0.00603)	(0.00628)	(0.00575)	(0.00590)
Importance Ability		0.000667	0.00421	0.00336	0.00412	0.00325
		(0.00530)	(0.00468)	(0.00472)	(0.00466)	(0.00519)
Importance Helping		0.000873	0.00258	0.00279	0.00427	0.00564
		(0.00329)	(0.00354)	(0.00350)	(0.00383)	(0.00359)
Importance Balance		0.00409	0.00536	0.00659*	0.00643*	0.00695**
		(0.00312)	(0.00322)	(0.00325)	(0.00317)	(0.00316)
Importance Like-minded		0.0000769	-0.000857	-0.00141	-0.00117	-0.00246
		(0.00411)	(0.00402)	(0.00403)	(0.00403)	(0.00407)
Importance Gender Share		0.000460	0.00198	0.00199	0.00112	0.00117
		(0.00321)	(0.00344)	(0.00362)	(0.00369)	(0.00367)
Importance People		-0.000627	-0.000877	-0.00100	-0.00217	-0.00283
		(0.00293)	(0.00331)	(0.00330)	(0.00327)	(0.00313)
Importance Job Security		0.00207	-0.000997	-0.000856	-0.00121	-0.000401
		(0.00445)	(0.00456)	(0.00464)	(0.00453)	(0.00461)
IT Top 3 Alternative			0.0292	0.0250	0.0156	0.0193
			(0.0194)	(0.0206)	(0.0204)	(0.0215)
Proposal Awareness			0.0236	0.0246	0.0202	0.0143
			(0.0273)	(0.0278)	(0.0268)	(0.0282)
IT Job Security Belief			0.00259	0.00187	0.00379	0.00464
			(0.00459)	(0.00481)	(0.00464)	(0.00477)
Low Rank Tech-Science				-0.00487	-0.00254	0.000490
				(0.00765)	(0.00787)	(0.00813)
Advice No One				-0.00653	-0.0150	-0.00894
				(0.0242)	(0.0226)	(0.0227)
No Parent Higher Educ				-0.00689	-0.00101	0.00618
				(0.0254)	(0.0241)	(0.0233)
No IT Relation				-0.0297*	-0.0292*	-0.0276*
				(0.0158)	(0.0158)	(0.0160)
Class Size					0.00482	0.00509
					(0.00397)	(0.00393)
Class Female Share					0.0791	-0.00544
					(0.0853)	(0.0819)
Technology					0.0707	0.0758
					(0.0618)	(0.141)
Grade 3					-0.0151	-0.0282
					(0.0447)	(0.0313)
Median GPA					-0.00187	-0.00217*
					(0.00194)	(0.00120)
Day Surveyed					-0.00630*	-0.00564*
					(0.00321)	(0.00312)
Program Female Share						-0.340
						(0.502)
Program Higher Educ						2.980*
						(1.557)
Program Foreign-Born						1.129*
						(0.593)
School Size						0.000132
						(0.000104)
School Share Start College						-0.715*
						(0.402)
Constant	0.242***	0.0726	-0.00390	0.0444	0.517	-1.611*
	(0.0204)	(0.0965)	(0.0872)	(0.0912)	(0.622)	(0.932)
R^2	0.010	0.073	0.097	0.102	0.131	0.157
Observations	780	732	665	660	660	642

Note: The table displays OLS estimates for treatment effect on stated IT probability of female classmates. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Table 37: Estimated IT Probability of Female Classmates, By Males With No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0115	0.0141	0.0242	0.0218	0.0167	0.0152
	(0.0267)	(0.0254)	(0.0235)	(0.0245)	(0.0264)	(0.0268)
Treatment 2	0.0192	0.0206	0.0263	0.0259	0.0190	0.0116
	(0.0283)	(0.0299)	(0.0305)	(0.0310)	(0.0301)	(0.0311)
Ability IT		0.0173***	0.0188***	0.0170***	0.0182***	0.0176***
		(0.00404)	(0.00439)	(0.00465)	(0.00454)	(0.00459)
GPA		0.00345	0.00932	0.00771	0.00327	0.00103
		(0.00941)	(0.00941)	(0.00931)	(0.00793)	(0.00841)
Ability		-0.0102	-0.0117	-0.0104	-0.00694	-0.00435
		(0.00957)	(0.00936)	(0.00957)	(0.00941)	(0.00900)
Importance Money		0.00572	0.00591	0.00542	0.00504	0.00424
		(0.00634)	(0.00630)	(0.00654)	(0.00649)	(0.00640)
Importance Status		0.00469	0.00225	0.00215	0.000679	0.000157
		(0.00488)	(0.00563)	(0.00551)	(0.00554)	(0.00542)
Importance Interest		0.00406	-0.000552	-0.000979	-0.00580	-0.00452
		(0.00999)	(0.00888)	(0.00911)	(0.00772)	(0.00788)
Importance Ability		-0.000191	0.00348	0.00337	0.00357	0.00114
		(0.00694)	(0.00539)	(0.00564)	(0.00549)	(0.00632)
Importance Helping		-0.00204	0.00245	0.00213	0.00249	0.00352
		(0.00529)	(0.00590)	(0.00576)	(0.00679)	(0.00672)
Importance Balance		0.00815*	0.00637	0.00791	0.00829	0.00669
		(0.00475)	(0.00544)	(0.00566)	(0.00563)	(0.00607)
Importance Like-minded		-0.00113	-0.00247	-0.00333	-0.00422	-0.00592
		(0.00640)	(0.00690)	(0.00731)	(0.00709)	(0.00743)
Importance Gender Share		0.00326	0.00523	0.00500	0.00458	0.00531
		(0.00492)	(0.00487)	(0.00539)	(0.00538)	(0.00567)
Importance People		-0.00508	-0.00662	-0.00677	-0.00734	-0.00647
		(0.00514)	(0.00568)	(0.00564)	(0.00561)	(0.00542)
Importance Job Security		-0.00295	-0.00445	-0.00349	-0.00246	-0.000848
		(0.00979)	(0.00942)	(0.00982)	(0.00939)	(0.00919)
IT Top 3 Alternative			0.0354	0.0295	0.0236	0.0349
			(0.0230)	(0.0243)	(0.0237)	(0.0266)
IT Job Security Belief			-0.00596	-0.00677	-0.00299	-0.00102
			(0.00573)	(0.00597)	(0.00685)	(0.00700)
Low Rank Tech-Science				-0.00934	-0.00224	0.00320
				(0.0112)	(0.0126)	(0.0142)
Advice No One				-0.00330	-0.0232	-0.0214
				(0.0309)	(0.0265)	(0.0252)
No Parent Higher Educ				0.0221	0.0251	0.0258
				(0.0424)	(0.0430)	(0.0429)
No IT Relation				-0.0171	-0.0176	-0.0193
				(0.0275)	(0.0257)	(0.0253)
Class Size					0.00599	0.00800
					(0.00595)	(0.00512)
Class Female Share					0.156	-0.0149
					(0.147)	(0.112)
Technology					0.0621	0.250
					(0.0907)	(0.197)
Grade 3					-0.0197	-0.0716
					(0.0731)	(0.0443)
Median GPA					-0.000912	-0.00253
					(0.00343)	(0.00181)
Day Surveyed					-0.00816*	-0.0102***
					(0.00479)	(0.00327)
Program Female Share						0.609
						(0.781)
Program Higher Educ						2.156
						(2.302)
Program Foreign-Born						0.983
						(0.824)
School Size						0.000209
						(0.000144)
School Share Start College						-1.213**
						(0.444)
Constant	0.244***	0.0584	0.0295	0.0799	0.288	-0.868
	(0.0218)	(0.179)	(0.167)	(0.180)	(1.023)	(1.387)
R^2	0.002	0.060	0.092	0.098	0.136	0.208
Observations	353	333	298	294	294	289

Note: The table displays OLS estimates for treatment effect on stated IT probability of female classmates. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$.

Table 38: Estimated IT Probability of Female Classmates, By Females With No Prior Proposal Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.0615**	0.0628**	0.0643**	0.0600**	0.0602**	0.0636**
	(0.0225)	(0.0242)	(0.0247)	(0.0258)	(0.0258)	(0.0259)
Treatment 2	0.0383	0.0319	0.0348	0.0251	0.0253	0.0299
	(0.0233)	(0.0234)	(0.0247)	(0.0248)	(0.0253)	(0.0267)
Ability IT		0.0221***	0.0242***	0.0237***	0.0239***	0.0239***
		(0.00599)	(0.00637)	(0.00657)	(0.00714)	(0.00713)
GPA		0.00836	0.0129*	0.0139*	0.0145**	0.0181**
		(0.00737)	(0.00757)	(0.00698)	(0.00697)	(0.00680)
Ability		-0.00855	-0.0162	-0.0166*	-0.0179*	-0.0223**
		(0.00983)	(0.00983)	(0.00877)	(0.00903)	(0.00929)
Importance Money		0.00251	0.00871	0.00950	0.0124	0.0116
		(0.00765)	(0.00817)	(0.00775)	(0.00769)	(0.00802)
Importance Status		-0.000590	-0.00402	-0.00331	-0.00507	-0.00509
		(0.00515)	(0.00555)	(0.00592)	(0.00617)	(0.00611)
Importance Interest		-0.0125	-0.0155	-0.0201*	-0.0180	-0.0192
		(0.0109)	(0.0110)	(0.0117)	(0.0116)	(0.0123)
Importance Ability		0.00778	0.0112	0.00933	0.00974	0.00857
		(0.00895)	(0.00861)	(0.00831)	(0.00841)	(0.00955)
Importance Helping		0.00529	0.00294	0.00372	0.00263	0.00394
		(0.00512)	(0.00544)	(0.00540)	(0.00530)	(0.00537)
Importance Balance		0.00189	0.00618	0.00782	0.00826	0.00923
		(0.00514)	(0.00587)	(0.00616)	(0.00605)	(0.00643)
Importance Like-minded		0.00559	0.00398	0.00444	0.00420	0.00511
		(0.00614)	(0.00631)	(0.00651)	(0.00657)	(0.00688)
Importance Gender Share		-0.00103	0.00101	0.00151	0.000493	0.000629
		(0.00412)	(0.00422)	(0.00445)	(0.00405)	(0.00403)
Importance People		-0.00242	-0.00311	-0.00451	-0.00251	-0.00327
		(0.00405)	(0.00391)	(0.00427)	(0.00413)	(0.00410)
Importance Job Security		0.00151	-0.00416	-0.00284	-0.00245	-0.00234
		(0.00645)	(0.00710)	(0.00693)	(0.00652)	(0.00668)
IT Top 3 Alternative			0.0604	0.0541	0.0399	0.0382
			(0.0588)	(0.0621)	(0.0648)	(0.0656)
IT Job Security Belief			0.0126*	0.0119	0.0128	0.0121
			(0.00736)	(0.00762)	(0.00785)	(0.00812)
Low Rank Tech-Science				0.00370	-0.000178	0.00149
				(0.0125)	(0.0119)	(0.0122)
Advice No One				0.0150	0.0256	0.0324
				(0.0358)	(0.0357)	(0.0367)
No Parent Higher Educ				-0.0526*	-0.0349	-0.0302
				(0.0289)	(0.0320)	(0.0307)
No IT Relation				-0.0295	-0.0315	-0.0328
				(0.0224)	(0.0232)	(0.0243)
Class Size					-0.00372	-0.00473
					(0.00574)	(0.00459)
Class Female Share					0.00606	-0.0908
					(0.0890)	(0.0966)
Technology					0.107	0.245
					(0.0870)	(0.214)
Grade 3					-0.0189	-0.0155
					(0.0395)	(0.0431)
Median GPA					-0.00231	-0.00163
					(0.00205)	(0.00199)
Day Surveyed					-0.00324	-0.000780
					(0.00365)	(0.00319)
Program Female Share						0.911
						(0.971)
Program Higher Educ						-0.321
						(2.299)
Program Foreign-Born						-0.204
						(0.840)
School Size						-0.0000401
						(0.000195)
School Share Start College						-0.0734
						(0.456)
Constant	0.230***	0.0153	-0.107	-0.0814	0.704	0.466
	(0.0146)	(0.126)	(0.148)	(0.146)	(0.628)	(1.448)
R^2	0.021	0.093	0.126	0.140	0.186	0.201
Observations	304	284	257	257	257	248

Note: The table displays OLS estimates for treatment effect on stated IT probability of female classmates. Cluster-robust standard errors clustered at the class level are displayed in parenthesis. Columns (1)-(5) include school fixed effects. Asterisks indicate significance, where $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.