Essays on Intrinsic Motivation of Students and Workers

ISBN: 978 90 3610 487 6

Cover design: Crasborn Graphic Designers bno, Valkenburg a.d. Geul

This book is no. 697 of the Tinbergen Institute Research Series, established through cooperation between Rozenberg Publishers and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.

Essays on Intrinsic Motivation of Students and Workers

Essays over intrinsieke motivatie van studenten en werknemers

Proefschrift

ter verkrijging van de graad van doctor aan de

Erasmus Universiteit Rotterdam

op gezag van de

rector magnificus

Prof.dr. H.A.P. Pols

en volgens het besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op

vrijdag 27 oktober 2017 om 13:30 uur

door

Max van Lent

geboren te Rotterdam

Erasmus University Rotterdam

Promotiecommissie

Promotor: Prof.dr. A.J. Dur

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Preface

During my Master studies in Economics at Erasmus University I became interested in doing research in Economics. In the end I was so fortunate to find a PhD position under the supervision of Robert Dur, Nick Zubanov, and later Josse Delfgaauw. Now, almost five years later, I have finished my PhD thesis and finally have the opportunity to look back and thank the people who helped me with this achievement.

I would like to thank my current and former colleagues. First I thank my supervisor Robert Dur. Robert, I really appreciate all the time and energy you put into supervising me. You were always willing to advise me on my research and other important matters. As a PhD student, at times it is difficult to appreciate the little bits of progress that one makes. You helped me to keep believing in the process and kept me motivated to pursue a career in academic research.

Next I would like to thank Nick Zubanov for his willingness to take me on as his first PhD student, and for the many great discussion we had about research. Without your trust in my abilities, I would not have been able to start a PhD at Erasmus University. Also I would like to thank Josse Delfgaauw, for his willingness to listen to my many research ideas, for advising me on my research projects, and for becoming my co-promotor after Nick left Erasmus University.

I am also indebted to my co-author Michiel Souverijn. Michiel, I enjoyed all our interactions and I learnt a lot from our discussions about our joint research project, research in general, and many other things.

Writing a PhD thesis is to some extent also teamwork. The environment at the Department of Economics is such that PhD students can always ask the staff for help and feedback. This atmosphere has improved the quality of my research, and led to the fact that I went to work with a smile almost every day. I am thankful to

the entire department for creating such a pleasant work environment.

Besides doing research, one important task of a PhD student is to teach bachelor and master students. I had the pleasure to work as a teaching assistant for Jurjen Kamphorst, Sacha Kapoor, and Dana Sisak. Sacha, Jurjen, and Dana, I enjoyed all the discussions we had about teaching and research.

Throughout the years I had the pleasure to share an office floor with many smart, motivated, and friendly researchers. I enjoyed our interactions, and therefore I would like to thank all of you, including among others: Albert Jan, Alexandra, Asim, Bart, Bram, Bruno, Esmee, Francine, Heiner, Huyen, Jan, Koen, Maria, Matthijs, Oke, Robin, Sait, Sander, Shwany, Tom, Tong, Uyanga, Violetta, and Zara.

Next I would like to thank Jeroen van de Ven, Dinand Webbink, and Aurelien Baillon for taking part in the doctoral committee, and Mirco Tonin and Bart Golsteyn for taking part in the large committee.

I would also like to thank my family. Mom and dad, thank you for supporting my studies, financially, but much more important, also emotionally. Motivating me to complete my studies, letting me believe in my own abilities, and supporting me in the decisions I made has been invaluable to me. Andrea, thank you for being there as my little sister.

Finally, I would like to thank Nathalie and Diego. Nathalie, during my entire PhD you supported me in many different ways. You distracted me from my research when needed, and allowed me to talk to myself or stare to the ceiling for hours when needed. You also helped me placing my job as a researcher in perspective and broadened my horizon in many ways. Without you the process of writing a PhD thesis would not have been nearly this smooth. I hope you know how much I appreciate everything that you do, although I may not say that often enough.

Contents

Chapter 1

Introduction

Economists study human behavior. In order to learn about human behavior, researchers often examine what people are actually doing. However, many of the things that people do, stem from their motivation to do so. Hence, in order to understand behavior, economists have studied peoples' motivations as well. Motivation can be grouped into roughly two categories, intrinsic and extrinsic motivation.

For decades economists have primarily focused on understanding extrinsic motivation. Extrinsic motivation is defined by Ryan and Deci (2000) as "a construct that pertains whenever an activity is done in order to attain some separable outcome" (p. 60). Separable outcomes in this definition include: being paid for one's performance, but also avoiding sanctions, or improving career perspectives. Empirical studies found that many people are motivated by extrinsic incentives (see most notably Lazear 2000).

More recently, economists have become interested in the implications of intrinsic motivation. Ryan and Deci (2000) define intrinsic motivation as "doing of an activity for its inherent satisfactions rather than for some separable consequence" (p. 56). Many papers have studied intrinsic motivation, often in the form of altruism. For instance, the role of intrinsic motivation in self-selection into jobs and performance on the job (see e.g. Besley and Ghatak 2005, Prendergast 2007, and Delfgaauw and Dur 2007), as well as the role of altruistic preferences in the decision to make donations to charitable organizations (see e.g. Andreoni 1989, 1990).

This thesis focuses on intrinsic motivation. In the second chapter I describe the results of a field experiment I ran together with my co-author Michiel Souverijn. In that chapter we examine the effects of motivating students to set goals on their study performance. In particular we study whether encouraging university students to set a grade goal, and further motivating them to set a more ambitious grade goal, has an effect on their study performance and drop out. In our setting, goals are not combined with any extrinsic rewards or punishments. Hence the effects from goal setting on performance stem from students' intrinsic motivation to achieve the goal. The third chapter which is joint work with my advisor Robert Dur and the fourth chapter which is single authored focus on workers' motivations to help others. There are several ways in which people can help others. Two prominent ways are: i) by helping others through exerting effort on the job and ii) by making contributions to a charitable organization. We study the relation between helping others by exerting on-the-job effort and helping others outside the workplace in the form of donating money and time (i.e. volunteering).

The remainder of this introduction is organized as follows. In the next two sections I discuss the concept of goal setting, and the literature on helping others on the job and outside the workplace. In the final section, I give an overview of the chapters.

1.1 Goal setting

Setting goals is a frequently observed phenomenon. For instance, many people set themselves goals. Famous examples of self-set goals are: a minimum number of kilos that someone who is on a diet wants to lose, or a maximum number of cigarettes one wants to smoke, or alcoholic beverages that one wants to consume. Besides people setting goals for themselves, we also observe goals being set by other people. For example, employers set goals for their employees during appraisal interviews, often in the form of targets. However with many of these goals there is no extrinsic reward or punishment for reaching or not reaching the goal. Hence, in order for goals to be successful, it must be the case that people are intrinsically motivated to reach their goals and therefore are willing to set goals in the first place.

There is an extensive literature on goal setting, starting with the seminal paper by psychologists Locke and Latham in 1979. Locke and Latham were the first to analyze the effects of goal setting using a series of field experiments. They distinguish between three types of goals: self-set goals, goals set in cooperation, and goals set by other people. They found that goal setting can increase performance in various tasks for all three types of goals.

Furthermore there is a large literature in psychology analyzing what the key elements are that make goals effective. Psychologists have found that goals should be formulated SMART, i.e. specific, measurable, attainable, relevant, and time bound (see Doran 1981) and that goals should be challenging, but still attainable (Locke et al. 1981).

More recently economists and management scientists have studied goal setting. Economic theory papers have shown that goals can function as reference points in order to increase performance for people who are loss averse or present biased, or that meeting goals can lead to a sense of self-achievement that makes pursuing goals worthwhile (see e.g. Suvorov and Van de Ven 2008, Hsiaw 2013, Koch and Nafziger 2011, Gomez-Minambres 2012, and Koch et al. 2014).

An increasing body of empirical literature in economics and management science tests the effects of goal setting. Some papers test the effects of goals on performance when goals are combined with monetary incentives. The monetary incentive is often a bonus that is received when the goal is reached. Other papers study the effects of goals without monetary incentives. The general finding in this literature is that goals can help to increase performance and especially so if goals are combined with monetary incentives. The fact that setting goals can increase performance (as compared to not setting goals), even without combining the goal with monetary incentives, is an indication that people intrinsically value reaching goals, and are therefore willing to set goals in the first place. The finding that goal setting increases performance holds when people set themselves goals as well as when the goals are set by other people, for example by a manager or a peer.

In chapter two we study whether goal setting can increase students' performance in an academic course. In addition we test whether motivating students to increase the difficulty of the goal can increase performance further.

1.2 Intrinsic motivation to help others

In chapter three and four we analyze the relationship between workers' altruistic preferences, their occupational choice, and their opportunities to help other people on the job, and outside the workplace. In this section we first report some evidence showing that helping people on the job and outside the workplace are frequently observed behaviors, and that the extent to which one has opportunities to help others at work differs between job types. Next I provide evidence that intrinsic motivation, often studied in the form of altruism, is an important driver of helping behavior on the job as well as outside the workplace.

Evidence from the International Social Survey indicates that many people find it important to have a job that allows them to help others, and many people also claim to have such a job. As typical examples of such jobs, one naturally thinks of nurses who help their patients to recover from an illness, or teachers that help children to learn how to read and write. However one can also think of helping others in a broader sense. For example, environmentalists who work for an organization that helps save the planet from global warming or prevent a particular animal species from extinction, or bureaucrats who make policies that improve the lifes of the poor. In contrast to these "public service jobs" there are job types that are generally believed to offer less opportunities to help others. Well known examples are investment bankers or bookkeepers at for profit organizations.

Helping others outside the workplace by making charitable donations is also frequently observed. Using data from the European Value Survey, Bauer et al. (2013) report that in European countries around 18% of the people perform voluntary work, and 27% donates money to non-profit organizations, although these numbers widely vary by country. Further, List and Price (2012) found that in rich countries typically a majority of people make some donations to charitable organizations.

There is a rich literature that tries to explain peoples' motives for charitable giving. One obvious reason to make a donation is because the donor cares about the recipients' well-being. However, there are many other alternative reasons. One may have strategic reasons to help others through taking a job as a volunteer, for instance in order to enhance one's career. But also because of image concerns or social pressure (see e.g. DellaVigna et al. 2012).

There is plenty of evidence showing that charitable giving is (at least partly) driven by peoples' altruistic preferences. For instance, using a laboratory experiment where things like image concerns or reputational concerns are absent, Andreoni and Miller (2002) found that a majority of people are willing to spend some money (anonymously) in order to help others.

1.3 Overview of the chapters

In chapter two we study the effects of motivating students to set a grade goal on study performance. We are interested to learn whether goal setting can increase student performance, and whether challenging students to be more ambitious by motivating them to set more difficult goals, can increase study performance further. In order to test our predictions we conducted a field experiment.

Our field experiment involved almost 1100 first-year economics students at Erasmus University Rotterdam. Each of these first-year students regularly has individual meetings with a mentor. Mentors are senior students who are randomly assigned to students. Mentors help their students to get used to studying at a university, teach them study skills, help them with their study motivation, monitor their performance, and give suggestions in order to increase their study performance.

Our experiment involves the second of three individual meetings between students and their mentor. In one treatment *(goal treatment)* we instructed mentors to ask their students whether they had a specific grade goal in mind for the main course they participated in at that moment, and if not, whether they wanted to set a grade goal. The second treatment, the *raise treatment* builds upon the *goal treatment*. In the *raise treatment* mentors received identical instructions as in the *goal treatment*, but were in addition instructed to encourage students to raise their goal if deemed appropriate. We subsequently measured study performance using the grades that the students obtained.

We predict that motivating students to set goals increases their performance. Having their mentor propose a more ambitious goal can, but need not, increase performance further. To be precise, a proposal to raise the goal increases performance when there is a cost of rejecting the proposal to raise (for example in the form of a psychological cost) and if the proposed raise is not too large. However, increasing the goal too much leads students to give up on their goal, in which case performance will be similar to the performance of a student who did not set a goal. Finally, performance is expected to be the same as without the proposal to raise if rejecting the proposed new goal is not so costly, and the alternative is the goal the student initially set.

We find that students whose mentor was instructed to motivate his students to set a grade goal perform 0.16 better on a 10-point scale (which is 9.3% of a standard deviation) than students in the control group. Sanders and Chonaire (2015) find by studying over 100 randomized controlled trials in education that the median effect size of an intervention is 0.1 of a standard deviation. Considering that our intervention is (almost) costless, the effect size we find is economically significant. We find that the effect in our study is mainly driven by students in the goal treatment dropping out less often than students in the control group. Students whose mentor was instructed to also motivate students to raise their goal do not perform significantly different from the control group. Finally, being asked to raise the goal in the raise treatment leads to a significant drop in performance as compared to similar students in the goal treatment.

There are multiple potential explanations for why challenging students to set more ambitious goals has a negative effect on performance. First, the raise proposed by the mentor may be too large, and hence students give up trying to reach their goal, leading to a performance similar to the control group. Alternatively, the proposal to raise the goal may lead to a decrease in motivation to reach the goal, and therefore students' performance decreased. This is in line with the psychology literature, that finds that often people are more motivated to reach self-set goals, than goals that are set by others or are set in cooperation.

In chapter three we examine the role of intrinsic motivation (in the form of altruistic preferences) in occupational choice, on-the-job effort provision, and charitable donations. We start by developing a theoretical model in which workers differ in their altruistic preferences. Altruistic workers receive utility from helping others, and are able to help others in two distinct ways i) by taking a public service job and exerting effort on the job and ii) by making a donation to a charitable organization. In our model workers make three decisions. First they choose whether to take a public service job or a regular job. Next they choose how much effort to exert at work and how much of their income to donate to charity.

From our theoretical model we derive the following testable predictions. First, the probability that a worker has a public service job (weakly) increases in the worker's altruism. Having a public service job provides the worker with opportunities to contribute to the well-being of others. This job feature is appreciated by altruistic workers, and hence these are the type of workers who self-select into public service jobs. Second, for a given job type, charitable donations (weakly) increase in workers' altruism. Third, given workers' altruism and income, workers who have a public service job donate less to charity than workers who have a regular job. The intuition behind this final result is that public service workers already contribute to the well-being of others by exerting effort on-the-job and, hence, by a substitution argument, they will donate less.

We empirically examine our predictions using data from the German Socio-Economic Panel Study (SOEP). The SOEP is a representative longitudinal study covering 30,000 persons in 11,000 households. It contains questions about individuals' education, earnings, employment, personality characteristics, and behavior. The key variables that we use for our analysis are self-reported altruism, money donations to charity, and job type or sector of employment.

Using data from the German SOEP we find some evidence for our predictions. In line with our theory, we find that workers who are more altruistic are more likely to take a public service job and, for a given job type, donate more money to charity. Furthermore, we find that workers in a regular job make significantly higher donations to charity than equally altruistic workers in a public service job. However, this difference moves close to zero and becomes statistically insignificant when we control for income.

In the fourth chapter we explore the relationship between workers' opportunities to help others on the job and volunteering behavior outside the workplace further. Based on the theoretical framework developed in Dur and van Lent (2016), i.e. based on the third chapter, we predict that helping people on the job and volunteering time outside the workplace are substitutes. We test this prediction by exploiting two sources of variation in workers' opportunities to help others at work over time, and measure the effect of this change on volunteering behavior outside work. We test our prediction using rich panel data from the Dutch Longitudinal Internet Studies for the Social sciences (LISS) Panel.

The LISS Panel consists of approximately 8,000 individuals and covers the years 2008 to 2016. The questionnaire contains detailed questions on leasure, work, schooling, personality, and politics, which allow us to test our prediction. The key question we use as a proxy for charitable behavior is "Considered all together, how much time do you spend on voluntary work per week, on average".

First, as a change in the ability to help others on-the-job, we study the effect of changes in sector of employment on volunteering. We expect, following our theory, that workers who switch from a private sector job to a public sector job decrease their time spent volunteering, while we expect the opposite for workers who make a job switch in the other direction. Second, we rely on a plausibly exogenous change in workers' ability to help others on the job by studying changes in the match of mission preferences of government workers with their employer. Workers are assumed to have a mission match when they voted for one of the political parties that is in office. The preferences are classified as a mismatch if the worker has voted for a political party that is not in office. We expect that government workers who have a mission match with their employer feel that they have more opportunities to help others at work than government workers who voted for a political party that is not in office. We have data covering three government coalition periods, and hence observe two changes in the composition of the parties that are in office.

We find that workers who switch from sector of employment, do not change their time spent on voluntary work significantly, although the coefficients always have the expected sign. That is, workers who switch from a private sector job to a public sector job (insignificantly) decrease their time spent volunteering. Further, government workers who voted for one of the political parties that is in office, decrease their volunteering by 15 minutes per week on average as compared to when they voted for a party that was not in office, which is in line with our theory.

Chapter 2

Goal Setting and Raising the Bar: A Field Experiment

Joint with Michiel Souverijn

2.1 Introduction

People often set goals. For example dieters commonly set a target weight, runners aim for a certain time, and managers set goals for employees in the form of targets. Using a series of field experiments, the psychologists Locke and Latham (1979) were the first to provide evidence that goals help to increase performance.[1] More recently, goal setting has also been studied by management scientists and economists. Economic theory papers have shown how goals can be used as reference points in order to increase performance for loss averse agents or hyperbolic discounters (see e.g. Suvorov and Van de Ven 2008, Hsiaw 2013, Koch and Nafziger 2011, and Koch et al. 2014), and that meeting goals can lead to a sense of self-achievement that makes pursuing goals worthwhile (Gomez-Minambres 2012). A rapidly growing empirical literature tests the effects of goal setting on performance in the laboratory and in the field.

[1] Locke and Latham found that goals set by an outsider (a peer or a manager), goals set in cooperation, and self-set goals can all lead to a better performance as compared to not setting goals.

This paper examines whether goal setting can help to increase student performance and to decrease drop out in an academic course. Furthermore, we are interested to learn whether challenging students to be more ambitious by increasing the goal's difficulty can increase performance further. This is relevant given the widely held belief that many students should be more ambitious, and the recently increased focus on student performance in higher education.

We start by developing a simple theory which explains how and when setting a goal and increasing a goal's difficulty can increase performance. We derive the following predictions. In line with the literature, people are willing to set a goal since setting a goal increases both performance and utility. Having an outsider propose a more ambitious goal can, but need not, increase performance further. To be precise, a proposal to raise the goal increases performance when there is a cost of rejecting the proposal to raise and if the raise is not too large.[2] Performance will be the same as without the proposal to raise if rejecting the raise is not so costly, and the alternative is the goal initially set. Finally, increasing the goal too much might lead students to give up on their goal, in which case performance will be similar to that of a student who did not set a goal.

We test our predictions by means of a field experiment among 1092 first-year economics students. Each of these first-year students regularly has individual meetings with a mentor (who is a senior student). Mentors help students to get used to studying at a university, teach them study skills, help them with their (study) motivation, monitor their performance, and give suggestions in order to increase their study performance. We ran our experiment during the second of three individual meetings between students and their mentor. In one treatment *(goal treatment)* we instructed mentors to ask their students whether they had a specific grade goal in mind for the main course they participated in at that moment, and if not, whether they wanted to set a grade goal. In another treatment *(raise treatment)* mentors received identical instructions as in the goal treatment, and were in addition instructed to encourage students to raise their goal if deemed appropriate. We subsequently measured performance using the grades the student obtained for the course.

[2] The cost of rejecting the proposal to raise the goal can for example be a psychological cost or a loss in reputation towards the mentor.

We find that students whose mentor was instructed to motivate students to set a goal perform 0.16 better on a 10-point scale (which is 9.3% of a standard deviation) than students in the control group. This effect is driven by students in the goal treatment dropping out less often than students in the control group. Students whose mentor was instructed to also ask students to raise their goal do not perform significantly different from the control group. Finally, being asked to raise the goal in the raise treatment leads to a significant drop in performance as compared to similar students in the goal treatment.

Setting goals can also have adverse effects such as a narrow focus and ignorance of non-goal tasks or even unethical behavior (see Ordonez et al. 2009). In our setting a concern is that students increase effort and performance on the course for which they set a goal at the expense of the other course they take at the same time. We estimate the effect of the treatment on performance in the other course, and do not find such a negative effect. This implies that motivating students to set a goal is actually good for study performance overall.

Next, we look at heterogeneous treatment effects. We test whether there are heterogeneous effects of the treatments dependent on the student's prior study results, the mentor's experience, mentor's gender, and a match between mentor's and student's gender. We find that motivating students to set goals increases performance mainly for students who were initially performing poorly. We do not find a significant difference in treatment effect for students with more experienced mentors, or for students who have the same gender as their mentor.

There is a rich literature in psychology studying goal setting and its effects on performance (see Locke 1996, Locke and Latham 2002, and Locke and Latham 2006 for literature reviews). Research in psychology groups goals in roughly three categories: goals set by an outsider, cooperatively set goals, and self-set goals. Our *goal treatment* and *raise treatment* come closest to self-set goals and cooperatively set goals, respectively. Further, the literature shows that other factors such as goal commitment, goal specificity, and how challenging the goal is are important predictors for the success of goals (see for example Hollenbeck et al. 1989, Locke 1996, and Seijts et al. 2004). Our finding that the attempt to raise goals decreases students' performance as compared to goal setting by the student may be explained by a change in commitment to the goal, leading to a decrease in (study) motivation and hence performance.

Our paper is related to a rapidly increasing number of experiments in economics that study the effects of different types of goal setting on performance in various contexts. Experiments range from self-set goals to goals set by others. In some papers goals are combined with monetary incentives (see e.g. Goerg and Kube 2012, Dalton et al. 2015, and Corgnet et al. 2015, 2016) and in other papers goals are set without monetary incentives (see e.g. Goerg and Kube 2012, Sackett et al. 2014, and Clark et al. 2016). These studies typically find that when ambitious but attainable goals are set, goals increase performance, and more so when they are combined with monetary incentives. Our main contribution to this literature is that we investigate the effects of raising goals, by increasing its difficulty in a cooperative manner.

Also closely related to our research is the literature on (non-monetary) incentives for students in education. This literature considers a number of ways besides setting goals, in which students performance can be increased.[3] Lavecchia et al. (2015) review studies of interventions in education designed to improve students' performance. The interventions target a wide range of behaviors varying from a too little focus on the future, overreliance on routines, student self-confidence, and the information about and number of choices in education. Further, Sanders and Chonaire (2015) show that in education usually (very) small effect sizes are found. The effect we find from goal setting is around the median effect size found in the sample of Sanders and Chonaire.[4]

Goal setting by students has received a lot of attention from psychologists, see e.g. Ames and Archer (1988) and Schunk (1990) and more recently from management scientists. Many of these papers have tested whether goal setting can increase students' performance (see also Linnenbrink 2005, Morisano et al. 2010, Bettinger and Baker 2013, Schippers et al. 2015, and Travers et al. 2015). Students not

[3] For example changes in the class size (see Angrist and Lavy 1999 and Bandiera et al. 2010), providing feedback to students (see Bandiera et al. 2015), and several financial and non-financial incentives (see Levitt et al. 2016).

[4] While the median effect size in Sanders and Chonaire (2015) is 10% of a standard deviation, our (almost) costless intervention has an effect of 9.3% of a standard deviation.

subjected to goal setting are typically subjected to other activities in these studies. As a consequence these papers are unable to estimate the causal effect of motivating students to set goals. In our experiment the only difference between the control and treatment groups is that in the treatment groups mentors encourage students to set a goal. Hence we are able to estimate the causal effect of motivating students to set goals on study performance. In addition we are the first to consider challenging the goals that students set by asking them to increase their goal's difficulty.

Besides the contribution of our paper to the literature on goal setting, incentives and performance in education, our paper can also be useful to management practitioners. There is a large and growing literature on designing the optimal contract (see Gibbons 2005 for a review), and recent work on the use of goals as an incentive device (see e.g. Gomez-Minambres 2012). Our result that an encouragement to increase a (self-set) goal in order to motivate students decreases performance is of particular interest. In a workplace where a manager evaluates his workers, it can be common practice to set goals or targets. Our findings are a first indication that challenging workers to increase their goal's difficulty might be detrimental for performance.

This paper is organized as follows. In the next section we explain the experimental context and describe the data. In section 3 we present a simple theoretical framework and derive our hypotheses. In section 4 we explain the empirical strategy. Section 5 presents the descriptive statistics, section 6 the results followed by a discussion and conclusion in the final section.

2.2 Experimental set-up and data description

2.2.1 Experimental context

The experiment involved 1092 first-year students enrolled in several undergraduate programmes at Erasmus School of Economics in Rotterdam, The Netherlands during the 2014-2015 academic year. The year is divided into five blocks of eight weeks. In each block students take 12 study credits (ECTS) worth of courses. All courses that students take at this point are obligatory, hence all students within a study programme take the same courses. Our experimental treatments take place during the second block when students have their second individual meeting with their mentor.

Each first-year student has a mentor. Mentors are senior students and are randomly assigned to students enrolled in the same programme at the start of the academic year. All mentors are employed by the university and are paid a flat wage. Our study involves all 84 mentors, and each mentor has 10 to 15 students. Mentors regularly meet with their students, both in groups and individually. The mentor-student meetings are intended to teach students study skills, monitor their motivation, and more generally to provide a point of contact within the university. Motivation and individual prospects are the primary subjects of the three individual mentor-student meetings held over the course of the academic year. The first individual mentor-student meeting takes place arround the start of the academic year in September, while the second and third take place in November and January, after the results of respectively the first and the second block of courses have been released. Our treatments are administered during the second individual mentor-student meeting.

While the first meeting at the start of the academic year primarily serves to discuss the student's motivation and to detect possible issues, the second and third meeting serve to evaluate results and prospects of the students. Due to university rules and national legislation, students with a weak performance record may be better off dropping out before February, which is in the third block of courses. Dropping out on time results in minimal grant loss and additionally allows students to re-enroll in the same programme the following academic year, which students that otherwise fail to meet first year requirements are not allowed to do. Thus, the second meeting is a natural moment to look forward towards the rest of the academic year and to discuss what results are necessary in order to make it sensible for the student to continue their current study programme. The last individual meeting after the release of the results for the second block serves mostly to determine whether it is better for the student to drop out given her motivation and study results.

Students take two courses in the second block, an introductory course in microeconomics worth 8 ECTS and a programme specific 4 ECTS course.[5] Our treatment is focused on the microeconomics course. The course is taught in Dutch (824 enrolled students) and English (268 enrolled students). The Dutch and English version are identical in all respects except for the lecturers and language spoken. The course follows a standard setup of three non-compulsory plenary lectures each week complemented by two compulsory tutorials taught by teaching assistants. The tutorials serve to review the course material, practice and discuss exercises, and in general to provide students an accessible way to obtain further explanation and clarification of the material. Tutorials are taught in 42 tutorial groups. One tutorial group consists of the students of two mentor groups. Examination of the course follows a standard format with two midterms counting 15% each and a written exam for the remaining 70%. For both midterms and the final exam students receive a grade on a 10 point scale, ranging from 1 to 10 with 10 being the best grade. In addition students could obtain a bonus, which was equal to at most half a point of the final grade, by participating in weekly online tests.

2.2.2 Experimental design

Our experiment revolves around the second individual mentor-student meeting. We instructed a random subset of 54 of the 84 mentors to motivate their students to set a course specific grade goal during this mentor-student meeting. As discussed before, this second meeting is an excellent opportunity for such a discussion as its purpose is to reflect on past performance and consider what results for the current courses are necessary. This means that discussion of the progress of the current courses is natural, and a focus on microeconomics is expected since it is the most important course in the second block due to its weight in ECTS. Our treatment builds on this discussion.

During meetings with all mentors in the period between 22 and 31 October 2014, we informed the mentors that some of them would be expected to take a somewhat different approach to the second individual meeting. Selected mentors were sent

[5] Students enrolled in the Economics and Business Economics, Fiscal Economics, and Law and Economics programmes take besides microeonomics an ICT course, while Econometrics students take a Calculus course.

instructions by e-mail about how to complement the discussion regarding the current courses one and a half week before the meetings. The instructions were accompanied by a simple flow diagram (see Appendix 2.A.1 and 2.A.2). All 54 selected mentors confirmed that they understood the instructions.

Randomly selected mentors were instructed to ask students whether they have a specific goal in terms of a grade in mind for the main course, microeconomics, and if so to elicit that grade goal. If the student did not have a grade goal in mind, the student was asked whether she wants to set one on the spot, again eliciting the goal set. Students were free not to set a goal. Mentors were asked to write down their evaluation of the goal of the student, evaluating the student's goal as either "too easy", "doable" or "too hard". The description of the treatment so far describes the *goal treatment*. Thus in this treatment, mentors are asked to induce their students to set themselves a specific grade goal for the main course in the second block.

A second group of mentors were randomly selected to perform the *raise treatment*. In the raise treatment mentors implement the goal treatment but are additionaly requested to attempt to raise the goal (if any) set by the student when deemed appropriate. If the mentor described the goal as "doable" or "too easy" the mentor was instructed to challenge the student by asking whether the student shouldn't be more ambitious and aim for a higher grade, specifically the student's self-set goal + 1 (e.g. if the student's goal was to get a 6 the mentor suggested aiming for a 7). The raise treatment serves to determine whether raising self-set goals can (further) improve study performance. Figure 2.1 illustrates the similarities and differences between the goal and raise treatment using a flowchart.

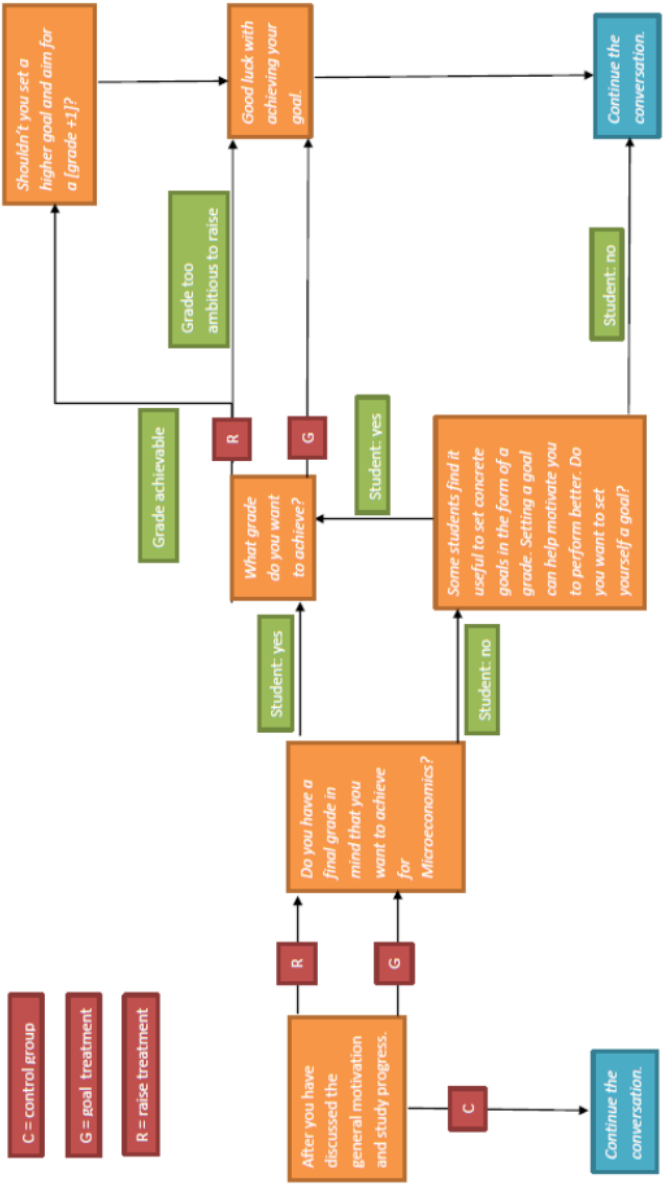

Figure 2.1: Description treatments

We chose to elicit a grade goal instead of other course related goals for multiple reasons. First, the final grade is (one of) the most important motivations to study for many students, hence students might find it more useful to set grade goals compared to other goals. Second, choosing an output goal (the final grade) instead of an input goal (e.g. study hours) leads to lower measurement error because we cannot perfectly measure study hours. Finally, a grade goal is specific and measurable, which are important factors that influence the success of a goal (Locke and Latham 2002).

As our measure of performance we do not take the final microeconomics grade. Instead we use a normalized version of the microeconomics grade without the first midterm result as our treatment is administered in the week of the first midterm. Hence, not all students have received treatment prior to the first midterm, while those that do have very limited time to respond.

Mentors were asked to record the outcome of the meetings on a form. We specifically asked mentors to note whether or not they brought up goals in order to identify treated subjects. Mentors record whether students set a goal, what the goal is, and their estimate of the difficulty of the goal. In the raise treatment mentors further record whether they asked students to raise their goal and whether or not the student accepted this higher goal. The mentor's estimate of the difficulty of the initial goal allows us to compare students in the raise treatment whose goal was challenged with similar students in the goal treatment whose goal was not challenged but would have been challenged if they were in the raise treatment.

Besides the forms filled in by the mentors selected to implement the treatments we obtain information on all the students from administrative data from the microeconomics course and the central administrative office. This gives us information on the student's performance in other courses, attendance of microeconomics tutorial sessions, gender, age, study programme, and mentor.[6] From the administration office we further obtained the mentor's gender and whether the mentor had experience in mentoring in previous years.

Only the mentors and lecturers were aware an experiment was being implemented, although mentors were not explicitly told so. Our introduction to all men-

[6]From students in Dutch study programmes who attended a Dutch high school, we also have highschool grades.

tors in a general mentor instruction meeting necessitated that we informed all mentors that some of them would be asked to implement a small change in the upcoming individual mentor-student meetings. However, those not sent specific instructions were not aware of the exact change implemented. We specifically instructed the mentors who were selected for a treatment not to talk to anyone regarding our request. Selected mentors may deduce the purpose of the research but were not informed beyond their own instructions provided in Appendix 2.A.1 and 2.A.2. Finally, both authors of this paper were involved in the microeconomics course as teaching assistants. Because of this we took precautionary measures to prevent ourselves from learning the treatment assignment.[7]

2.2.3 Assignment procedure

The assignment of students to both treatments and the control group is randomized at the mentor level. Assignment at the mentor level was chosen in order to increase compliance and prevent contamination. With assignment at the student level, a given mentor would be charged with treating her students differently, in a random order over the talks (students select a timeslot), likely leading to mistakes. In addition to accidental non-compliance, student level assignment might also result in more selective non-compliance by mentors selecting the treatment for their student(s) that they think is most appropriate.

The assignment of mentors to treatment was randomized in a stratified manner as follows. First, given that the tutorial group has a large impact on student performance as it is the main instruction method for many students, we ensure that a tutorial group is always of mixed composition in terms of treatments and control. This serves to create similar conditions for students in all treatments, but comes with the risk of contamination because students from treatment and control are in the same tutorial group. Randomization takes place within the various study pro-

[7] The randomization was programmed by one of the authors who received the list of mentors linked to tutorial groups. A researcher from the department was asked to perform the randomization and send only the list of mentor contacts and treatment assignment to the other author. Since the author receiving this information was unaware which mentors belong to which group it was impossible for either of the authors to relate mentors to (half of) a tutorial group.

grammes offered by the school as the effect of treatment can differ by programme due to the selection of students in a programme and the difficulty of the other course offered. Finally, several teaching assistants teach multiple tutorial groups. We therefore enforce that classes taught by the same teaching assistant have an (even) mix of control and treatment groups.[8] In doing so we ensure that teaching assistants who teach classes in two different study programmes have a mix of control and treatment groups.

Randomization takes place by taking one random draw for each teaching assistant. Draws were compared between teaching assistants teaching the same number of mentor groups. The first mentor group is assigned to the control group if the draw belongs to the highest third of the draws. The middle and lowest third of the draws were assigned to the goal and raise treatment respectively. The assignment of the other groups taught by a teaching assistant then follows from the assignment of the first group by cycling through the list of possible assignments in order. The procedure is illustrated in Figure 2. We prioritized first the control and then the goal treatment. The final result of this randomization is that 30 mentors are in the control group, 28 in the goal treatment and 26 are in the raise treatment. This corresponds to 389 students in control, 367 in the goal treatment and 336 students in the raise treatment.

[8]For example, if a teaching assistant teaches two groups he teaches four mentor groups of which at least one group is assigned to each treatment and at least one group is a control group.

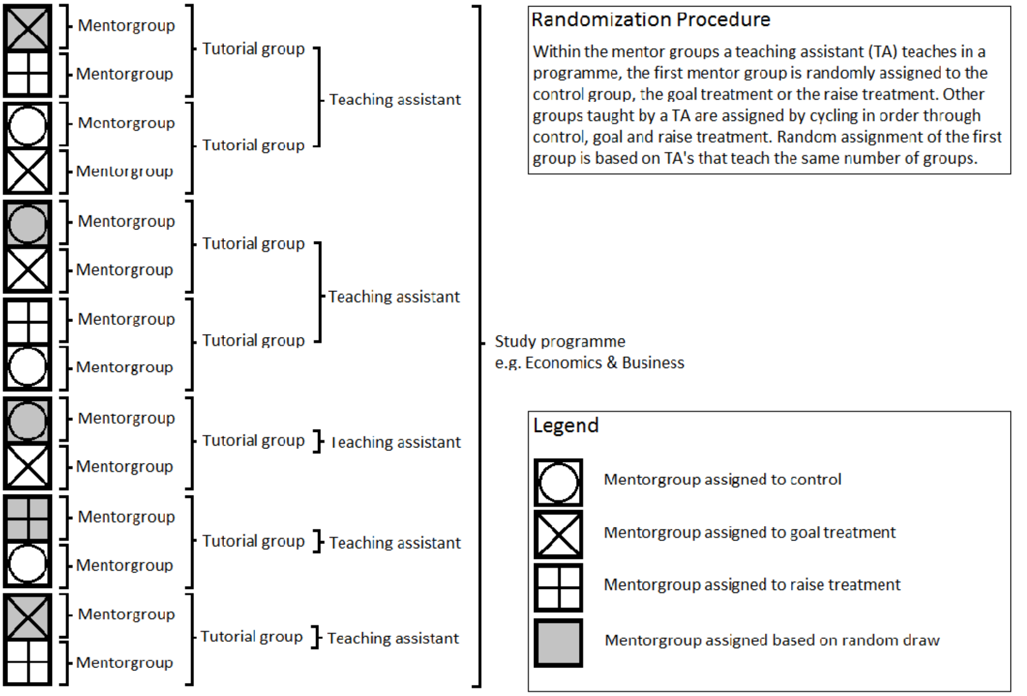

Figure 2.2: Randomization procedure

2.3 Theoretical framework and predictions

We are interested in the effects of goal setting and attempts to raise goals on students' study performance. To fix ideas, let us consider the following stylized framework.

Consider a student who values obtaining a high grade but dislikes to study. Let her utility be given by:

$$U = e - \frac{1}{2\theta}e^2$$

where e is her study effort which results in grade e. The student's ability is given by θ such that more able students have a lower cost of study effort. In this scenario the student optimally sets $e = \theta$ yielding utility $\frac{1}{2}\theta$.

Now let the student set a goal to motivate herself. Assume that the student values meeting her goal and that her utility from reaching this goal increases in goal difficulty. Meeting a goal may be intrinsically rewarding (see e.g. Gomez-Minambres 2012) or there may be some external motivation, for instance reputational concerns towards someone who is aware of the goal. Specifically, let the student's utility function in case she sets a goal g be given by:

$$U = e + I\left(e \geq g\right) g - \frac{1}{2\theta}e^2,$$

where $I\left(e \geq g\right)$ is an indicator function that equals 1 if the goal is met (i.e. if $e \geq g$) and 0 otherwise.[9] Since the student already exerts $e = \theta$ without a goal, setting a non-challenging goal $g \leq \theta$ does not affect her study performance. In that case she would be best off setting a goal $g^{NC} = \theta$, which yields her utility $U^{NC} = \frac{3}{2}\theta$.

Next consider the student setting a goal that challenges her to exert more effort, $g > \theta$. The student optimally meets such a goal by exerting $e = g$.[10] Given this, the student sets her goal to maximize her utility resulting in the optimal challenging goal $g^C = 2\theta$. The student obtains utility $U^C = 2\theta$ from setting herself the challenging goal, exceeding the utility $U^{NC} = \frac{3}{2}\theta$ derived from setting the non-challenging goal. Thus the student is best off setting a challenging goal for herself, boosting her study performance. This demonstrates our first prediction:

Prediction 1: Setting goals increases student performance.

Now consider what happens when the goal is raised above g^C by an outsider. Given that the student is better off under her optimal goal g^C as compared to either not setting a goal or setting an unchallenging goal she will still be better off under goals that deviate from g^C slightly as compared to not setting a goal ($U = \frac{1}{2}\theta$) or setting a non-challenging goal ($U^{NC} = \frac{3}{2}\theta$). Thus changing the goal from g^C to a higher goal can improve performance.[11] This leads us to our second prediction:

[9] Most economic theory papers on goal setting model the agent's utility function assuming loss aversion. Agents get utility if they reach their goal and a disutility from not reaching this goal. Since in our simplified model effort maps directly into a grade, i.e. without any noise or uncertainty, agents never end up in the loss domain. Hence, these richer models would yield the same predictions as our simplified model. In case there is noise or uncertainty and agents are loss averse, the results marginally change. Some agents may no longer be willing to set goals, goals become less ambitious, but there is still some room to raise goals.

[10] Note that the student will never choose $e > g$, because then she would have a strictly higher utility if she would set a goal g', such that $e = g' > g$.

[11] Note that although performance (i.e. e) increases when a goal higher than g^C is achieved, utility will be lower compared to the student setting and reaching g^C.

Prediction 2: Raising goals can increase student performance.

A raised goal can lead to higher performance if the student accepts the proposal to raise the goal. A student will accept this proposal to raise if there is a cost of rejecting the goal that is proposed by the outsider, and if the proposed raise is not too high.[12] If the proposed raise is too high, the student will not accept the proposed goal. This leads to a similar performance as when the student was not asked to raise the goal (this happens when the student's outside option is the initial goal), or this leads to performance that is similar to setting non-challening or even no goals (this happens when the student's outside option is no goal or a non-challenging goal). Alternatively, since the goal is raised by an outsider, the student may not derive as much utility from meeting the goal as from self set goals.[13] This leads the student to perform worse because she is less motivated to reach the goal.

2.4 Empirical strategy

We estimate the effects of motivating students to set goals and attempts to raise students' self-set goals in two ways. First we estimate an intention-to-treat effect, comparing the results of students of mentors assigned to treatments to the results of students of mentors assigned to the control group. Random assignment of mentors to treatments coupled with random assignment of students to mentors should result in ex ante similarity between students. We thus attribute differences between students in the control and treatments after our intervention to the intervention. We estimate the intention-to-treat (ITT) effect by:

$$P_i = \beta_0 + \beta_1 G_i + \beta_2 R_i + \beta_3 X_i + \varepsilon_i$$

where P_i is student i's study performance, X_i a vector of control variables and ε_i the error term. G_i and R_i are treatment dummies indicating whether a student's mentor was assigned to the goal or raise treatment respectively. To be more precise

[12] Costs of rejecting the proposal to raise the goal can for example be psychological or reputational costs.

[13] See e.g. Hollenbeck et al. (1989) for evidence on commitment to self-set goals versus assigned goals.

on student performance, P_i is not the final grade of a student. The final grade for the course is composed of two midterm exams (both with weight 15%) and a final exam (with weight 70%). Since the mentor-student meeting is in the same week as the first midterm, students hardly change their study behavior for the first midterm, and so we expect the treatment to only affect the later exams of the course. Hence we take as student performance a normalized combination of the second midterm and the final exam. Our performance measure is hence calculated as (0.15*midterm2+0.7*final)/0.85.[14] The coefficients β_1 and β_2 are the intention-to-treat estimates of the effect of having a mentor who was assigned to treatment. The intention-to-treat effect is an imperfect measure of the effect of a student setting a goal or of attempts to raise that goal as there is bound to be some non-compliance. Not all students who are intended to get treated will get treated, for instance due to more pressing concerns in the meeting such as personal circumstances of the student. Likewise, although mentors not assigned to treatment are unaware of the nature of the treatment, some students of mentors that were assigned to the control group might self-treat by setting a goal and discuss this with the mentor. Thus while this estimate does not isolate the effect of setting and attempting to raise goals per se, it does provide an unbiased estimate of the intention to treat. Further, as the intention-to-treat effect relies on assigned, not actual, treatment non-compliance is likely to result in an underestimation of the actual effect.

Given that we ask treated mentors to report which students set themselves a goal and which students they asked to raise their goal, it may be tempting to directly compare students setting goals to those that do not. However, this would yield a misleading estimate of the effect of treatment if selection into or out of treatment is not random as it would compare individuals that are not ex ante identical. Instead we estimate the effect of treatment on those students whose treatment status is changed as a result of the experiment, also known as the local average treatment effect (LATE). In a first stage we regress actual treatment status on student characteristics and treatment assignment. Here treatment assignment serves as an

[14] The weights assigned to the second midterm and the final exam in our performance measure, 0.15 and 0.70 respectively, are the same as the weights used in the compostion of the final grade for students.

instrument for actual treatment. Predicted treatment status then takes into account the observable characteristics of those in treatment and can be used in a second stage regression to explain study performance.

Thus the effect of setting a goal on those induced to set a goal may be estimated using as a first stage:

$$T_i = \varphi_0 + \varphi_1 G_i + \varphi_2 R_i + \varphi_3 X_i + \eta_i$$

where T_i indicates whether student i actually sets a goal, η_i is the error term and G_i and R_i are the dummy variables indicating whether the student's mentor was assigned to the goal or raise treatment respectively. This first stage is then followed by estimating:

$$P_i = \beta_0 + \beta_1 \widehat{T_i} + \beta_2 X_i + \varepsilon_i$$

Here again P_i is student i 's study performance, X_i a vector of control variables and ε_i the error term. The effect of interest is the coefficient β_1 of predicted treatment status $\widehat{T_i}$ following from the first stage regression.

There are two main reasons to include covariates in our regressions. First, since we assign treatment randomly conditional on the student's programme and teaching assistant we include dummies for the tutorial groups which subsume both these categories. Second, we include statistics on past study performance. Past study performance is highly predictive of present study performance and hence including measures of past performance reduces noise in the data, allowing for more precise estimates. We additionally include the student's gender, the mentor's gender and a dummy for the mentor's experience since, as will be discussed later, actual treatment depends on these variables to some extent. Since treatment is assigned at the mentor level and students' performance can be affected by something that is mentor specific (e.g. mentors' social skills), there is the possibility of confusing treatment effects with unobservable mentor level effects. To deal with this the best we can, we cluster the errors of the regressions at the mentor level.

We assign students that do not complete the course a failing grade for those grade components that they do not complete. By giving the highest and lowest possible failing grade we derive lower and upper bounds of the total effect of treatment.[15] The highest failing grade is a 4.4 and the lowest a 1.0 at a 1 to 10 scale. Students who score a 4.5 or higher can still pass the course by scoring well in other courses. In our results we will focus on the lowest grade as the lowest possible failing grade is the grade that is actually given to students who do not pass the course. Further, for context consider that those who do not take the final exam but do take the second midterm score a 1.5 on average compared to the overall average of 5.7. The total effect of our treatments that we measure in this manner is composed of an effect on the intensive margin and an effect on the extensive margin. We also provide separate estimates for the effect on study performance for those students who complete the course, and for the effects on course participation (demonstrating selection effects).

2.5 Descriptive statistics

Our dataset contains information on 1092 students, 824 of whom are enrolled in a Dutch language programme with the remaining 268 students enrolled in an English language programme. Given that students are randomly assigned to mentor groups at the start of the academic year and the mentors are randomly assigned to treatment and control we do not expect to find any ex ante differences between the two treatment groups and the control group. Table 2.1 gives the descriptive statistics for the control (C), goal (G) and raise (R) group, as well as giving the p-value for two-sided comparisons of the means of these groups. Although the control and treatment groups appear to be comparable, there are some differences between the groups. Specifically, the characteristics of mentors of students in the treatment and control groups differ.[16] Students in the control group are significantly more likely to have a female mentor whereas students in the raise treatment are more likely to have an experienced mentor.[17] Furthermore treatment students in a Dutch language eco-

[15] By assigning the highest and lowest possible failing grade we get a lower and upper bound respectively because (as we will show later) the positive treatment effect conditional on completing the course is combined with a lower drop out rate.

[16] At the time of the randomization the information on mentor characteristics was not available to us. Hence we could not stratify our randomization on mentor characteristics.

[17] We define an experienced mentor as a mentor who mentored students in earlier years.

nomics track (as opposed to students in an English language economics track) scored lower for the 8 credits accounting course in the first block than students in the control group, but there is no such difference regarding the mathematics course, which is more important for microeconomics.[18] In the analysis we control for differences in observables.

Table 2.1: Descriptives by assigned treatment

	Control		Goal		Raise		C - G	C - R	G - R
	mean	sd	mean	sd	mean	sd	p	p	p
Age	18.72	1.71	18.63	1.39	18.75	1.27	0.57	0.85	0.39
Female	0.29	0.46	0.30	0.46	0.30	0.46	0.87	0.95	0.93
Female mentor	0.52	0.50	0.31	0.46	0.34	0.47	0.00***	0.00***	0.46
Experience mentor	0.31	0.46	0.38	0.49	0.50	0.50	0.03**	0.00***	0.00***
EC Accounting	6.45	1.61	6.13	1.51	5.96	1.73	0.06*	0.01**	0.31
ECX Accounting	5.82	1.72	5.95	1.91	5.74	1.92	0.70	0.79	0.56
EC Math	5.98	1.56	5.87	1.43	5.91	1.63	0.49	0.70	0.79
ECX Math	6.48	1.51	6.64	1.63	6.66	1.38	0.58	0.51	0.96
ET Matrix Alg.	6.48	1.94	6.13	1.88	6.02	2.38	0.32	0.29	0.79
ETX Matrix Alg.	7.54	2.11	6.92	1.81	7.58	2.18	0.28	0.95	0.31
ET Precalculus	6.46	1.50	6.04	1.78	5.72	2.20	0.17	0.05**	0.41
ETX Precalculus	7.42	1.79	6.54	2.29	7.25	1.98	0.13	0.74	0.31
ET Statistics	5.09	2.07	4.45	1.68	4.43	2.23	0.07*	0.13	0.96
ETX Statistics	6.35	2.51	5.50	2.31	5.29	2.17	0.23	0.13	0.78
Microeconomics	6.48	1.76	6.48	1.62	6.29	1.89	0.95	0.19	0.20
Midterm I	4.89	2.25	4.80	2.10	4.78	2.23	0.58	0.55	0.94
Attendance	10.66	2.98	10.66	3.15	10.71	2.85	0.98	0.81	0.84
Dropout	0.14	0.35	0.11	0.31	0.14	0.34	0.21	0.94	0.26
Max. Observations	389		367		336				

Students enroll in an economics (EC) track or an econometrics (ET) track in a Dutch or international (X) programme. Tracks in the Dutch and international programme are identical. Different tracks feature different courses, although some courses (e.g. Microeconomics) are common to all tracks.

At first sight Table 2.1 suggests that the treatments had no effect as there is no significant difference between the various groups in terms of the final grade received for the microeconomics course. However this simple direct comparison does not take into account the characteristics of students.

Selection into or out of treatment is an issue affecting the generalizability of

[18] In Table 2.1 we tested for differences between control and treatment groups using t-tests. We obtain similar results if we use nonparametric tests.

the results to the whole population. In our experiment there are three sources of selection out of the treatment. First, despite our best efforts to get all mentors to co-operate and ensure their understanding of the instructions, not all mentors assigned to treatment applied the treatment or took notes when administering the treatment. There are seven mentors for whom we do not have data about what happened during the individual student-mentor meetings. Anecdotal evidence suggests that some mentors have administered the treatment but not recorded the results while others did not administer the treatment at all. Thus this missing data forms a combination of measurement error and selection out of treatment. On average these mentors have less experience (5 out of 7 have no experience) than other mentors assigned to treatment (25 out of 47). Six of these seven mentors were assigned to the raise treatment, which was somewhat more demanding for mentors as mentors were asked to challenge their students goals. Mentors may also feel more apprehension to administer treatment when their students had weak prior performance. However, compared to other students assigned to treatment, students of non-complying mentors do not differ in terms of prior performance.

The missing data on treatment administration has diverse effects on our estimated treatment effects. Estimation of an intention-to-treat effect requires knowledge of assigned treatment only. Thus, the missing data on treatment administration has no effect on our estimates of the intention to treat effect. However, the estimates of the treatment effect on the treated (LATE) are affected as those estimates require knowledge of treatment administration to students. The possibly non-random missing data, caused by mentors who did not administer the treatment, may lead to biased estimates of the LATE.

Second, there is some treatment dilution as mentors do not administer the treatment to all students. Mentors assigned to treatment ask students for their grade goal in 93% of the cases although they were instructed to administer the treatment to all. Moreover, mentors are selective in which students they target for treatment. Specifically, students who performed poorly in previous courses are less likely to be asked about their goals as is shown in Table 2.2. In cases in which mentors did not ask students about their goals they often noted a lack of time due to the necessity to discuss other issues. Also, conditional on receiving the data from the mentor, we find that more experienced mentors are less likely to administer treatment.[19] In the raise treatment, mentors were instructed to attempt to raise the student's goal when he/she deemed the goal to be either too easy or doable. Of the 193 students setting a goal in the raise treatment 163 set a goal that met this requirement. However, mentors attempt to raise the goal in only 95 of these cases (58%), including all 47 cases where the goal is deemed too easy.[20] Overall students who are asked to raise their goal have slightly higher grades than those not asked, although differences are largely insignificant.[21] See Table 2.3 for more descriptives of the comparison between students asked and not asked to raise their goal.

Table 2.2: Students asked and not asked to set a goal within the treatment groups

	Not asked to set goal		Asked to set goal		
	Mean	Observations	Mean	Observations	p-value
Age	18.50	26	18.71	308	0.43
Female	0.30	37	0.27	483	0.69
Female mentor	0.22	37	0.34	492	0.14
Exp. mentor	0.62	37	0.46	492	0.06
EC Math	5.02	19	5.87	294	0.02
ECX Math	5.60	6	6.71	78	0.08
ET Precalculus	4.60	3	6.20	64	0.14
ETX Precalculus	5.50	2	7.43	22	0.24
EC Accounting	4.55	19	6.12	293	0.00
ECX Accounting	4.85	6	5.88	77	0.20
ET Matrix Alg.	4.47	3	6.35	63	0.10
ETX Matrix Alg.	6.70	2	7.85	22	0.46
ET Statistics	2.77	3	4.83	61	0.06
ETX Statistics	3.50	2	5.95	22	0.14

See Table 2.1 for an explanation of terms.

[19] Experienced mentors ask 90.5% of their students to set a goal, while non-experienced mentors ask 95% of their students to set a goal.

[20] In addition, there are 9 instances where the mentor asks a student to raise the goal even though she estimated the goal to be too difficult.

[21] The low number of observations for the Dutch econometrics courses is due to the fact that three of the four Dutch econometrics mentors assigned to the raise treatment failed to provide data.

Table 2.3: Students asked and not asked to raise their goal in the raise treatment

	No raise proposed		Raise proposed		
	Mean	Observations	Mean	Observations	p-value
Age	18.79	84	18.59	75	0.29
Female	0.26	127	0.25	100	0.87
Female mentor	0.29	128	0.38	104	0.17
Exp. mentor	0.58	128	0.45	104	0.06
EC Math	5.63	70	6.04	74	0.13
ECX Math	6.32	21	7.24	17	0.03
ET Precalculus	6.26	7	6.97	3	0.73
ETX Precalculus	7.31	13	7.88	4	0.63
EC Accounting	5.69	69	6.24	75	0.06
ECX Accounting	5.25	21	6.31	17	0.10
ET Matrix Alg.	6.31	7	6.40	3	0.97
ETX Matrix Alg.	7.58	13	8.80	4	0.30
ET Statistics	5.36	7	7.40	3	0.22
ETX Statistics	5.44	13	6.47	4	0.37

See Table 2.1 for an explanation of terms.

Also 12% (59) of the 492 students asked for a goal do not set a goal. These are all students who previously did not have a goal in mind. While students are more likely to set a goal if they have a female mentor there are no significant differences between those setting and not setting a goal in terms of past performance as shown in Table 2.4. Of all students asked to raise their goal half accept a higher goal. Again there is no significant difference in terms of past study results, but students are less likely to accept a raise from more experienced mentors (p-value 0.03), see Table 2.5. Furthermore, the level of the initial goal set has no influence on the acceptance of a suggested raise of the goal.

It is of interest to note that 270 of the 492 students (55%) asked to set a goal already had a grade they wanted to achieve in mind. The fact that many students already have a grade goal in mind implies that any effect of our treatment comes either from those who previously did not have a goal, or from the fact that students make the goal known to their mentor. The average initial goal set by the student is 6.9, a histogram of the goals set is shown in Figure 2.3. As expected higher (lower) goals are more likely to be deemed too hard (too easy) to achieve for the student by their mentor. Mentors appear to be able to gauge goal difficulty, as a regression

Table 2.4: Students that set and do not set goals when asked to set a goal

	Set Goal		No goal set		
	Mean	Observations	Mean	Observations	p
Age	18.74	265	18.58	43	0.48
Female	0.27	424	0.27	59	0.94
Female Mentor	0.35	433	0.22	59	0.05
Exp. Mentor	0.47	433	0.41	59	0.39
EC Math	5.85	254	5.99	40	0.60
ECX Math	6.67	73	7.16	5	0.49
ET Precalculus	6.28	57	5.57	7	0.32
ETX Precalculus	7.62	20	5.55	2	0.19
EC Accounting	6.12	252	6.17	41	0.85
ECX Accounting	5.96	72	4.78	5	0.18
ET Matrix Alg.	6.28	57	7.00	6	0.39
ETX Matrix Alg.	7.89	20	7.40	2	0.74
ET Statistics	4.90	55	4.18	6	0.38
ETX Statistics	6.03	20	5.20	2	0.62
Midterm I	4.77	426	4.47	55	0.32

See Table 1 for an explanation of terms.

Table 2.5: Students that accept and reject raise when asked to raise the goal

	Reject raise		Accept raise		
	Mean	Observations	Mean	Observations	p-value
Age	18.53	38	18.65	37	0.60
Female	0.22	50	0.28	50	0.49
Female mentor	0.46	52	0.29	52	0.07
Exp. mentor	0.56	52	0.35	52	0.03
EC Math	5.93	37	6.15	37	0.57
ECX Math	6.78	9	7.75	8	0.10
ET Precalculus	4.70	1	8.10	2	.
ETX Precalculus	8.85	2	6.90	2	0.34
EC Accounting	6.52	38	5.95	37	0.13
ECX Accounting	6.12	9	6.51	8	0.70
ET Matrix Alg.	4.60	1	7.30	2	.
ETX Matrix Alg.	9.90	2	7.70	2	0.33
ET Statistics	6.10	1	8.05	2	.
ETX Statistics	7.25	2	5.70	2	0.54
Initial goal	6.60	52	6.53	52	0.62

See Table 1 for an explanation of terms.

of the difference between the final grade achieved and the initial goal set on the estimate of the mentor shows in Table 2.6. Goals that were expected to be too difficult were not achieved on average whereas goals that were too easy are indeed beaten by a significant margin. Furthermore all point estimates of the judgment categories differ significantly from each other, indicating that mentors differentiate well between the three categories. On average students failed to meet their goal by 0.4 of a point. There may be a concern that mentors assigned to the raise treatment are more likely to report that they expect the student's goal te be too difficult, in order to avoid challenging the students to raise their goal. We test whether the distribution of the mentor's estimates of the students' goal differs across treatments. We do not find evidence of such an effect.

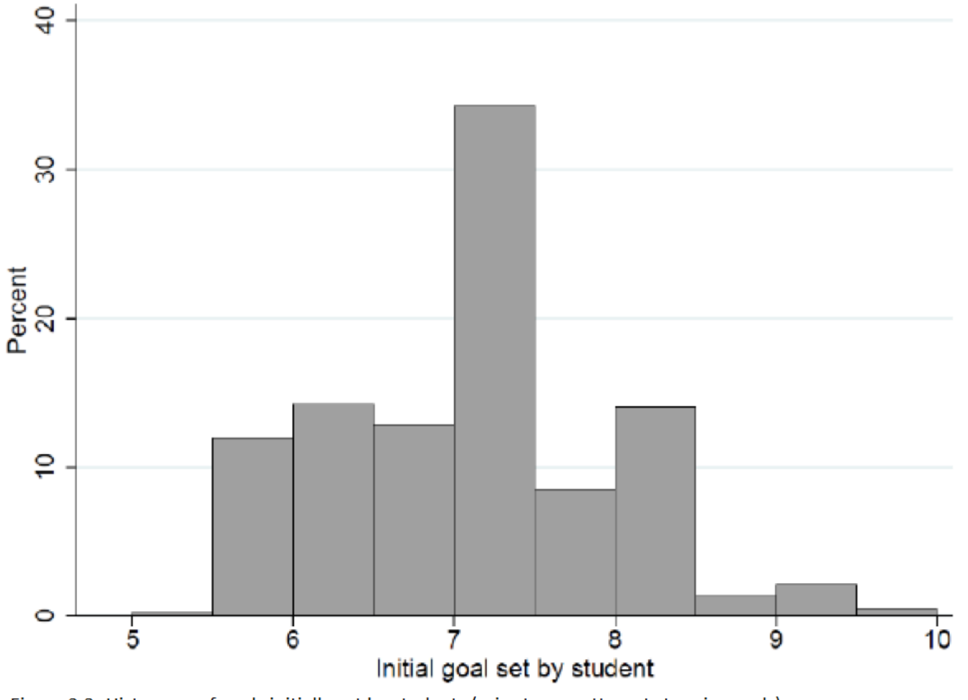

Figure 2.3: Histogram of goals initially set by students (prior to any attempts to raise goals).

Of the students who were asked to raise their goal we see that 50 percent (52) rejects the goal the mentor proposed. The average goal proposed does not differ (two-sided p-value of 0.62) between students who accept and reject the goal.

Table 2.6: Mentor estimates are accurate

	grade - goal
Goal too hard	-1.507***
	(0.261)
Goal too easy	0.337***
	(0.412)
Baseline: doable	-0.446***
	(0.261)
Observations	406
R^2	0.111

Standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Finally, there are some differences between students participating in Dutch language and international (English) programmes. The programmes are identical in all respects, featuring the same courses, study materials, and examinations, but have a somewhat different application procedure. Students applying for a Dutch language programme need to have only a high school diploma meeting the requirements, whereas those applying for an international programme are additionally selected based on a motivation letter. This suggests that students in the international language programmes might be better motivated. Consistent with this, Table 2.7 shows that, with the exception of an accounting course, students enrolled in international programmes scored significantly higher in the courses completed prior to the experiment. In our analysis we control for programme enrolment and additionally provide separate estimates of the effects within the Dutch and international programmes.

Table 2.7: Previous course results in Dutch and international programmes

	International		Dutch		
	Mean	n	Mean	n	p
EC Math	6.58	172	5.92	531	0.00
EC Accounting	5.84	170	6.18	529	0.02
ET Matrix Alg.	7.39	72	6.23	162	0.00
ET Statistics	5.84	71	4.67	158	0.00
ET Precalculus	7.14	71	6.10	164	0.00

See Table 2.1 for an explanation of terms.

2.6 Results

We first provide the total effect of the treatments, imputing a failing grade for students who did not complete the course. We then provide the results for students that complete the course before turning our attention to the results for students who did not complete the course.

2.6.1 Total effect

We estimate the total effect of the treatments by imputing the highest and lowest possible grade that would result in failing to pass the course for those graded aspects of the course that the student did not complete. As discussed in section 4, we focus on the case in which we impute a missing grade as 1.0, as this appears to be the most relevant case.

Table 2.8 gives the result of the intention to treat estimations. We find a weakly significant ($p < 0.1$) positive effect of 0.16 of a gradepoint (i.e. 9.3% of a standard deviation) for students in the goal treatment and an insignificant negative effect of the raise treatment. The positive effect of assignment to the goal treatment is in line with our hypothesis that setting goals improves student performance. The insignificant negative effect in the raise treatment shows that attempts to raise a goal backfire, resulting in performance similar to students in the control group. The results are estimated separately for men and women in columns 3 and 4 of Table 2.8. We see that men hardly respond to the treatments, and the effects are (mainly) driven by women. Women in the goal treatment show a substantial positive effect of 0.36, amounting to approximately 20% of a standard deviation of the grade. There is also a significant negative effect of -0.26 of a gradepoint of the raise treatment. Columns 5 and 6 of Table 2.8 provide separate estimates for students in Dutch and international programmes. These estimates show a widely divergent response to the treatments in these two groups, with Dutch programme students responding positively to the goal treatment while students in international programmes respond to the raise treatment in a strongly negative manner. Finally, in the second column of Table 2.8 we show the results excluding the students of mentors who did not hand in a form. These students are less likely to have been subjected to treatment, therefore the second column may give an indication of the effect size when compliance rates are higher than they were in our experiment. Recall from the descriptive statistics section that students of mentors not handing in forms do not differ from those of other mentors in the treatment groups in observable characteristics. The positive effect of the goal treatment is stronger in these estimates while the effect of the raise treatment is again negative but insignificant. The overall picture that emerges from the intention to treat estimates is that setting goals can help, but attempting to raise goals undoes any positive effect of setting goals and may even result in worse performance as compared to students that were assigned to the control group.

The effects of actually having set a goal during the individual student-mentor meeting and of having been asked to raise the goal is given in Table 2.9. In the first column we provide the overall effect of having set a goal in the meeting without differentiating between treatments. This gives the relevant effect if one does not expect raising the goal set to have any effect. However there are differences between the effect of the goal and the raise treatment as shown in the second column. Setting a goal by itself has a significantly positive effect on student performance under the goal treatment. Setting a goal under the raise treatment has no such positive effect, the point estimate of the effect is even negative. In column 3 we compare students who set a goal in the two treatments with each other. Specifically column 3 shows that the difference between the goal and the raise treatment is due to the fact that in the raise treatment some students are asked to raise their goal, which on average

Table 2.8: Intention to treat effect: total effect

Grade	Overall	Excl. 7 mentors	Male	Female	Dutch	International
Missing grade=1.0						
T: Goal	0.164*	0.256***	0.140	0.359**	0.333***	-0.102
	(0.090)	(0.088)	(0.110)	(0.172)	(0.115)	(0.119)
T: Raise	-0.156	-0.113	-0.0181	-0.262*	0.0179	-0.421**
	(0.101)	(0.102)	(0.126)	(0.148)	(0.117)	(0.154)
Missing grade=4.4						
T: Goal	0.099	0.167**	0.074	0.303*	0.251**	-0.102
	(0.079)	(0.079)	(0.092)	(0.159)	(0.095)	(0.119)
T: Raise	-0.138	-0.110	-0.017	-0.227	0.040	-0.421**
	(0.089)	(0.089)	(0.103)	(0.146)	(0.094)	(0.154)
Observations	955	868	678	277	719	236
Tutorgroups	84	77	84	81	60	24
R^2 (Upper)	0.619	0.630	0.621	0.691	0.615	0.641
R^2 (Lower)	0.616	0.624	0.621	0.695	0.610	0.641

Standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

lowers performance by a substantial 0.87 gradepoint (i.e. more than half a standard deviation) as compared to similar students who set a goal but were not asked to raise their goal. These results are in line with the intention to treat estimates, showing that setting a goal during the individual student-mentor meetings improves performance, but attempts to raise those goals undo that positive effect and may result in even lower performance.[22]

[22] To make sure that we compare students who are asked to raise their goal in the raise treatment with their counterparts in the goal treatment we controlled for the mentor's estimate about the difficulty of the students goal. There might be a concern that mentors in the raise treatment report a biased estimate because they want to avoid asking students to raise their goal. We tested for such an effect by comparing treatment effects for those students of which the mentor reports that the goal is too difficult. If mentors in the raise treatment bias their estimate in order to avoid asking students to raise their goal we would expect the treatment effect to be more positive in the raise treatment than in the goal treatment. We do not find such an effect. In addition we compare the distribution of mentors' estimates about the goals across the treatments. Because of randomization the distributions should be similar. We find no evidence that the distribution differs across treatments.

Table 2.9: Local average treatment effect: total effect

Grade	Overall	By Treatment	AskedToRaise
Missing grade=1.0			
Set Goal	0.027		
	(0.113)		
Set Goal T: Goal		0.257**	
		(0.118)	
Set Goal T: Raise		-0.263	
		(0.164)	
Asked to Raise			-0.870***
			(0.334)
Missing grade=4.4			
Set Goal	-0.014		
	(0.101)		
Set Goal T: Goal		0.164	
		(0.104)	
Set Goal T: Raise		-0.238	
		(0.146)	
Asked to Raise			-0.492
			(0.316)
Controls	yes	yes	yes
Instruments	T. assignment	T. assignment	R. assignment
Observations	966	966	411
Tutorgroups	84	84	47
R^2 (Upper)	0.613	0.618	0.639
R^2 (Lower)	0.610	0.613	0.634

Standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

The total effect of our treatments discussed above consists of two effects. First the treatments may have an impact on the students who complete the course inducing them to alter their efforts. This is the effect on the intensive margin. Second, our treatments may affect the extensive margin, the decision to participate in the course. These two effects cannot be interpreted separately as this risks the confusion of selection effects on the extensive margin for the effects of treatment on the intensive margin. We turn to these two effects now.

2.6.2 Intensive margin

Table 2.10 gives the intention-to-treat estimates for those students that complete the course. The results are largely in line with the overall estimates provided in Table 2.8. We find that the overall positive effect of being assigned to the goal treatment is no longer significant for the students that complete the course. But results in the female and Dutch programme subsamples are similar and significant. The results confirm the overall impression that setting goals can improve student performance, and that raising goals has an insignificant negative effect on performance.

The effects of having actually set a goal during the individual student-mentor meeting and of having been asked to raise the goal is given in Table 2.11. Also these results are largely in line with the overall treatment effect, and show the positive impact of actually setting a goal which is negated by being asked to raise the goal.

Table 2.10: Intention to treat effect: intensive margin

Grade	Overall	Excl. 7 mentors	Male	Female	Dutch	International
T: Goal	0.112	0.193**	0.069	0.361**	0.265***	0.011
	(0.078)	(0.077)	(0.093)	(0.178)	(0.091)	(0.125)
T: Raise	-0.147	-0.117	-0.007	-0.262*	0.054	-0.428**
	(0.092)	(0.095)	(0.103)	(0.151)	(0.091)	(0.177)
Controls	yes	yes	yes	yes	yes	yes
Observations	940	854	661	279	697	243
Mentorgroups	84	77	84	82	60	24
R^2	0.609	0.616	0.626	0.674	0.605	0.627

Standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 2.11: Local average treatment effect: intensive margin

Grade	Overall	By Treatment	Asked to Raise
Set Goal	0.072		
	(0.088)		
Set Goal T: Goal		0.251***	
		(0.096)	
Set Goal T: Raise		-0.146	
		(0.117)	
Asked to Raise			-0.409
			(0.292)
Controls	yes	yes	yes
Instruments	T. assignment	T. assignment	R. assignment
Observations	854	854	408
Tutorgroups	77	77	47
R^2	0.614	0.617	0.631

Standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

2.6.3 Extensive margin

The results above indicate a positive effect of the goal treatment on course performance for those who complete the course. Differences between the total effect estimates and the estimates on the intensive margin may be due to selection effects induced by the treatments. For instance, our treatments may affect course completion by creating greater commitment. To study the effects of our treatments on course completion we estimate a linear probability model in much the same way as above. Given that students have to attend at least 10 out of 13 tutorial sessions we limit our estimation to the sample of students who attended at least 3 sessions such that all students were still able to meet this requirement by the time the treatment took place. In the control group 6.2 percent (24) of the students having attended at least 3 sessions dropped out of the course. This dropout rate is lowered by 2 percentage points on average in the goal treatment as can be seen in Table 2.12 providing the intention to treat estimates on the dropout rate.[23] The results on the dropout rate are similar to those on course performance given course completion in that the goal treatment again has an effect whereas the raise treatment does not have an effect but has an oppositely signed coefficient. In contrast to the effect on the course grade however, the reduction in dropouts is concentrated among men rather than women. This is most likely due to the fact that women have a substantially lower baseline dropout rate than men (6.8% for men compared to 2.8% for women in the control group, two-sided p-value 0.12).

Table 2.12: Intention to treat effect: dropout

Dropout	Overall	Excl. 7 mentors	Male	Female
T: Goal	-0.020**	-0.029***	-0.0215**	-0.016
	(0.008)	(0.008)	(0.010)	(0.014)
T: Raise	0.005	0.0005	0.00002	0.009
	(0.008)	(0.008)	(0.012)	(0.012)
Observations	955	868	678	277
Tutorgroups	84	77	84	81
R^2	0.169	0.183	0.175	0.269

Standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

The pattern that the goal treatment has desirable effects while the raise treatment has undesirable effects continues to hold when considering the effect on those who actually set goals as shown in Table 2.13. Those in the goal treatment who actually set a goal show a 3.7 percentage point lower dropout rate than those in either the control or the raise treatment. Among those students who set a goal, those who are asked to raise their goal are 12 percentage points more likely to drop out than those who are not asked to raise their goal. Even taking into account that the comparison group consists of students with a lower dropout rate of 3.9 percentage point due to the effect of setting a goal itself on the dropout rate discussed above this is a sizeable effect. This result shows that attempts to raise a student's goal in order to improve performance can backfire by leading to a substantially lower chance of course completion.

[23] No estimates on subsamples for the Dutch and international programmes are provided as there are too few dropouts from the international programmes, resulting in collinearity.

Table 2.13: Local average treatment effect: dropout

Dropout	Overall	By Treatment	Asked to Raise
Set Goal	-0.020**		
	(0.008)		
Set Goal T: Goal		-0.037***	
		(0.010)	
Set Goal T: Raise		0.0005	
		(0.010)	
Asked to Raise			0.120***
			(0.017)
Controls	yes	yes	yes
Instruments	T. assignment	T. assignment	R. assignment
Observations	868	868	416
Tutorgroups	77	77	47
R^2	0.176	0.183	0.214

Standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

2.6.4 Further results

In this section we present a number of additional analyses that shed light on further questions. To start, we consider whether there is a heterogeneous effect of treatment due to differences in ability. We measure ability by taking the average of the grades achieved in the first block, and centering this grade average by subtracting the overall mean average score of 6.2 (std. dev. 1.65). We then interact the ability measure with students' treatment assignment. The intention-to-treat estimates in Table 2.14 show that students who performed better in previous courses respond less to the goal treatment. Thus our intervention had a stronger effect on weaker students than it did on top students. There is no such heterogeneous effect regarding the raise treatment.[24]

[24]For students who attended a Dutch high school we also have high school grades. If we use high school grades (as a measure of ability) for this subsample we find a qualitatively similar result but a decrease in power because of the smaller sample size.

Table 2.14: ITT interaction treatment with GPA in preceding block

	Overall	Excl. 7 mentors	Male	Female	Dutch	International
T: Goal	0.154**	0.177**	0.046	0.598***	0.274***	0.196**
	(0.077)	(0.085)	(0.095)	(0.157)	(0.094)	(0.092)
T: Goal × GPA	-0.156**	-0.147**	-0.187*	-0.260**	-0.152	-0.182*
	(0.071)	(0.071)	(0.097)	(0.100)	(0.093)	(0.105)
T: Raise	-0.084	-0.041	-0.007	0.011	0.082	-0.314**
	(0.092)	(0.100)	(0.114)	(0.175)	(0.089)	(0.149)
T: Raise × GPA	0.003	0.039	0.034	-0.109	-0.031	0.089
	(0.075)	(0.091)	(0.105)	(0.106)	(0.092)	(0.118)
Block 1	0.748***	0.754***	0.748***	0.784***	0.754***	0.743***
	(0.043)	(0.043)	(0.058)	(0.065)	(0.056)	(0.072)
Observations	896	815	631	265	661	235
Tutorgroups	84	77	84	80	60	24
R^2	0.490	0.505	0.502	0.568	0.486	0.509

GPA is the mean centered GPA of students calculated over all courses they participated in prior to microeconomics.
Standard errors in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Second, as we have seen above, students set higher goals in front of a female mentor (two-sided p-value of 0.012). This suggests that the motivation to set a goal may differ depending on the gender of the mentor. It is thus natural to ask whether our treatments have heterogeneous effects depending on the mentor's gender. Overall there is no sign of a heterogeneous treatment effect depending on the gender of the administering mentor as shown in Table 2.15.

The desire to impress a member of the opposite gender may result in a heterogeneous treatment effect based on the gender combination of mentor and student. Estimates on male or female students reveal no such significant interaction effect, although the signs of the point estimates do conflict in the expected manner which is consistent with such an effect. In the subsample of Dutch students there is a clear interaction effect of gender on treatment response. The point estimates suggest that having a female mentor completely reverses the effect of the treatments such that the raise treatment has an insignificant negative impact when administered by a male mentor but a positive impact when administered by a female mentor (p-value of difference between male and female mentor administering the raise treatment is 0.002). Male and female mentors have the same effect on Dutch programme students in the goal treatment. Furthermore, no gender differences are found in the sample of international students, although this may be due to a lack of power.

Another possible channel through which treatment may be affected is the experience of the mentor. More experienced mentors may project more authority or may be better able to fit the treatment into the conversation in a natural manner. A heterogeneous treatment effect based on the mentor's experience may also speak to a possible channel through which setting a goal in the individual mentor-student meeting affects performance. If students care for their reputation in the eyes of their mentor they may value this reputation more if the mentor is more experienced. Taken combined, we expect more experienced mentors to strengthen the treatment effects. Recall however that we have already seen some evidence speaking against a better implementation of the treatments by more experienced mentors in the form of a weakly lower rate of inducement (two-sided p-value of 0.06) and goals that are approximately three tenths of a point lower.

Table 2.15: ITT interaction treatment with gender of mentor

Grade	Overall	Excl. 7 mentors	Male	Female	Dutch	International
Female mentor	-0.0002	-0.010	-0.053	-0.146	0.159	-0.105
	(0.134)	(0.136)	(0.148)	(0.300)	(0.113)	(0.282)
T: Goal	0.171	0.218*	0.002	0.554**	0.387***	0.007
	(0.113)	(0.117)	(0.128)	(0.262)	(0.082)	(0.156)
T: Goal × Fem. mentor	-0.198	-0.083	0.085	-0.711	-0.520**	0.002
	(0.228)	(0.212)	(0.241)	(0.535)	(0.258)	(0.427)
T: Raise	-0.178	-0.131	-0.121	-0.430**	-0.091	-0.186
	(0.111)	(0.121)	(0.133)	(0.214)	(0.092)	(0.271)
T: Raise × Fem. mentor	0.070	0.033	0.262	0.336	0.449**	-0.487
	(0.178)	(0.169)	(0.212)	(0.395)	(0.205)	(0.292)
Observations	940	854	661	279	697	243
Tutorgroups	84	77	84	82	60	24
R^2	0.609	0.616	0.626	0.678	0.609	0.629

Standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

The estimation results including a heterogeneous effect for experienced mentors is given in Table 2.16. We see that more experienced mentors do not have a significant positive impact on the raise treatment overall. Men in the goal treatment with a more experienced mentor show an increase in performance whereas there is no such increase in performance when they have an inexperienced mentor. Female students in the goal treatment seem to do worse with an experienced mentor compared to an unexperienced mentor, although this effect is not significant. This may suggest that men respond more to authority. Although there appears to be a significant negative interaction effect of mentor experience on assignment to the goal treatment for international students, the effect of having a more experienced mentor implementing the treatment is no different from that of an unexperienced mentor (p-value of 0.21). These results show that generally the students do not appear to be more responsive to more experienced mentors. Although we suggested that students might be more responsive to a more experienced mentor due to reputational concerns, this finding does not discredit the reputation explanation for why goals can improve performance. For instance, students may not distinguish that much between different mentors, or value their reputation in the eyes of their mentor more based on other factors such as the mentor's own ability.

We are fully aware that there are two different effects of setting a goal in our goal treatment. The effect of thinking about a goal and setting a goal for oneself, and the effect of sharing this goal with the mentor. Thinking about a goal may create a reference point with which to compare one's performance as posited in the literature. This may result in higher performance by giving positive utility if the goal is met or exceeded and negative utility if performance falls short. Sharing the goal with the mentor may result in reputational concerns towards the mentor, in the sense that the mentor may evaluate the student based on her performance relative to her goal. Empirically our best way to learn whether sharing the goal with the mentor leads to the increased performance, is by considering when reputational concerns are likely to be stronger and comparing students in those situations with similar students who face weaker reputational concerns. We posit two such situations, facing a more experienced mentor who is likely better in evaluating students performance,

Table 2.16: ITT interaction treatment with experience of mentor

Grade	Overall	Excl. 7 mentors	Male	Female	Dutch	International
T: Goal	0.067	0.202*	-0.142	0.416*	0.124	0.123
	(0.100)	(0.102)	(0.124)	(0.225)	(0.140)	(0.091)
Experienced Mentor	0.087	0.047	-0.172	0.544*	0.052	0.760**
	(0.137)	(0.125)	(0.133)	(0.280)	(0.124)	(0.303)
T: Goal × Exp. Mentor	0.129	-0.032	0.606***	-0.250	0.292	-1.217***
	(0.200)	(0.192)	(0.229)	(0.424)	(0.231)	(0.348)
T: Raise	-0.040	-0.088	0.124	-0.075	0.141	-0.254
	(0.132)	(0.137)	(0.144)	(0.264)	(0.137)	(0.268)
T: Raise × Exp. Mentor	-0.198	-0.073	-0.091	-0.502	-0.136	-0.862
	(0.167)	(0.159)	(0.183)	(0.433)	(0.188)	(0.557)
Observations	940	854	661	279	697	243
Tutorgroups	84	77	84	82	60	24
R^2	0.610	0.616	0.629	0.676	0.606	0.630

Standard errors in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

and facing a mentor of the opposite gender who may be more valuable to impress. For neither of these situations we find a heterogeneous impact on the treatment effect, suggesting that goals primarily work through creating a reference point for oneself. Of course our proxies may not capture enough variation in the strength of reputational concerns.

Furthermore, asking students to raise their goal can have effects through two different channels. The challenge of the goal itself can have an effect, i.e. if students get utility from reaching a goal they may exert additional effort if the goal becomes more challenging. Another channel is that asking the student to raise her goal can give the student information about her ability. Depending on the substitutability or complementarity of ability and effort this can lead to a decrease or increase in effort and performance. Here too, our best way to deal with this is comparing the treatment effects for students with experienced mentors with the treatment effects for students with unexperienced mentors. The reason is that we expect that students who have experienced mentors expect their mentor to be more able to know the student's ability, and hence the information aspect is stronger. We find that there is no significant difference in treatment effects for students who have experienced and unexperienced mentors. This implies that either the information component is small, or that there is not much heterogeneity in the extend to which the message contains information by experience of the mentor.

We find a consistent pattern in our data that female students respond stronger to our treatments than male students. At first sight this may seem surprising. There is a very rich literature on heterogeneous gender effects to monetary incentives and non-monetary incentives when there is a competition element. Many papers find that males respond stronger to competitive incentives or information about their (relative) ranking, see for example Gneezy et al. (2003), Barankay (2011), and Niederle and Vesterlund (2011), while others find that there is no gender difference, see Dreber et al. (2011) and Delfgaauw et al. (2013). An important difference between these incentives and the incentives in our treatments is that goal setting in this experiment does not have any competitive element, which might drive the gender effect in the current literature.

Finally, a potential concern of goal setting in multitasking environments is that goals lead subjects away from other (non-incentivized) tasks. Our students take one other course at the same time as microeconomics. Doing our previous analyses with the other course's grade as a dependent variable shows that there is no evidence of such a substitution effect (these results are available on request). Hence, the positive effect of goal setting in this study is a net increase in performance.

2.7 Discussion and conclusion

We conducted a field experiment in order to test the effects of encouraging students to set goals and encouraging students to increase the ambitiousness of their goals during mentor-student meetings in a university study programme. We designed two treatments. In the *goal treatment* we instructed mentors to encourage students to set a grade specific goal. In the *raise treatment* we gave mentors the same instruction and in addition instructed them to raise this goal if deemed appropriate.

We find that students in the goal treatment perform better than students in the control group. Students whose mentor was assigned to the goal treatment score 0.16 gradepoints (i.e. 9.3% of a standard deviation) higher than students in the control group. Students in the raise treatment perform similarly to students in the control group, although there are some indications that their performance is even lower. This is true in terms of both the dropout rate and the grades achieved that are conditional on completing the course. The null effect of the raise treatment is in line with the goal becoming unacceptable due to the raise, indicating that the size of the raise was too high. Finally, being asked to raise the goal leads to a significant drop in performance as compared to similar students in the goal treatment.

An alternative explanation for the result that students in the raise treatment perform worse than students in the goal treatment is the nature of the goal. While in the goal treatment students set themselves a goal, a proposal to raise this self-set goal can be seen as a goal of a different kind, namely a cooperatively set goal (or even an assigned goal). Changing the nature of the goal can change the commitment of the student to the goal (see Hollenbeck et al. 1989), which implies that the intrinsic motivation (i.e. the utility gain when reaching the goal) changes between the two treatments. As a consequence students perform worse in the raise treatment than in the goal treatment. Further, if some students in the control group set themselves a goal then this could even lead to a lower performance of students in the raise treatment as compared to the control group.[25]

Next, we looked at heterogeneous treatment effects. First, we find that students that performed poorly prior to the experiment benefit most from setting goals. Second, we expected stronger effects for students who are assigned to more experienced mentors. The reason for this is that we expect experienced mentors to be better able to incorporate our treatments in their meetings, and because these mentors might have more authority. We find that overall there is no heterogeneous effect of experience on the treatments. There is an effect on male students suggesting male students are more affected by authority. This however does not imply that overall reputational concerns of students towards their mentor do not play a role, as students may care more about (unobservable) characteristics other than experience of their mentor. Third, students' motivation to set a goal might differ by the gender of their mentor, as well as whether student and mentor are of the same gender. Overall we find that there is no effect of a mentor's gender on the treatment effects. More surprisingly, if we focus only on the students in Dutch education programmes, we see that the students assigned to the raise treatment perform better when their mentor is female, and worse when their mentor is male as compared to the control group. This might indicate that female mentors are more able to motivate the initially less motivated students by challenging them than male mentors.

To summarize we have shown that students setting and sharing goals with their mentors can help raise study performance, and more so for initially poorly performing students. We have furthermore shown that although it may be tempting to try to push students to raise the bar a bit higher, raising the bar can be more demotivating than inspiring. Hence, one should be cautious in attempting to push students beyond what they themselves aim to achieve, even if that bar appears to be low.

It is interesting to learn whether these results are generalizable to other settings,

[25] Our finding that 55% of students that are asked about goals already have a goal in mind supports this idea.

for example manager-worker settings. Our findings may have implications for the optimal design of appraisal interviews. In order to generalize our findings we need more (experimental) evidence in other settings.

Finally, our paper is (relatively) silent on the mechanisms that drive goal setting. It is interesting to learn to what extent present bias preferences and loss aversion, as is posited in economic theory papers as important drivers that make goals work, are predictors of the success of goal setting. For example our result that goal setting works mostly for initially poor performing students may be explained by poor performing students having stronger present bias preferences, are more loss averse, or by the fact that extra effort more easily increases performance when initial performance is low. One way to test how the effect of goal setting on performance interacts with people's present bias preferences and loss aversion is by running a laboratory experiment with a sample of the students that participated in this study.

2.A Appendix

2.A.1 Appendix

Dear X,

Following our introduction during the tutor instruction session, we request you to adjust the progress meetings with your students. Your participation contributes to research regarding the possibilities to increase students' study success by improving the tutor meetings.

The instructions regarding the progress meetings that you conduct in the week of 17th to 21st November follow.

After you have discussed the general motivation and study progress of the student, you are expected to ask some additional questions while discussing the current courses the student follows. These questions relate to Microeconomics. The intention is to motivate the students to set a goal. Ask the questions in italics.

Do you have a final grade in mind that you want to achieve for Microeconomics?

If YES: *What grade do you want to achieve?*

(if the student answers: I want to pass the course, then try to specify this, for example: Are you aiming for 5,5 or a 6?)

If NO: *Some students find it useful to set concrete goals in the form of a grade. Setting a goal can help motivate you to perform better. Do you want to set yourself a goal?*

If YES: *What final grade do you want to achieve for Microeconomics?*

If NO: continue the conversation as usual.

If the student set a goal:

Good luck with achieving your goal.

It is important that you follow the instructions as much as possible. However, do try to incorporate the questions into the conversation naturally. Attached, you find a flowchart summarizing the script. You can use this flowchart to refresh your memory prior to the meeting.

We request you to complete the attached form after the meeting with each student. You can print this form yourself, or pick up a copy at H8-23 or H8-24. It can be useful to make notes. Please, read the form carefully before the meetings.

After the meetings we would like to receive the completed forms. The completed forms can be handed in at H8-23 or H8-24 or can be emailed to vanlent@ese.eur.nl or souverijn@ese.eur.nl. We request that you hand in the form at Friday 28th November at the latest.

For research purposes we request that you do not discuss these instructions with others.

If you have any questions, do not hesitate to contact us. You can find us in H8-23 or H8-24, and you can reach us at vanlent@ese.eur.nl, phone: 010 408 1793 or souverijn@ese.eur.nl, phone: 010 408 9038.

Max van Lent

Michiel Souverijn

P.S. Could you please confirm to us by email that you have received this email and that you have read the instructions.

2.A.2 Appendix

Dear X,

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Do you have a final grade in mind that you want to achieve for Microeconomics?

If YES: *What grade do you want to achieve?*

(if the student answers: I want to pass the course, then try to specify this, for example: Are you aiming for 5,5 or a 6?)

If NO: *Some students find it useful to set concrete goals in the form of a grade. Setting a goal can help motivate you to perform better. Do you want to set yourself a goal?*

If YES: *What final grade do you want to achieve for Microeconomics?*

If NO: continue the conversation as usual.

If you (as a tutor) think the goal (grade) set is achievable:

Shouldn't you set a higher goal and aim for a [grade +1]? [So if the student chooses a 6 as a goal and you think this is achievable, propose to aim for a 7.]

If the student set a goal:

Good luck with achieving your goal.

It is important that you follow the instructions as much as possible. However, do try to incorporate the questions into the conversation naturally. Attached, you find a flowchart summarizing the script. You can use this flowchart to refresh your memory prior to the meeting.

We request you to complete the attached form after the meeting with each student. You can print this form yourself, or pick up a copy at H8-23 or H8-24. It can be useful to make notes. Please, read the form carefully before the meetings.

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Chapter 3

Serving the Public Interest in Several Ways: Theory and Empirics

Joint with Robert Dur

3.1 Introduction

Many people feel a need to serve the public interest or to increase the well-being of others, even of complete strangers. Andreoni and Miller (2002) study such altruistic preferences in the lab and find that a majority of people are willing to spend some money (anonymously) in order to increase the well-being of unknown others.[1] In practice, two common ways of serving the public interest are making a donation to charity and taking a job that involves helping others. Both these altruistic behaviors are prevalent in modern societies. List and Price (2012) report data showing that in rich countries typically more than half of the population make donations to charity. Data from the International Social Survey (2005) suggest that a sizeable majority of people aspire – and many of them have – a job in which they can increase the well-being of others.

In this paper we develop a coherent framework to study the role of altruistic

[1] See also Beckman et al. (2002) and Falk et al. (2005), among others.

preferences in job choice, on-the-job effort provision, and charitable donations. We set up a simple theoretical model, and subsequently test the model's predictions using rich survey data. In our model, people differ in their altruism and can serve the public interest in two ways: by making a charitable donation and by taking a public service job and exerting effort on the job. People make three decisions: whether to take a public service job or a regular job, how much effort to exert at work, and how much of their income to donate to charity.

Our theoretical analysis yields the following predictions. First, as in related models that we discuss below, the likelihood of having a public service job (weakly) increases in a worker's altruism. The reason is that holding a public service job gives opportunities to contribute to the well-being of others at relatively low cost, which is appreciated by – and hence attracts – altruistic workers. Second, and quite naturally, for a given job type, charitable donations (weakly) increase in workers' altruism. Third, and perhaps more surprising, for a given altruism and income, workers holding a regular job donate more to charity than workers holding a public service job. The intuition behind this result is that public service workers already contribute to the well-being of others by exerting effort on the job and, hence, by a substitution argument, they donate less.

Our study is related to a rapidly expanding theoretical literature in economics studying self-selection and workplace behavior of intrinsically motivated workers, see for example Francois (2000, 2007), Besley and Ghatak (2005), Prendergast (2007), Delfgaauw and Dur (2007, 2008), Brekke and Nyborg (2008), Dal Bó et al. (2013), Dur and Zoutenbier (2015), Manna (2015), Cassar (2016a), and Barigozzi and Burani (2016). In many of these studies, intrinsic motivation takes the form of altruism. We enrich this literature by allowing workers to serve the public interest in several ways – not only by exerting effort on certain types of jobs, but also by making charitable donations.

Our theoretical predictions point to a possible flaw in the empirical literature. Numerous public administration scholars and several economists have examined whether workers in some sectors or job types are more altruistic than in others (see Perry et al. 2010 and Perry and Vandenabeele 2015 for overviews). Many of these studies measure a worker's altruistic preferences using data on the worker's behavior outside the workplace, among others on the worker's donations to charity (e.g. Brewer 2003, Houston 2006, Rotolo and Wilson 2006, and Lee 2012). Our theory suggests that this measure is flawed and leads to an underestimation of altruism of workers in public service jobs. Indeed, our theory does not rule out that workers in public service jobs on average donate less to charity than workers in regular jobs do, and yet are more altruistic. This is particularly likely when public service jobs offer ample opportunities to serve the public interest, such that workers in those jobs feel less of a need to make further contributions outside the workplace.[2]

We empirically examine our predictions using data from the German Socio-Economic Panel Study (SOEP). The SOEP is a representative longitudinal study covering 30,000 persons in 11,000 households. It contains questions about individual's education, earnings, employment, personality characteristics, and behavior. The key variables that we use for our analysis are self-reported altruism, money donations to charity, and job type or sector of employment. Following Becker et al. (2012) and Dur and Zoutenbier (2015), we measure a worker's altruism by his response to the question: "How important do you find it to be there for others currently?" Donations to charity are measured by the response to the question: "Did you donate money last year (not counting membership fees)?" If the answer to this question is yes, the respondent is asked to report the total amount donated. Lastly, in line with the literature, we use several definitions of what a public service job exactly is.[3]

[2] See Buurman et al. (2012) and Tonin and Vlassopoulos (2015) for related, though less precise, arguments. Another related paper is the recent study by Aldashev et al. (2016) that examines rent extraction, charitable donations, and self-selection of altruistic and selfish managers into for-profit and not-for-profit organizations, and finds that multiple equilibria may arise. Our theory also relates to the literature on moral licensing in social psychology, which posits that people tend to take immoral decisions following past good deeds (see Merritt et al. (2010) for a recent review).

[3] In the literature there is no agreement on what a public service job exactly is. Following Perry and Wise (1990)'s concept of public service motivation, many papers compare workers employed in the public sector with those employed in the private sector, for example Vandenabeele (2008), Steijn (2008), and Christensen and Wright (2011). Other papers also compare workers employed in different industries or job types, see for example Gregg et al. (2011), Houston (2011), Christensen and Wright (2011), and Kjeldsen and Jacobsen (2013). In our empirical work we use two definitions. First, we define public service jobs as jobs in the public sector and regular jobs as jobs in the private sector. Later, we define public service jobs as jobs in certain industries (health, sport and education, and public administration) and regular jobs as jobs in the remaining industries. The results we

Consistent with our theory, we find that workers who are more altruistic are more likely to take a public service job and, for a given job type, donate a higher amount to charity. Furthermore, we find that workers in a regular job make significantly higher donations to charity than equally altruistic workers in a public service job. However, this difference moves close to zero and becomes statistically insignificant when we control for income. Moreover, the result turns out to be sensitive to the exact definition of a public service job and the estimation method.

Studying workers' charitable behavior and self-selection into jobs is interesting in itself as well as relevant from a policy perspective. Studies like ours contribute to the body of knowledge about the prevalence of work motivations in different job types and sectors, which can be used when designing HR-policies. Moreover, as our study provides insights into the drivers of charitable donations, our results may be useful for charitable organizations in designing and targeting their promotion activities.

The remainder of this paper is organized as follows. In the next section we develop and analyze our theoretical model and derive predictions. In Section 3 we describe the data and the empirical strategy. Section 4 presents our empirical results. Section 5 concludes.

3.2 Theory

3.2.1 Model

We develop a model where workers take three decisions: they choose between a regular job ($s = 0$) and a public service job ($s = 1$), how much effort to exert on the job ($e_{s,i} \geq 0$), and how much of their income to donate to charity ($d_{s,i} \geq 0$). Workers are heterogeneous in two ways. First, they differ in their altruism denoted by γ_i. We assume altruism is impure, as in Andreoni (1990). That is, a worker receives a 'warm-glow' utility from making a contribution to the well-being of others, but he does not directly care about other's utility. This approach is in line with earlier related models such as Besley and Ghatak (2005), Delfgaauw and Dur (2008),

obtain are roughly the same.

Dur and Zoutenbier (2015), and Aldashev et al. (2016).[4] Tonin and Vlassopoulos (2010) provide field-experimental evidence supporting this assumption. The altruism parameter γ_i follows a continuous uniform distribution with boundaries $[0, \overline{\gamma}]$ with $\overline{\gamma} > 0$. Second, workers differ in a fixed benefit (or cost) from choosing a public service job, denoted by ε_i. This variable is meant to represent worker i's preference for job aspects other than those stressed by our theory, such as commuting time, pension plans, and other job (dis)amenities. ε_i is drawn from a continuous uniform distribution with boundaries $[\underline{\varepsilon}, \overline{\varepsilon}]$ where $\underline{\varepsilon} < 0 < \overline{\varepsilon}$. We shall assume a sufficiently rich type space (sufficiently low $\underline{\varepsilon}$ and sufficiently high $\overline{\varepsilon}$), so that in equilibrium any possible altruism type γ_i is present in both types of jobs.

A worker's utility depends on his private consumption, on his cost of effort, the fixed benefit or cost ε_i when working in a public service job ($s = 1$), and – if the worker is altruistic ($\gamma_i > 0$) – on his contribution to the well-being of others. More specifically, we assume that worker i's utility increases linearly in his private consumption, that his effort costs are quadratic, and that his 'altruistic utility' is log-linear in his contributions to the well-being of others:[5]

$$U_i(d_{s,i}, e_{s,i}) = w_{s,i} - d_{s,i} - \frac{1}{2}\theta e_{s,i}^2 + \gamma_i \ln(d_{s,i} + \beta_s e_{s,i}) + s\varepsilon_i,$$

where $w_{s,i}$ denotes worker i's wage when working in sector s, private consumption is the difference between the worker's wage ($w_{s,i}$) and his donation to charity ($d_{s,i} \geq 0$), the parameter θ is a measure for the cost of effort, and β_s is the effect of a unit of effort in job s on the well-being of others. For simplicity, we assume $\beta_0 = 0$ and $\beta_1 > 0$. That is, only effort in a public service job increases the well-being of others, while effort in a regular job does not. However, our key predictions are similar if on-the-job effort would increase the well-being of others in all jobs but more so in public service jobs. Besides exerting effort in a public service job, workers can serve the public interest by donating money to charity, and we assume that these

[4] For an overview of theoretical papers applying different types of altruism, see Francois and Vlassopoulos (2008).

[5] The linearity of utility in private consumption implies that we abstract from income effects. This greatly simplifies the analysis without missing out on important insights. In the empirics, we run analyses with and without controlling for income.

two instruments are substitutes. For convenience, we assume that they are perfect substitutes.[6] Furthermore, we assume that workers are paid for performance in regular jobs, while workers receive a flat wage in a public service job. More precisely, wages in regular and public service jobs equal $w_0 = a + xe_0$ and $w_1 = z$, respectively, where x equals the marginal product of effort of workers in a regular job (assuming perfect competition in the labor market) and z is such that the demand for public services equals the supply of those services provided by workers in public service jobs in equilibrium. The assumption of flat wages in public service jobs is in line with the stylized fact that pay is typically less dependent on performance in those jobs.[7] Our key predictions need not change if we allow for performance pay in all jobs.

The timing of the events is as follows. First, nature draws each worker's γ_i and ε_i. Second, workers choose either a regular or a public service job. Finally, workers choose their effort and donations.

3.2.2 Analysis

We solve the model by backward induction and first derive the on-the-job effort and charitable donations a worker chooses for a given job type. Next, we will analyze which worker types, in terms of γ_i and ε_i, sort into which job type. Along the way, we will formulate predictions that will be empirically examined in Section 4.

If worker i has a regular job ($s = 0$), his optimization problem reads

$$\max_{e_{0,i}, d_{0,i}} \ a + xe_{0,i} - d_{0,i} - \frac{1}{2}\theta e_{0,i}^2 + \gamma_i \ln(d_{0,i}).$$

Optimal effort $e_{0,i}^* \geq 0$ and optimal donations $d_{0,i}^* \geq 0$, are found by simultaneously

[6] Volunteering is another important way to serve the public interest. We abstract from volunteering in our analysis, because volunteering can have meaningful private returns in the labor market as well, see e.g. the field-experimental evidence in Baert and Vujić (2016) and the references therein. Yeomans and Al-Ubaydli (2016) study the relation between volunteering for and making charitable donations to the same non-profit firm and find some evidence for substitutability.

[7] For example, Burgess and Metcalfe (1999) report that incentive pay is more prevalent in private sector jobs than in public sector jobs. Likewise, in the education industry, pay is generally based on experience and academic degrees and not on effort or performance, see e.g. Podgursky (2007).

solving the following first-order conditions:

$$\frac{\partial U(\cdot)}{\partial e_{0,i}} = x - \theta e^*_{0,i} = 0,$$

$$\frac{\partial U(\cdot)}{\partial d_{0,i}} = -1 + \frac{\gamma_i}{d^*_{0,i}} = 0,$$

which results in:

$$e^*_{0,i} = \frac{x}{\theta}, \tag{3.1}$$

$$d^*_{0,i} = \gamma_i. \tag{3.2}$$

Hence, workers with a regular job all exert the same level of effort, independent of their altruistic preferences. Altruistic workers with a regular job donate a part of their income to charity, and the more so the stronger their altruistic preferences. Selfish workers (those with $\gamma_i = 0$) would like to extract money from charities ($d^*_{0,i} < 0$), but the non-negativity constraint naturally prevents this, and so their donations equal zero.

If worker i has a public service job, his optimization problem reads

$$\max_{e_{1,i},d_{1,i}} \; z - d_{1,i} - \frac{1}{2}\theta e^2_{1,i} + \gamma_i \ln(d_{1,i} + \beta_1 e_{1,i}) + \varepsilon_i.$$

Optimal effort $e^*_{1,i} \geq 0$ and optimal charitable donations $d^*_{1,i} \geq 0$ are found by simultaneously solving the first-order conditions:

$$\frac{\partial U(\cdot)}{\partial e_{1,i}} = -\theta e^*_{1,i} + \frac{\gamma_i \beta_1}{d^*_{1,i} + \beta_1 e^*_{1,i}} = 0,$$

$$\frac{\partial U(\cdot)}{\partial d_{1,i}} = -1 + \frac{\gamma_i}{d^*_{1,i} + \beta_1 e^*_{1,i}} = 0,$$

which gives after solving:

$$\text{if } \gamma_i \leq \frac{\beta_1^2}{\theta} \Rightarrow e^*_{1,i} = \sqrt{\frac{\gamma_i}{\theta}} \text{ and } d^*_{1,i} = 0; \tag{3.3}$$

$$\text{if } \gamma_i > \frac{\beta_1^2}{\theta} \Rightarrow e^*_{1,i} = \frac{\beta_1}{\theta} \text{ and } d^*_{1,i} = \gamma_i - \frac{\beta_1^2}{\theta}. \tag{3.4}$$

Clearly, not all of the altruistic workers in a public service job make donations to charity. Those with altruism lower than or equal to β_1^2/θ only exert effort and do not supplement it by making charitable donations. The reason for this is that, up to some point, exerting effort on the job is a less costly way to serve the public interest than making charitable donations. Consequently, workers with relatively low levels of altruism will only make use of this less costly instrument, and the more so, the more altruistic the worker is. When work effort reaches a critical level, making charitable donations becomes the less costly option at the margin. As a result, workers whose altruism is higher than β_1^2/θ use both effort and donations to serve the public interest. Note that starting at the treshold level of altruism of β_1^2/θ, higher altruism results in an increase in donations, while effort remains the same. Thus, as compared to models where people can only serve the public interest through on-the-job effort, we find that adding the option to make charitable donations truncates effort for public service jobs. Note that the level at which effort is truncated critically depends on the effectiveness of effort as compared to that of charitable donations, as measured by β_1. Clearly, when on-the-job effort is more effective in raising the well-being of others, effort plays a bigger role at the expense of charitable donations. Lastly, note that (3.2), (3.3), and (3.4) imply that, for a given altruism, a worker's charitable donations are always higher when holding a regular job as compared to holding a public service job. The reverse holds, however, for total contributions to the public interest $(d + \beta e)$ for workers with altruism smaller than β_1^2/θ. The intuition is that workers with a public service job can contribute to the public interest at a lower cost, and hence contribute more. For workers with altruism equal to or higher than β_1^2/θ, total contributions are similar across job types for a given level of altruism. The reason is that, for those workers, the marginal costs of charitable donations drives their total contribution, which is independent of job type.

The choices that workers make are depicted in Figure 3.1.

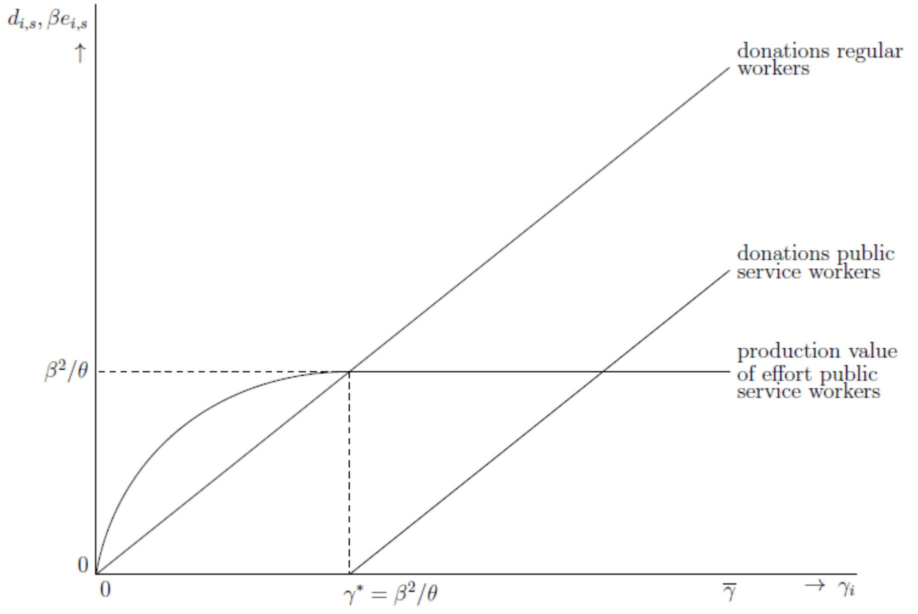

Figure 3.1: Contributions to the public interest by regular and public service workers for all levels of worker's altruism γ_i.

In Section 4, we will empirically examine the following predictions regarding worker's charitable donations:

Prediction 1: For a given job, charitable donations (weakly) increase in a worker's altruism.

Prediction 2: For a given worker's altruism, charitable donations are higher when holding a regular job as compared to when holding a public service job.

We shall examine whether these predictions find support in the data, with and without controlling for worker's income in the regressions.

Now that we have analyzed the behavior of workers in a given job type, we examine which worker types sort into which job type. Substituting (3.1) and (3.2) into the utility function gives, after some rewriting, the utility derived from taking a regular job:

$$U_i(d_{0,i}, e_{0,i}) = a + \frac{x^2}{2\theta} - \gamma_i + \gamma_i \ln(\gamma_i).$$

Workers taking a public service job attain utility:

$$\begin{aligned} U_i(d_{1,i}, e_{1,i}) &= z - \frac{\gamma_i}{2} + \gamma_i \ln(\beta_1 \sqrt{\frac{\gamma_i}{\theta}}) + \varepsilon_i \text{ when } \gamma_i \leq \frac{\beta_1^2}{\theta}; \\ U_i(d_{1,i}, e_{1,i}) &= z + \frac{\beta_1^2}{2\theta} - \gamma_i + \gamma_i \ln(\gamma_i) + \varepsilon_i \text{ when } \gamma_i > \frac{\beta_1^2}{\theta}, \end{aligned}$$

which follows from substituting (3.3) and (3.4) into the utility function. Comparing the utilities attained in a regular and public service job, it follows that workers with $\gamma_i \leq \beta_1^2/\theta$ choose a public service job if:

$$z - a - \frac{1}{2}\frac{x^2}{\theta} + \frac{1}{2}\gamma_i + \gamma_i \ln\left(\beta_1 \sqrt{\frac{\gamma_i}{\theta}}\right) - \gamma_i \ln(\gamma_i) \ + \varepsilon_i \geq 0. \tag{3.5}$$

There is an interior solution for any possible γ-type if $\overline{\varepsilon}$ is sufficiently large and $\underline{\varepsilon}$ is sufficiently low. It is also straightforward to derive that the left-hand side of the inequality increases with γ_i. Hence, for workers whose altruism is smaller than or equal to β_1^2/θ, it holds that those with stronger altruistic preferences are more likely to choose a public service job. The intuition is that a public service job offers an opportunity to serve the public interest at a relatively low cost, which is more attractive for workers with stronger altruistic preferences as they make more use of it. For workers with $\gamma_i > \beta_1^2/\theta$, we find that they prefer a public service job if:

$$z - a + \frac{\beta_1^2}{2\theta} - \frac{x^2}{2\theta} + \varepsilon_i \geq 0. \tag{3.6}$$

Hence, for these highly altruistic workers, the attractiveness of a public service job does not increase with the worker's altruism. The reason is that all workers within this group use the opportunity to serve the public interest on the job to the same extent, see equation (3.4) above. Hence, the probability of choosing a public service job does not further increase with altruism starting at $\gamma_i = \beta_1^2/\theta$.

The preferences for job type are depicted in Figure 3.2.

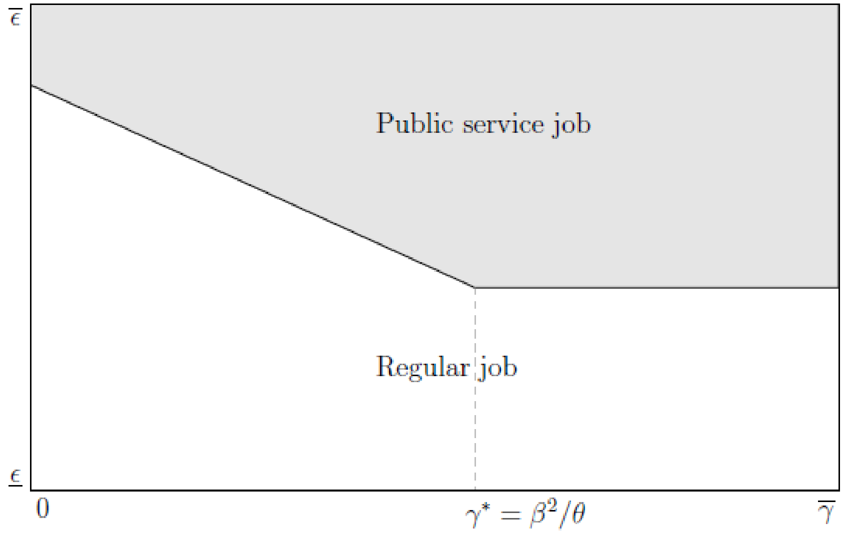

Figure 3.2: Worker's choice of job type

In equilibrium, the wage for public service jobs z will be such that supply of and demand for services are equal:

$$\int_{0}^{\gamma^*}\int_{\varepsilon(\gamma)}^{\overline{\varepsilon}} \sqrt{\frac{\gamma_i}{\theta}} f(\varepsilon,\gamma) d\varepsilon d\gamma + \int_{\gamma^*}^{\overline{\gamma}}\int_{\varepsilon(\gamma^*)}^{\overline{\varepsilon}} \frac{\beta_1}{\theta} f(\varepsilon,\gamma) d\varepsilon d\gamma = D$$

where $\varepsilon(\gamma)$ is the relation resulting from condition (3.5) holding with equality, $f(\varepsilon,\gamma)$ is the probability density function, and D represents the demand for public services measured in units of effort (which may well depend on the cost per unit, but is assumed to be constant here for convenience). Without loss of generality, we assume a mass of workers equal to unity. Note that when z goes up, $\varepsilon(\gamma)$ goes down, implying an increase in supply.

The prediction that will be studied in the next sections resulting from the analysis of job choice above is:

Prediction 3: Workers who are more altruistic are (weakly) more likely to choose a public service job.

3.3 Data and empirical strategy

We use data from the German Socio-Economic Panel Study (SOEP).[8] The SOEP is an unbalanced panel which contains survey questions about employment, earnings, preferences, and personality measures among others (see Wagner et al. 2007). Our key variables of interest are self-reported monetary donations to charity, altruistic preferences, and job type or sector of employment. We measure charitable donations by the response to the question: "Did you donate money last year (not counting membership fees)?"[9] The respondents who answered this question with "yes" were subsequently asked how much money they donated in total. Following Becker et al. (2012) and Dur and Zoutenbier (2015), we measure altruistic preferences by the respondent's answer to the question: "How important are the following things [being there for others] currently for you?" Answers are given on a four point scale, ranging from "not at all important" to "very important". Finally, we allow for two distinct definitions of what regular and public service jobs are. We start with defining public service jobs as jobs in the public sector and regular jobs as jobs in the private sector.[10] Next, we define public service jobs as jobs in certain industries (health, sport and education, and public administration) and regular jobs as jobs in the remaining industries. We exclude all people without a job from our sample.

One may be sceptical about the reliability of the questionnaire data we use, particularly about the self-reported altruistic preferences and donations. For instance, it might well be that people paint a too rosy picture of their altruistic preferences and their generosity. Even worse, such misrepresentation may correlate with job type. Recent findings from an incentivized experiment by Abeler et al. (2014), however, suggest that we should not be too sceptical about self-reported data. They find among a representative sample of the German population that participants forego considerable amounts of money to avoid lying.[11] Moreover, lying appears to

[8] Detailed information about the SOEP can be found at http://www.diw.de/en/soep.

[9] In the questionnaire, it is further stated that "We understand donations here as giving money for social, church, cultural, community, and charitable aims, without receiving any direct compensation in return. These donations can be large sums of money but also smaller sums, for example, the change one puts into a collection box. We also count church offerings."

[10] It is not possible to distinguish between for-profit and not-for-profit employers in the private sector. This likely results in a downward bias in our estimates.

[11] See also Abeler et al. (2016) who use data from 72 experimental studies and find that people

be uncorrelated with sector of employment (personal communication with Johannes Abeler). Relatedly, Falk et al. (2016) examine the predictive power of survey questions for incentivized choices and find a sizeable correlation of 0.4 between stated and revealed willingness to donate part of a windfall gain to a charity.

We restrict our analysis to the year 2010, because this is the only year in which the question about charitable donations is included in the survey. The question that measures a respondent's altruism is taken from the 2008 wave, which is the most recent wave that includes this question. We have a sample of 7,527 respondents of which 26.2% is employed in the public sector and the remaining 73.8% is employed in the private sector (the corresponding figures for the alternative definition of a public service job are 33.0% and 67.0%).

To examine whether there is support for our predictions, we run an ordinary least squares (OLS) regression with money donations to charity as the dependent variable.[12] Our main specification is:

$$C = \alpha + \beta \cdot A + \psi \cdot S + \kappa \cdot I + \phi \cdot X + \eta,$$

where C is the amount of charitable donations, A is a worker's self-reported altruism, S is a dummy variable that equals one if a worker has a public service job, I is worker's income, X is a vector of other control variables, and η is the residual. In line with theoretical predictions 1 and 2, we expect that an increase in altruism leads to an increase in donations ($\beta > 0$) and that, for a given altruism, having a public service job instead of a regular job decreases donations ($\psi < 0$). While our theoretical model abstracts from income effects, we allow for those in the empirical analysis by including the worker's income. To examine theoretical prediction 3 regarding the altruism of workers with a public service job, we estimate the following regression equation:

$$S = \delta + \mu \cdot A + \lambda \cdot Z + \omega,$$

where S is a dummy variable equal to one if the worker has a public service job, A is

lie surprisingly little.

[12] As a robustness check, we also estimated a tobit model and a negative binomial regression model, and found very noisy estimates with those models.

the worker's altruism, Z is a vector of other control variables, and ω is the residual. In line with theoretical prediction 3 we expect that workers' probability to sort into a public service job increases in altruism ($\mu > 0$). The specification we estimate is identical to Dur and Zoutenbier (2015) who study the same issue using an earlier wave of the German Socio-Economic Panel.

In Table 3.1 we display the descriptive statistics of our sample. Since in most of our empirical analysis we compare public sector workers with private sector workers, we distinguish between these two in the descriptive statistics as well. There are several striking differences between public and private sector workers. For instance, the average donation made by public sector workers is 121.95 euros, while private sector workers on average donate 107.37 euros. There is quite a bit of variation in donations in both sectors. Public sector workers report to be more altruistic than private sector workers, though the difference in the average is small. Furthermore, public sector workers are on average older, are more often female, and are much higher educated than private sector workers. Also, public sector workers earn on average a higher yearly income, while the standard deviation of their income is much lower than the standard deviation of incomes in the private sector.

Table 3.2 shows the correlations between our variables of interest. Charitable donations and altruism are positively correlated and the same is true for charitable donations and public sector employment and for altruism and public sector employment. Figure 3.3 plots the average charitable donations by sector of employment and altruism. Charitable donations tend to increase with a worker's altruism. Moreover, it turns out that, for a given altruism, public sector workers on average donate more than private sector workers.[13] While this runs counter to our theoretical predictions, we should keep in mind that these are raw correlations, which do not control for important heterogeneity between public and private sector employees, among others in education, gender, and income. To control for these, we now turn to regression analysis.

[13]None of the respondents in the lowest altruism category (those who state that they find it not important at all to be there for others) donate any money to charity. Hence the lack of bars for this category in Figure 3.

Table 3.1: Descriptive Statistics

	Total	Public (26,2%)	Private(73.8%)
Donations: mean	111.20	121.95	107.37
standard deviation	522.26	411.40	556.38
Altruism (1): %	0.2	0.2	0.2
Altruism (2): %	6.6	5.2	7.1
Altruism (3): %	68.9	69.1	68.9
Altruism (4): %	24.3	25.5	23.8
Altruism: mean	3.17	3.20	3.16
standard deviation	0.54	0.53	0.54
Age: mean	45.5	46.4	45.2
standard deviation	11.1	10.8	11.2
Female: %	48.8	56.3	46.1
Yearly income: mean	21287.17	23077.86	20650.17
standard deviation	17324.48	12535.22	18694.91
Nr. of children in HH: mean	0.55	0.50	0.57
standard deviation	0.87	0.84	0.88
Married: %	64.2	64.5	64.1
Single: %	22.2	20.8	22.7
Widowed: %	1.6	1.5	1.7
Divorced: %	9.8	10.9	9.4
Separated: %	2.2	2.3	2.1
Education: less than HS: %	7.1	5.5	7.7
Education: HS: %	63.0	47.3	68.6
Education: more than HS: %	29.9	47.2	23.7
Tenure: mean	12.4	15.7	11.2
standard deviation	10.6	11.7	9.9
Religion: other religion: %	0.3	0.3	0.2
Islamic: %	1.8	1.0	2.1
Protestant: %	30.9	33.3	30.1
Catholic: %	28.0	30.2	27.3
Other christian: %	1.9	1.5	2.0
Not religious: %	37.1	33.7	38.3
Observations	7527	1975	5552

Table 3.2: Correlations

	1	2	3	4	5	6	7	8	9	10	11
1.Donation	1,000										
2.Public sector	0.012	1,000									
3.Altruism	0.023**	0.029**	1,000								
4.Age	0.118***	0.049***	-0.137***	1,000							
5.No. of children in HH	0.005	-0.034***	0.076***	-0.231***	1,000						
6.Female	-0.061***	0.089***	0.177***	-0.034***	-0.040***	1,000					
7.Income	0.378***	0.062***	-0.066***	0.154***	0.032***	-0.338***	1,000				
8.Marital Status	-0.037**	0.012	-0.005	-0.053***	-0.191***	0.067***	-0.050***	1,000			
9.Education	0.145***	0.202***	0.019*	0.088***	0.001	-0.043***	0.324***	-0.018	1,000		
10.Religion	-0.065***	-0.016	-0.062***	0.037**	-0.121***	-0.035***	0.057***	0.077***	0.070***	1,000	
11.Tenure in years	0.084***	0.186***	-0.085***	0.502***	-0.139***	0.113***	0.260***	-0.072***	0.056***	0.005	1,000

Note: correlations are calculated using 7527 observations; *,**,*** indicate significance at the 0.10, 0.05, 0.01 level, respectively.

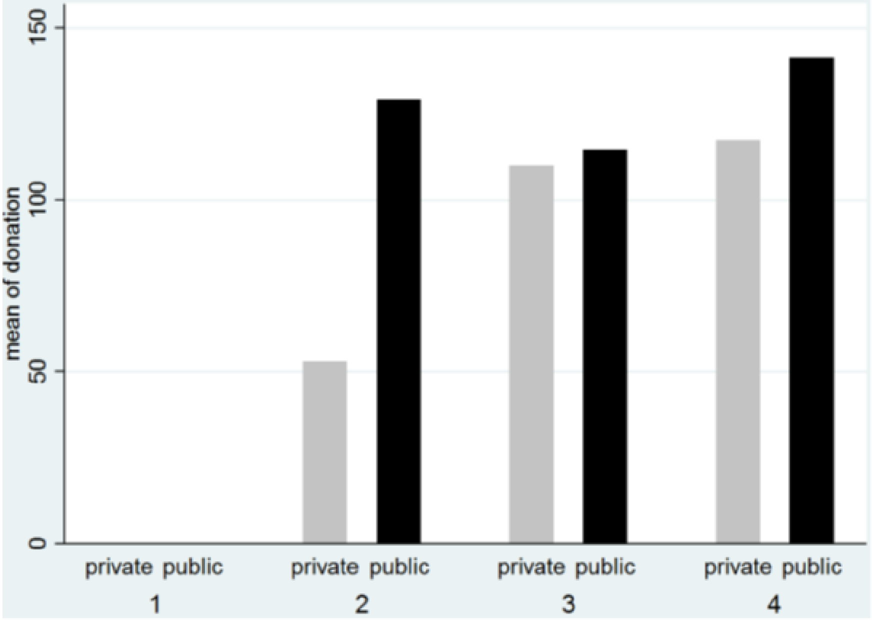

Figure 3.3: Mean of donations by altruism category and sector of employment.
1, 2, 3, 4 refer to the respondents' answers to the question: "How important are the following things [being there for others] currently for you?" Answers are given on a four point scale, ranging from "not at all important" (1) to "very important" (4).

3.4 Results

Table 3.3 reports the results of regressing charitable donations (measured in euros) on a worker's altruism, sector of employment, and a rich set of demographics. We include altruism in the most flexible manner, i.e. we take up three dummies for altruism categories 1, 2, and 4, while category 3 –workers who answered they find it "important" to be there for others– forms the baseline category. We find evidence in line with predictions 1 and 2. That is, charitable donations increase with self-reported altruism and, for a given level of altruism, public sector workers donate significantly less than private sector workers. The difference is 32.51 euro, which is close to 30% of mean donations. The second column of Table 3.3 adds the worker's income as a control in a very flexible manner by taking up 10 dummies for income categories. The estimates show a positive convex relation between donations and income. More importantly, controlling for income moves the coefficient for public sector employment close to zero. Clearly, without controlling for income, the public sector dummy picked up that workers in the public sector make smaller donations because they earn less than comparable others in the private sector. The coefficient for the lowest altruism category also moves quite a bit, though we should keep in mind the very small number of observations in this category (see Table 3.1), implying imprecise estimates. Many of the other control variables have the same sign and are of similar size as compared to earlier studies. For example, highly educated workers donate more than lower educated workers (cf. Bekker and Wiepking 2011), though the difference decreases with almost 40 percent when controlling for income. Contrary to earlier studies, we don't find that females donate more than males (cf. Mesch et al. 2006). However, we should keep in mind that, in contrast to earlier studies, our regressions control for self-reported altruism, which is strongly positively correlated with gender (see Table 3.2).

Table 3.4 shows the same regressions using a different definition of a public service job, namely jobs in the health industry, sport and education industry, and public administration.[14] The results are qualitatively the same, even though the coefficient for public service job is smaller and far from significant even when we do not control for income.

[14]The other industries are: Agriculture, Fisheries, Energy/Water, Mining, Chemicals, Synthetics, Earth/Clay/Stone, Iron/Steel, Mechanical Engineering, Electiral Engineering, Wood/Paper/Print, Clothing, Food, Construction, Wholesale, Trading Agents, Retail, Train System, Postal System, Other transport, Financial Institutions, Insurance, Restaurants, Service Industries, Trash Removal, Legal Services, Other Services, Church, Private Household.

Table 3.3: OLS regression comparing public and private sector workers.

Dependent variable: Donations		
Public Sector	-32.51**	-1.57
	(14.08)	(13.52)
Altruism (1)	-117.85	-81.55
	(123.72)	(117.47)
Altruism (2)	-56.91**	-58.86***
	(24.02)	(22.81)
Altruism (4)	29.88**	27.36**
	(14.12)	(13.40)
Age	-13.68***	-13.43***
	(3.94)	(3.81)
Age*Age	0.21***	0.20***
	(0.04)	(0.04)
No. of children in HH	25.13***	16.35**
	(7.94)	(7.60)
Female	-52.30***	-14.26
	(12.24)	(12.90)
Education: HS	30.77	24.02
	(23.63)	(22.50)
Education: More than HS	195.88***	118.90***
	(25.17)	(24.79)
Tenure in years	1.60**	0.67
	(0.66)	(0.66)
Constant	430.23***	425.80***
	(152.51)	(145.10)
Control for Income	NO	YES
Control for marital status	YES	YES
Control for religion	YES	YES
Observations	7527	7527

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10. Baseline category Altruism:3, Education: Less than High school. Income is included using 10 dummies for income categories with a range of 10,000, i.e. [0-10,000]; [10,001-20,000]; ... ;[100,001 and higher].

Table 3.4: OLS comparing public service industries with the other industries.

Dependent variable: Donations		
Public Service	-13.72	-1.11
	(12.88)	(12.34)
Altruism (1)	-117.38	-83.71
	(121.00)	(115.66)
Altruism (2)	-51.11**	-54.08**
	(23.04)	(22.03)
Altruism (4)	32.53**	29.70**
	(13.54)	(12.94)
Age	-17.58***	-17.29***
	(3.81)	(3.70)
Age*Age	0.26***	0.24***
	(0.04)	(0.04)
No. of children in HH	27.05***	18.26**
	(7.63)	(7.35)
Female	-49.58***	-11.66
	(12.04)	(12.69)
Education: HS	33.83	25.61
	(22.74)	(21.80)
Education: More than HS	185.73***	113.97***
	(24.38)	(24.19)
Tenure in years	1.47**	0.70
	(0.62)	(0.63)
Constant	468.98***	476.22***
	(148.71)	(142.46)
Control for Income	NO	YES
Control for marital status	YES	YES
Control for religion	YES	YES
Observations	7348	7348

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10. Baseline category Altruism:3, Education: Less than High school. Income is included using 10 dummies for income categories with a range of 10,000, i.e. [0-10,000]; [10,001-20,000]; ... ;[100,001 and higher].

All our results so far are based on the full sample of workers. Motivated by Lewis and Frank (2002), Buurman et al. (2012), and Dur and Zoutenbier (2015) we replicated our results using a subsample of highly educated workers. The main reason for this is that it might be that highly educated workers have more on-the-job opportunities to serve the public interest than less educated workers. Our results are in line with this. We find that for the subsample of highly educated workers, working in the public sector goes hand in hand with a bigger drop in charitable donations, which remains substantial (but loses significance) even when we control for income.

Lastly, we examine selection into type of job. Table 3.5 reports the results of a linear probability model similar to Dur and Zoutenbier (2015), where the dependent variable in column 1 is employment in the public sector whereas the dependent variable in column 2 is holding a job in health, education, or public administration. In addition to altruism and the usual demographics, we follow Dur and Zoutenbier by including two other self-reported preference measures: laziness and risk aversion. In line with prediction 3, we find in column 1 that workers with stronger altruistic preferences are more likely to end up in the public sector, though the coefficient is marginally insignificant (p=0.104). We find a much higher and significant estimate when employing the alternative definition of a public service job, see column 2. For each point increase on the altruism scale, the likelihood of employment in health, education, or public administration increases by 3.3 percentage points, which is sizeable given the average likelihood of having such a job of 33.0%. These results as well as the other coefficients are well in line with Dur and Zoutenbier (2015), who used an earlier wave of the German Socio-Economic Panel. It is worth noting that the coefficient for the worker's laziness is marginally insignificant (p=0.109 and p=0.105, respectively).

Table 3.5: Linear probability model of selection of workers

Dependent variable:	**Public sector**	**Public service**
Altruism	0.015	0.033***
	(0.009)	(0.010)
Laziness	0.005	0.006
	(0.003)	(0.003)
Risk aversion	0.011***	0.008***
	(0.002)	(0.002)
Age	0.007**	-0.004
	(0.003)	(0.003)
Age*Age	0.000**	0.000
	(0.000)	(0.000)
Female	0.069***	0.213***
	(0.010)	(0.011)
German nationality	0.082***	0.076***
	(0.026)	(0.027)
No. of children in HH	-0.019***	-0.007
	(0.007)	(0.007)
Education: HS	-0.015	0.033
	(0.020)	(0.021)
Education: More than HS	0.205***	0.301***
	(0.021)	(0.022)
Constant	-0.132	0.047
	(0.094)	(0.099)
Control for marital status	YES	YES
Control for region	YES	YES
Observations	7470	7240

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Baseline category Altruism:3, Education: Less than High school.

3.5 Concluding remarks

We have studied the role of a worker's altruistic preferences in occupational choice, on-the-job effort provision, and donations to charity. We developed a simple model producing three key predictions: 1) Given job type, workers with stronger altruistic preferences make higher donations to charity; 2) Given a worker's altruism, those working in a public service job donate less than workers in a regular job; and 3) Workers with stronger altruistic preferences are more likely to take a public service job. We examined data from the German Socio-Economic Panel Study – which contains rich data on (self-reported) altruism, charitable donations, and job type – and found support for our predictions, though some results are sensitive to the exact definition of a public service job or the estimation method. Our analysis implies that we should be careful with using charitable donations as a proxy for altruistic preferences in studies that compare workers in different sectors. Indeed, our theory predicts and the evidence indicates that workers in public service jobs are more altruistic, and yet make smaller donations to charity than their empirical counterparts in regular jobs. The reason suggested by our theory is a simple substitution argument: Since workers in public service jobs serve the public interest on the job, they are less inclined to make substantial charitable donations.

In our theoretical model, workers differed not only in altruism, but also in their preference for other job (dis)amenities specific to public service jobs, such as job protection or flexible working hours. In future work, we wish to study how the provision of these (dis)amenities affects the self-selection of worker types to public service jobs. Regarding empirical work, it would be interesting to follow workers over time, in particular when they switch job types for plausibly exogenous reasons, or experience a change in the mission of the organization they work for (as in Zoutenbier 2016). The release of the next wave of the SOEP may provide opportunities to do so. The lab may also provide a useful test bed for more directly testing the substitutability between on-the-job contributions to society and charitable donations (see e.g. Gerhards 2015, Banuri and Keefer 2016, Cassar 2016b, and Carpenter and Gong 2016).

Chapter 4

Increasing the Well-being of Others On-the-job and Outside the Workplace

4.1 Introduction

Recently there has been an increase in the demand for volunteers. For example, the refugee crisis in Europe has let charitable organizations to call for more support in the form of donations and volunteering.[1] It is important to learn what drives peoples' giving behavior, in order to target and attract volunteers. For instance, is it a good idea to try and recruit people who in their day-to-day work life are involved with helping others, or is it better to focus recruitment resources on people who lack opportunities to help on-the-job?

In this paper we explore the relationship between workers' opportunities to help others on-the-job and volunteering behavior outside the workplace. Following Dur and Van Lent (2016) we predict that helping people on-the-job and outside the workplace are substitutes. If workers have more opportunities to help others in public sector jobs than in private sector jobs, then workers who switch from the public to the

[1] The Red Cross in the UK has e.g. started a project which is intended to attract volunteers especially to offer refugees help during the current refugee crisis in Europe (see: http://www.redcross.org.uk/What-we-do/Refugee-support).

private sector are expected to decrease their contributions to others on-the-job, and hence will by a substitution argument increase their charitable contributions outside work. Workers who switch in the opposite direction are expected to decrease their charitable contributions. To test this prediction we estimate the effect of a change in sector of employment on volunteering using rich data from the Dutch LISS Panel.

The LISS Panel consists of approximately 8,000 individuals and covers the years 2008 to 2016. The questionnaire contains detailed questions on leisure, work, schooling, personality, and politics, which allow us to test our prediction. The key question we use as a proxy for charitable behavior is "Considered all together, how much time do you spend on voluntary work per week, on average".

Workers' motivations to switch jobs may not be exogenous to their willingness to volunteer. For example, workers who switch from sector of employment may be different from other workers in many aspects. Therefore in addition to our focus on job switchers, we also analyze a plausibly exogenous change in workers' ability to help others on-the-job, by studying a change in the match of mission preferences of government workers.

Following Zoutenbier (2016), government workers are assumed to have a match in mission preferences when they voted for one of the political parties that is in office. The preferences are classified as a mismatch if the worker has voted for a political party that is not in office. We expect that government workers who have a mission match with their employer feel that they have more opportunities to help others at their work than government workers who do not have a match of mission preferences. Hence, because of a substitution argument, we predict that government workers who share the mission of their employer volunteer less than government workers who do not share the mission. The LISS Panel contains data covering three government coalition periods, and hence we observe two changes in the composition of the parties that are in office.[2] We are therefore able to rely on within worker variation in mission preferences.

Our main findings are the following. First, workers who switch from sector of employment do not change their time spent on voluntary work significantly, although

[2]Note that the Netherlands has a government in office that usually consists of multiple political parties, but an individual can vote for only one political party.

the coefficients always have the expected sign. That is, workers who switch from a private sector job to a public sector job (insignificantly) decrease their time spent volunteering, while workers who switch in the opposite direction (insignificanty) increase their time spent on voluntary work. Second, we find that government workers who voted for one of the political parties that is in office, and hence are more able to help others on-the-job, decrease their volunteering by 15 minutes per week on average which is in line with our prediction.

One obvious reason for people to volunteer is in order to help others. However, there can be other reasons for workers to volunteer. One potentially important alternative motivation to volunteer is to increase job perspectives. For instance, because a worker obtains skills through volunteering that are useful in the labor market, or because volunteering gives the employer a positive signal about the worker's personality, see for example Baert and Vujić (2016). One may expect the benefits of volunteering for career enhancement to be larger in the beginning of a worker's career, since in this phase other signals about the worker's ability and personality are more scarce. Hence, in order to reduce the channel of career concerns as a reason to volunteer, we estimate our specification also for the subsample of more experienced workers (i.e. the workers for whom we expect career perspectives to be less of a reason to volunteer).

Using the subsample of workers that are over 40 years of age we find significant and stronger effects than for the full sample. These experienced workers who switch from the private to the public sector decrease their time spent volunteering by on average 37 minutes per week. Government workers who are over 40 years of age and previously had a match in mission preferences, but after the national election not anymore, increase their time spent volunteering by on average 23 minutes per week.

This paper is most closely related to Dur and Van Lent (2016). Both papers study the relationship between workers' occupational choice, altruistic preferences, and prosocial behavior outside the workplace. However there are also important differences between both papers. The main differences are the following. This paper explores panel data while Dur and Van Lent use cross sectional data.[3] We study a

[3] One important advantage of panel data is that there is less of a concern for omitted variable bias, since individual fixed effects control for all time invariant factors, observed and unobserved.

sample of Dutch workers, while Dur and Van Lent study German workers. Besides analyzing job switchers, this paper also uses a plausibly exogenous change in workers ability to help others on-the-job by studying changes in the match of mission preferences between government workers and their employer. Finally, we have rich data on time spent volunteering, while Dur and Van Lent (2016) have richer data on money donations to charity. Time donations are different from money donations in several respects. On the one hand, donating time is more personal and may therefore be more closely related to helping others on-the-job than to money donations. On the other hand, workers may also choose to volunteer for other reasons than to help other people, for instance in order to increase career perspectives.

Our research is also related to a body of literature that studies the relationship between workers' time use on activities on-the-job and outside the workplace. Examples are the time spent on physically intensive work on-the-job and outside the workplace (see e.g. Tudor-Locke et al. 2011), time spent on work in the household and paid work (see e.g. Krantz-Kent 2009), and the effect of framing compensation schemes on time spent on-the-job and volunteering (see e.g. DeVoe and Pfeffer 2007). These papers generally find that workers' on-the-job behavior affects their behavior outside work. We contribute to this literature by studying the relation between time spent on helping others on-the-job and outside the workplace.

This paper is also related to a body of literature in economics that studies workers' intrinsic motivation in the workplace. Some theory papers have studied workplace behavior of intrinsically motivated workers, see for example Francois (2000, 2007), Besley and Ghatak (2005, 2016), Prendergast (2007), Brekke and Nyborg (2008), and Delfgaauw and Dur (2008, 2010). An increasing number of empirical papers have tested some of these theoretical predictions, see for example Dur and Zoutenbier (2014, 2015), Zoutenbier (2016), and Carpenter and Gong (2016). Our paper contributes to this literature by empirically testing the relation between workers' opportunities to help others on-the-job and volunteering behavior outside the workplace.

Moreover, there is a literature in public administration that studies whether workers in some sector or jobs are more altruistic than in others. In order to answer this question, researchers often study only peoples charitable behavior outside the workplace, see for example (Brewer 2003, Houston 2006, Rotolo and Wilson 2006, and Lee 2012). Based on our substitution argument, this analysis is flawed and leads to an underestimation of public sector workers' altruistic preferences. For a more extensive discussion of this argument, see Dur and Van Lent (2016).

Finally, this paper is related to a literature that analysis why people with similar characteristics and preferences have different volunteering rates. For example Hackl et al. (2012) study the state's role in influencing workers' decision to volunteer, using data from the European Value Survey and the World Value Survey. They find that volunteering participation rates vary greatly across countries, even after controlling for individual workers' characteristics. The authors explain variation in volunteering by differences in institutional and political factors. We study whether occupational choice leads similar people in terms of preferences to make different volunteering decisions. However we study only workers within one country.

This paper is structured as follows. The next section describes the data and empirical strategy. In the third section we discuss the results, and the fourth and final section contains the conclusion.

4.2 Data and empirical strategy

In this paper we use data from the Longitudinal Internet Studies for the Social sciences (LISS) panel. The LISS panel is an unbalanced panel consisting of approximately 8,000 individuals. Participants are selected through random sampling from the population register by Statistics Netherlands. Individuals complete online questionnaires every month, and are paid for each completed questionnaire. The first wave was conducted in 2008 and the most recent wave was conducted in 2016. The panel includes modules on Social Integration and Leisure, Work and Schooling, Personality, and Politics and Values. Each of these modules are administered once a year. For our analysis we use data from the years 2008 to 2015.

The key variables used for this paper are sector of employment and the number of hours spent on voluntary work on average per week. The sector of employment is measured using the question: "In what type of organization do you work?" The organization types the participant could choose from are: "public or semi-public sector" and "private company". The number of hours spent volunteering are measured by the question: "Considered all together, how much time do you spend on voluntary work per week, on average?".

The econometric specification that we use in order to estimate the effect of a change in job type on volunteering reads:

$$CH_{i,t} = \alpha_i + \beta P_{i,t} + \psi X_{i,t} + \tau_t + \varepsilon_{i,t} \tag{4.1}$$

where $CH_{i,t}$ is charitable behavior outside the job of person i at time period t; α_i is the individual fixed effect; $P_{i,t}$ a dummy variable that equals one if a worker has a public sector job; $X_{i,t}$ is a vector of (time varying) control variables; and τ_t is the time fixed effect. As a measure of charitable giving we use the respondents' average number of hours spent volunteering per week. We estimate time volunteering using Ordinary Least Squares with time and year fixed effects. A disadvantage of using a linear specification for volunteering is that this specification can predict negative values for the number of hours a worker volunteered. Further, this specification does not take into account that many workers spend zero hours per week on average on voluntary work. We have also estimated a fixed effects Poisson specification. A Poisson specification deals in a better way with the large fraction of zeros in the data, and does not allow values to be negative, but a disadvantage of this model is that data should be discrete (i.e. the dependent variable should be count).[4] These results do not differ much from those estimated using OLS and are available upon request. Since we expect that helping others on the job and outside the job are substitutes, we predict that $\beta < 0$.

Since switching jobs is endogenous, we also analyze the effect of a plausibly exogenous change in workers' ability to help others on-the-job on charitable behavior outside work. Following Zoutenbier (2016) we use changes in the composition of the political parties that are in office, and workers' political preferences in order to

[4] To be more precise, we estimate the Poisson specification with robust standard errors. This relaxes the assumption that the conditional mean should equal the conditional variance.

establish workers' mission preferences. For political preferences we used the question: "For which party did you vote in the parliamentary elections of [22 November 2006 / 9 June 2010 / 12 September 2012]?" Participants are considered a match if the political party they voted for in the election is in office in that same time period. When mission preferences match we assume that the ability of government workers to help others is larger than for government workers whose preferences do not match. Note that we focus here on government workers instead of all public sector workers. The reason is that we expect that the effect of the political parties in office on the work that people do is larger for government workers than for other public sector workers.

In order to estimate the effect of a change in mission preferences on charitable behavior (outside the job) we estimate the following equation:

$$CH_{i,t} = \alpha_i + \delta G_{i,t} + \phi M_{i,t} + \gamma (G_{i,t} * M_{i,t}) + \varphi X_{i,t} + \tau_t + \varepsilon_{i,t} \tag{4.2}$$

where $G_{i,t}$ is a dummy that equals one if the worker is employed in the government sector and zero if not employed in the government sector; $M_{i,t}$ is a dummy that equals one if the worker has voted for a political party that is in office and zero if the worker voted for another party. We expect that government workers who voted for one of the political parties that are in office believe they are better able to help others on their job than workers with non-matching preferences. Hence because of the substitution argument we predict that $\gamma < 0$.

Table 4.1 displays the descriptive statistics. Our full sample consists of 21,395 observations of 6,573 individuals, of which 21.3% spent some time volunteering. On average respondents volunteer 58 minutes per week, and 37.9% of the respondents is employed in the public sector.

Table 4.1: Descriptive Statistics

	Total	Public (37.9%)	Private(62.1%)
Volunteering: mean	0.97	1.11	0.89
standard deviation	3.78	4.30	3.43
Volunteering: %	21.3%	23.8%	19.8%
Age: mean	43.00	44.97	41.80
standard deviation	12.05	11.61	12.16
Number of children: mean	1.06	1.01	1.09
standard deviation	1.14	1.15	1.14
Net income: mean	1723.85	1750.21	1707.76
standard deviation	3362.78	2987.31	3572.66
Hours at work: mean	30.22	29.20	30.85
standard deviation	14.52	13.15	15.25
Distance: mean	26.57	27.27	26.14
standard deviation	22.03	21.39	22.41
Tenure: mean	11.36	13.48	10.07
standard deviation	10.49	11.15	9.84
Observations	21395	8110	13285
Number of individuals	6573	2483	4387

Comparing charitable behavior of workers between sectors, we see that public sector workers on average perform more voluntary work. Further, workers in the public sector are older, have less children, and work less hours. Since the coefficient for the public sector dummy in our specification is identified by those people who switch from the public to the private sector or vice versa, it is interesting to learn how often respondents switch between sectors. Of the 6,573 individuals, 463 switch at least once from sector of employment between 2008 en 2015 (i.e. 7.0% of the respondents in the sample).

Finally, one worry may be that workers' ability to change their time spent on voluntary work is limited (e.g. because people are habitual or because many volunteering activities require commitment for a long time). From the data we see that in our sample the within-worker variation of time spent volunteering is 2.23 hours, compared to the between-worker variation of 3.94 hours. Hence, although the within-worker variation is less than the between variation we expect that the within-worker variation is enough to be able to expect workers' job choice and behavior to affect volunteering behavior.

4.3 Results

4.3.1 Job switchers and charitable behavior

Table 4.2 shows the estimation of equation (4.1) using Ordinary Least Squares with individual and time fixed effects. We cluster standard errors at the individual level to correct for correlation of the error term for individuals over time. The first column displays the effect of sector of employment on time spent on voluntary work without control variables. We find that workers who switch from the private to the public (public to the private) sector decrease (increase) their volunteering by 9 minutes on average per week, but this effect is highly insignificant.

Table 4.2: Fixed effects Ordinary Least Squares

Dependent variable: Volunteering		
Public sector	-0.150	-0.128
	(0.215)	(0.212)
Hours at work		-0.005**
		(0.002)
Net income		-0.000
		(0.000)
Distance		-0.003
		(0.004)
Tenure		-0.011
		(0.008)
Individual and time fixed effects	YES	YES
Observations	21395	21395
Number of individuals	6573	6573

Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.10.
Standard errors are clustered on the individual level.

In the second column we add job characteristics that vary over time and are expected to be important to control for.[5] The job characteristics we include are the actual average hours worked per week and the distance from home to work in minutes, since we expect these characteristics to differ over time and have a direct impact on the ability to spend time volunteering. Further, we include income because income can be used to help others by making money donations, which may influence workers willingness to volunteer (see Andreoni et al. 1996, and more recently Feldman 2010). Another reason to include income as a control variable is because paying taxes over one's income can, by some people, also be seen as a donation to society. Finally we include tenure on-the-job, since workers can also switch jobs within sector, and a new work environment in itself can have an effect

[5]Note that we only need to consider time varying variables as controls, since variables that are time invariant are already taken up by the individual fixed effect, and are thereby already controlled for. Control variables as education or marital status are also not included here, since they hardly vary for the workers in the sample period.

on volunteering. If we compare the first column of Table 4.2 with the second, we see that the additional control variables do not change the result much. The coefficient changes from -0.150 to -0.128 and remains highly insignificant. We see that most control variables are individually insignificant, with hours at work as the exception.[6] The relation between hours at work and volunteering is negative, as expected.

We can also analyze whether job choice has an effect on the decision to volunteer, i.e. the extensive instead of the intensive margin. We estimate a Binary Logit specification, with the dependent variable equal to one if the worker has volunteered, and equal to zero if the worker has not volunteered. We find that there is also no significant effect on the extensive margin. The results are available upon request.

Many empirical papers that attempt to compare jobs in which workers have plenty of opportunities to help others with jobs that offer less of these opportunities compare jobs in the public sector with jobs in the private sector. Other papers compare jobs in different industries. Hence, we also estimate equation (4.1) comparing workers in different industries. We define a public service job (i.e. a job that offers plenty of opportunities to help others) as a job in the Education, Government, Healthcare and Welfare industry, or Environmental Services, and the other job types as regular jobs.[7] We report the results in Table 4.3. The public service dummy is negative as predicted but again highly insignificant.

[6] Comparing the model with and without time varying controls we find that the null hypothesis that the coefficients of the added control variables all equal zero is rejected.

[7] The remaining industries include: agriculture forestry fishery hunting, mining, industrrial production, utilities production distribution or trade, construction, retail trade, catering, transport storage and communication, financial, business services, environmental services, culture, and other services.

Table 4.3: Fixed effects Ordinary Least Squares

Dependent variable: Volunteering		
Public service	-0.099	-0.085
	(0.233)	(0.229)
Hours at work		-0.004*
		(0.002)
Net income		-0.000
		(0.000)
Distance		-0.004
		(0.003)
Tenure		-0.009
		(0.006)
Individual and time fixed effects	YES	YES
Observations	22896	22896
Number of individuals	7027	7027

Standard errors in parenthese, *** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Standard errors are clustered on the individual level.

All the variation in the public sector dummy stems from those workers who switch between sectors. It is not unlikely that workers who switch from the public to the private sector (or vice versa) are inherently different from those workers that do not switch. If this is the case it may be worthwhile to look at those workers who switch from sector of employment at least once during the sample period. In Table 4.4 we compare the descriptive statistics of the workers who switch at least once, with the workers that never switch. We see that workers who switch at least once volunteer more hours, work less hours, live further away from their job, and have a lower income. Also more workers switch from the public sector to the private sector than vice versa. Since workers that switch from sector of employment are so different from those that do not switch, it may be the case that the difference in charitable behavior for switchers is now partly captured by the control variables. If we estimate equation (4.1) for the sample of job switchers we get qualitatively similar results as for the full sample. The results are available upon request.

Table 4.4: Descriptive Statistics

	Total	Switchers (7.0%)
Volunteering: mean	0.97	1.19
standard deviation	3.78	3.90
Volunteering: %	21.3%	22.2%
Age: mean	43.00	38.05
standard deviation	12.05	13.33
Number of children: mean	1.06	1.07
standard deviation	1.14	1.19
Net income: mean	1723.85	1388.26
standard deviation	3362.78	1032.66
Hours at work: mean	30.22	27.32
standard deviation	14.52	14.19
Distance: mean	26.57	28.25
standard deviation	22.03	22.89
Tenure: mean	11.36	5.85
standard deviation	10.49	7.59
Observations	21395	1735
Number of individuals	6573	463

Switching sector of employment may be endogenous to charitable giving outside work. Workers for example can decide to switch jobs because they anticipate that they want to help others more in the future. If this, or something else that is directly related to charitable behavior, is the reason for a switch in sector of employment, our results would be biased.[8] In order to reduce the probability that workers switch

[8]But there are many other reasons why workers switch jobs that are likely to be more important

for reasons that are related to charitable giving, we ideally want to look at people who have to switch jobs for reasons that are exogenous to volunteering.

In the questionnaire respondents are asked whether and why they are looking for a new job. One possible answer category is that the respondent is looking for a new job because he or she is uncertain whether their current job will continue to exist. Some respondents switched from sector of employment the year after they said that they were looking for a new job because they were uncertain whether their job would continue to exist. For those workers we are more certain that they are not switching jobs because they want to have a better opportunity to help others. Hence we also estimate equation (4.1) including these workers only. We find no significant effect of a change in sector of employment on charitable behavior. However, a reason for the insignificant coefficient may be that the sample size is too small.[9]

Stability of altruistic preferences

In the models we estimated so far we did not include altruism as a control variable. The reason is that in most of the literature altruism is assumed to be an individual characteristic that is stable over time. By using individual fixed effects we then automatically control for workers' altruistic preferences. However, it may be the case that workers' altruistic preferences change after they switch from sector of employment. For instance because workers learn in their new public sector job that helping others is much more intrinsically rewarding than they expected and as a consequence they become more willing to help others. Alternatively, workers' altruistic preferences change because their social environment changes (a recent field experiment bij Kosse et al. 2016 finds evidence that social environment has a causal effect on altruistic preferences).

In our data we have two questions that we can use to elicit workers' altruistic preferences, and hence we can test whether altruistic preferences change when workers switch from sector of employment. Participants are asked to describe how

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for many people. Job related reasons to switch jobs are for example the social environment (Abassi and Hollman 2000), job-related stress (Firth et al. 2004), organizational culture (Park and Kim 2009) or compensation schemes. But also family reasons can be a reason to change jobs.

[9] Only 188 people switch the year after they said that there were looking for a new job because they are uncertain whether their current job will exist in the future.

accurately each statement describes them: "I feel little concern for others" and "I am not interested in other people's problems". Both questions can be answered on a 5 point scale ranging from "very inaccurate" to "very accurate". We then construct our altruism parameter by taking the average of the answers to the two questions. We subsequently estimate the effect of a change in sector of employment on altruism and do not find any evidence that a change in sector of employment leads to a change in altruistic preferences (see Appendix 4.A.1).

Volunteering and career concerns

One obvious reason for people to volunteer is in order to help others. However, there can be many reasons for people to volunteer. One potentially important alternative motivation for people to volunteer is to increase their career perspectives. For instance, by volunteering one may obtain skills that are relevant for the labor market, or one may be able to signal something about his or her personality that is valued by potential employers. Baert and Vujić (2016) find using a field experiment that volunteering has a positive effect on the probability to be invited for a job interview. One may expect that some of the positive effects of volunteering for the labor market are of particular importance at the beginning of one's career.[10] Therefore, we expect that older workers volunteer less for career enhancement. Hence, in order to be able to better estimate the substitutability between helping others on-the-job and outside the job through volunteering, we next estimate equation (4.1) for older workers only. To be precise, we estimate equation (4.1) for workers who are over 40 years old. In Table 4.5 we report the results of the more experienced workers. We see that more experienced workers who switch to the public sector decrease their time spent volunteering by 37 minutes on average per week. In column two we see that this result is robust for adding the time varying control variables.

[10] For example, volunteering can provide a signal about the worker's personality. This signal is likely to be more informative in the beginning of the worker's career when information about the worker's personality is more scarce.

Table 4.5: Fixed effects Ordinary Least Squares, sample: age>40

Dependent variable: Volunteering		
Public sector	-0.611*	-0.620*
	(0.326)	(0.324)
Hours at work		-0.009**
		(0.004)
Net income		-0.000
		(0.000)
Distance		-0.002
		(0.006)
Tenure		-0.016*
		(0.009)
Individual and time fixed effects	YES	YES
Observations	12541	12541
Number of individuals	3606	3606

Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.10.
Standard errors are clustered on the individual level.

Highly educated job switchers

Previous research (see e.g. Lewis and Frank 2002 and Dur and Zoutenbier 2014, 2015) has found that more altruistic workers select into public sector jobs, and that these patterns are stronger for the sample of workers that is highly educated. One interpretation of this finding is that in the public sector especially the highly educated are able to help others on-the-job and therefore the selection pattern is stronger for highly educated workers. If the difference in the opportunity to help others on-the-job between the public and private sector is larger for highly educated, then this would, following our substitution argument also imply that the difference in volunteering would be larger. In Table 4.6 we estimate equation (4.1) for the subsample of highly educated workers.[11] We find that the public sector dummy is

[11] We define workers as highly educated if they have either completed a degree in higher vocational training or have (at least) an undergraduate degree at a university.

again negative, but not significantly different from zero.

Table 4.6: Fixed effects Ordinary Least Squares, sample: Highly educated

Dependent variable: Volunteering		
Public sector	-0.055	-0.036
	(0.324)	(0.328)
Hours at work		0.000
		(0.003)
Net income		0.000
		(0.000)
Distance		-0.004
		(0.003)
Tenure		0.001
		(0.013)
Individual and time fixed effects	YES	YES
Observations	6878	6878
Number of individuals	2316	2316

Standard errors in parenthese, *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Standard errors are clustered on the individual level.

4.3.2 Match of mission preferences and charitable behavior

So far we have focused on analyzing the relationship between helping others on-the-job and outside the workplace, using job switchers. Since switching from sector of employment is endogenous, we now provide an alternative for identifying a change in the ability to help others on-the-job by exploiting plausibly exogenous variation in opportunities to help others on the current job.

Zoutenbier (2016) analyzed using the same data (but exploiting a smaller time span), the effect of a (mis)match of mission preferences on job satisfaction for government workers. He defines workers to have a mission match when they voted for a political party that is in office. He then exploits the fact that the composition of the government changes over time, and hence whether government workers have a match with the mission of the government also changes over time. Zoutenbier finds that government workers who voted for a coalition party are more satisfied with the type of work they do.

If we assume that government workers believe they are better able to help others when the organization's preferences are in line with the worker's preferences, we can use changes in the match of mission preferences. Using the substitution argument, we predict that government workers who voted for a political party that is in office, are better able to help others on-the-job and as a consequence they will volunteer less.

In order to test this prediction we estimate equation (4.2) and report the results of the full sample in Table 4.7. In column 1 we see the effect of a match of mission preferences with the coalition of government workers and non-government workers. We see that government workers who voted for one of the political parties that is in office (i.e. workers with a match in mission preferences) volunteer on average 15 minutes less per week. When including the time varying control variables in column 2, we find that the results hardly change.

Table 4.7: Fixed effects Ordinary Least Squares

Dependent variable: Volunteering		
Government	0.209	0.218
	(0.262)	(0.267)
Match	0.079	0.077
	(0.070)	(0.070)
Government*Match	-0.249*	-0.247*
	(0.136)	(0.136)
Hours at work		-0.005**
		(0.002)
Net income		-0.000
		(0.000)
Distance		-0.002
		(0.004)
Tenure		-0.008
		(0.008)
Individual and time fixed effects	YES	YES
Observations	16504	16504
Number of individuals	5382	5382

Standard errors in parenthese, *** $p<0.01$, ** $p<0.05$, * $p<0.10$.
Standard errors are clustered on the individual level.

Since in the Netherlands the government in our sample period always consisted of multiple political parties, we estimate a match of mission preferences using alternative definitions for robustness. Following Zoutenbier (2016) we create a dummy that equals one only if the worker voted for the largest political party in government, and we use the workers' stance toward all political parties. By doing this we see that the coefficient of interest oftentimes becomes statistically insignificant.

Using the same arguments as before, we expect the effects to be stronger for more experienced workers (see Table 4.8) and for highly educated workers (see Table 4.9). We find that indeed the effects are larger for the sample of workers that is at least 40 years old. To be precise government workers who previously had a match in mission preferences, but after election not anymore, increase their volunteering with on average 23 minutes per week. For the subsample of highly educated workers we find a similar increase in the size of the coefficient, although the coefficient becomes insignificant.

Table 4.8: Fixed effects Ordinary Least Squares, sample: age>40

Dependent variable: Volunteering		
Government	0.037	0.033
	(0.502)	(0.511)
Match	0.101	0.100
	(0.096)	(0.095)
Government*Match	-0.381**	-0.382**
	(0.172)	(0.173)
Hours at work		-0.006*
		(0.003)
Net income		-0.000
		(0.000)
Distance		-0.003
		(0.007)
Tenure		-0.010
		(0.009)
Individual and time fixed effects	YES	YES
Observations	10752	10752
Number of individuals	3331	3331

Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.10.

Standard errors are clustered on the individual level.

Table 4.9: Fixed effects Ordinary Least Squares, sample: Highly educated

Dependent variable: Volunteering		
Government	0.564	0.570
	(0.444)	(0.441)
Match	0.119	0.119
	(0.110)	(0.110)
Government*Match	-0.377	-0.379
	(0.235)	(0.235)
Hours at work		-0.002
		(0.004)
Net income		0.000
		(0.000)
Distance		-0.003
		(0.003)
Tenure		-0.004
		(0.011)
Individual and time fixed effects	YES	YES
Observations	6235	6235
Number of individuals	2133	2133

Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.10.
Standard errors are clustered on the individual level.

4.4 Concluding remarks

In this paper we studied the relationship between workers' prosocial behavior on-the-job and outside the workplace. We predict that there is substitutability between workers' opportunities to help others on-the-job and volunteering outside the workplace. Using rich panel data from the Longitudinal Internet Studies for the Social Sciences (LISS) we test this prediction in two distinct ways. First, we compare volunteering behavior of workers who switch between public sector and private sector jobs. This stems from the assumption that workers in the public sector often have plenty of opportunity to help others on-the-job, while for workers in the private sector the opportunities to help others are more scarce. Second, we analyze the change in match of mission preferences of government workers on volunteering behavior. Government workers are considered a match if they voted for one of the political parties that is in the coalition government. Using the variation in political parties that are in the coalition government over time, government workers switch from a match to a mismatch in preferences and vice versa. We predict that government workers who voted for one of the political parties that is in office, feel that they have plenty of opportunties to help others on-the-job, and hence they will volunteer less.

We find some support for our prediction. We find that workers who switch from a public to a private sector job (or vice versa) do not significantly change their volunteering behavior. However, we do find results that are in line with our prediction when we focus on changes in the match of mission preferences for government workers. We find that government workers with a mission that matches their employer's mission, volunteer on average 15 minutes less per week. Besides volunteering for the purpose of helping others, workers can also volunteer for career concerns. Since we expect the effect of volunteering on career perspectives to be larger for young workers, we also focus on the subsample of older workers. We indeed find stronger effects for older workers, suggesting that some of the young workers volunteer for career enhancement.

The fact that we find that there is some substitutability between opportunities to help other people on-the-job and volunteering implies that job design can lead to crowding out (and crowding in) of charitable behavior. This is something that policy makers and socially responsbile organizations should take into account when designing jobs.

There can be many reasons why we do not find stronger support for our predictions. One reason can be that helping others on-the-job is not a (strong) substitute for volunteering outside the workplace in cases where the beneficiaries of the help on-the-job and outside the job are a very different type or group of people.

In this paper we rely on job switchers in order to estimate the relationship between helping others on-the-job and outside work. There are many reasons for workers to switch jobs, some of them may be directly related to the willingness to do good on-the-job, this may bias the results. Hence a cleaner way to estimate the effect of a job switch on workers' willingness to help others outside work, would be if the decision to switch is entirely exogenous to workers' willingness and ability to help others.

The ideal setting to test our hypothesis would therefore be, to have randomly assigned workers change jobs and estimate their charitable behavior before and after the job switch. It is off course very unlikely that such an experiment can take place. A more plausible alternative would be to exploit exogenous variation created from closure of a large workplace. If there would be a firm that is closed and the employer is obliged to find a new employer for its employees, we could test our predictions. We would compare workers' charitable behavior outside the job before and after the plant closure. Also here two issues arise. First, the change in job type or tasks should be large enough (i.e. the difference in opportunities to help others on-the-job should be sufficiently large). Second, workers can still self-select into other jobs instead of working for the proposed new employer. This would again result in a non-random subsample of workers that can be studied. Hence, unless the above issues are properly dealed with, this type of exogeneous variation is not obviously better than our approach.

4.A Appendix

4.A.1 Appendix

Table 4.A.1: Fixed effects Ordinary Least Squares

Dependent variable: Altruistic preferences		
Public sector	-0.039	-0.043
	(0.047)	(0.047)
Hours at work		0.001
		(0.001)
Net income		0.000
		(0.000)
Distance		0.000
		(0.001)
Tenure		-0.001
		(0.002)
Individual and time fixed effects	YES	YES
Observations	14305	14305
Number of individuals	5931	5931

Standard errors in parenthese, *** p<0.01, ** p<0.05, * p<0.10.
Standard errors are clustered on the individual level.

Chapter 5

Summary and Directions for Further Research

In this thesis I have studied intrinsic motivation of students and workers. In chapter two I studied whether and how goal setting can be used in order to increase student performance. In chapter three and four I explored the relationship between workers' altruistic preferences, their occupational choice, and their charitable behavior. Next I will summarize the main findings in the following section, followed by some directions for further research in the last section.

5.1 Summary

In chapter two we studied the effects of motivating students to set goals on study performance. We were interested to learn whether motivating students to set goals can increase their study performance, and whether challenging students to be more ambitious by motivating them to set more difficult goals, can increase study performance further. In order to test our predictions we conducted a field experiment involving 1092 first-year economics students from Erasmus University Rotterdam.

We ran our experiment during the second of three individual meetings between students and their mentor (who is a senior student). In one treatment *(goal treatment)* we instructed mentors to ask their students whether they had a specific grade goal in mind for the main course they participated in at that moment, and if not, whether they wanted to set a grade goal. In another treatment *(raise treatment)* mentors received identical instructions as in the goal treatment, but were in addition instructed to encourage students to raise their goal if deemed appropriate. We subsequently measured performance using the grades the student obtained for the course.

We found that motivating students to set goals increases their performance significantly. This effect is mainly driven by students in the goal treatment dropping out less often as compared to students in the control group. Students whose mentor was instructed to also motivate students to raise their goal do not perform significantly different from the control group. There are several potential explanations for why challenging students to set more ambitious goals impacts performance negatively. First, the revised goal that the mentor proposes may be too difficult. Goals that are too difficult may be impossible to reach for the student, and hence the student gives up, leading to a performance similar to the control group where students were not motivated to set goals. An alternative explanation is that the proposal to raise the goal may lead to a decrease in motivation to reach the goal, and therefore students' performance decreased. This is in line with the psychology literature that finds that often people are more motivated to reach self-set goals than goals that are set by others or are set in cooperation. Finally, being asked to raise the goal leads to a significant drop in performance as compared to similar students in the goal treatment that would have been asked to raise the goal if they would have been assigned to the raise treatment.

In chapter three we studied the role of altruistic preferences in job choice, on-the-job effort provision, and charitable donations. We developed a simple theoretical model. In our model people differ in their altruistic preferences and can serve the public interest in two ways: they can make charitable donations, and they can decide whether to take a public service job and exert effort on the job. People make three decisions: first they decide whether to take a public service job or a regular job, next they decide how much effort to exert at work, and how much of their income to donate to charity. Our theory predicts that (i) the likelihood of having a public service job (weakly) increases in a worker's altruism, that (ii) for a given job type, charitable donations (weakly) increase in workers' altruism, and that (iii) for a given altruism and income, workers holding a regular job donate more to charity than workers holding a public service job. The intuition for the third prediction stems from the fact that public service workers already contribute to the well-being of others by exerting effort on the job and, hence, by a substitution argument, they donate less.

We empirically tested our predictions using data from the German Socio-Economic Panel Study (SOEP). Consistent with our theory, we find that workers who are more altruistic are more likely to take a public service job and, for a given job type, donate more money to charity. Furthermore, we find that workers in a regular job make significantly higher donations to charity than equally altruistic workers in a public service job. However, when we control for workers' income, this difference moves close to zero.

The fourth chapter builds on the third chapter. In the fourth chapter I further explore the relationship between workers' altruistic preferences, workers' opportunities to help others on the job and outside the workplace in the form of voluteering. Based on the theoretical framework developed in Dur and Van Lent (2016), (i.e. based on the third chapter), I predict that helping people on-the-job and volunteering time outside the workplace are substitutes. I examine this prediction using rich panel data from the Dutch LISS Panel. I exploit two sources of variation in workers' opportunities to help others on the job over time and measure the effects of these changes on volunteering behavior. The first source of variation was a change in the sector of employment. The second source of variation was a change in the allignment of mission preferences between government workers' and their employer. I classify mission preferences to be alligned for government workers who voted for one of the political parties that was in the coalition government in the period following a national election. I find some evidence for our prediction.

5.2 Further research

In chapter two we studied the effects of motivating students to set grade goals on study performance. One interesting direction for further research is to study the effects of non-grade goals on study performance. Clark et al. (2016) already took a step in this direction by motivating students to set goals with respect to an input, in their case the number of online practice exams that a student wants to complete. An interesting alternative are goals that relate to the level of understanding of the course. These goals are more difficult to measure, but the motivation to reach these goals may be higher.

To our surprise we found that a proposal to increase the difficulty of the goal that the student has set (insignificantly) decreases performance as compared to the control group. A potential explanation for this finding is that students' motivation to reach their goal has decreased because of the proposal to raise the goal. One interesting direction for further research is to study how revising a goal affects the motivation to reach the goal. Current work in progress by myself addresses this question from one angle. Using a series of surveys I motivate students in the first survey to set goals and ask them how motivated they are to reach their goals. A randomly selected group of students are explicitly offered the opportunity to revise their goals during the second of three surveys, while others are not. In the second and third survey I then ask all students how motivated they are to reach their goals. This allows me to see how goal motivation changes when students change their self-set goals.

In chapter three we studied the relation between workers' altruistic preferences, their occupational choice, and their opportunities to help others on-the-job and outside the workplace. In our theoretical model workers differed in two respects, their altruistic preferences and their preferences for other job (dis)amenities specific to public service jobs, such as job protection or flexible work hours. In future work it would be interesting to study how these job (dis)amenities affect workers' self-selection and work incentives.

Samenvatting en suggesties voor vervolgonderzoek (Summary in Dutch)

In dit proefschrift heb ik intrinsieke motivatie van studenten en werknemers bestudeerd. In hoofdstuk twee heb ik bestudeerd of en hoe het zetten van doelen gebruikt kan worden om studieprestaties van studenten te verbeteren. In hoofdstuk drie en vier heb ik de relatie tussen werknemers hun altruïstische voorkeuren, baankeuze, en liefdadigheidsgedrag onderzocht. Nu zal ik de voornaamste bevindingen samenvatten, gevolgd door een aantal suggesties voor vervolgonderzoek.

Samenvatting

In hoofdstuk twee bestudeerden we de effecten van het motiveren van studenten om doelen te zetten op hun studieprestaties. We waren geïnteresseerd of studenten motiveren om doelen te zetten studieprestaties kan verbeteren, en of het uitdagen van studenten om ambitieuzer te zijn door het stellen van moeilijkere doelen, studieprestaties verder kan verbeteren. Om onze predicties te testen hebben we een veldexperiment uitgevoerd onder 1092 eerstejaars economie studenten van de Erasmus Universiteit Rotterdam.

We hebben ons experiment geïmplementeerd gedurende de tweede van drie individuele gesprekken tussen studenten en hun mentor (mentoren zijn ouderejaars studenten). In één treatment *(goal treatment)* hebben we mentoren geïnstrueerd om hun studenten te vragen of ze een specifiek cijferdoel in gedachten hadden voor het belangrijkste vak wat ze op dat moment volgden, en als ze geen doel in gedachten hadden, of ze een doel wilden zetten. In een andere treatment *(raise treatment)* kregen mentoren dezelfde instructie als in de goal treatment, maar werden ze ook geïnstrueerd om studenten aan te moedigen om hun doel te verhogen als ze dat gepast vonden. Vervolgens hebben we de prestaties gemeten door te kijken naar de cijfers die de studenten voor het vak behaald hebben.

We hebben gevonden dat studenten motiveren om doelen te zetten resulteert in betere studieprestaties. Dit resultaat wordt voornamelijk veroorzaakt doordat studenten in de goal treatment minder vaak uitvallen dan studenten in de controle groep. Studenten wiens mentor geïnstrueerd was om studenten ook te motiveren om hun doel te verhogen presteren niet significant anders dan studenten in de controle groep. Er zijn meerdere potentiële verklaringen voor de bevinding dat studenten uitdagen om moeilijkere doelen te zetten een negatief effect heeft op prestaties. Ten eerste, het nieuwe doel dat de mentor voorstelt kan te hoog zijn. Doelen die te hoog zijn kunnen onhaalbaar zijn voor de student, en daarom geven studenten op, wat leidt tot een prestatie die vergelijkbaar is met de prestaties in de controle groep. Een alternatieve verklaring is dat het voorstel om het doel te verhogen leidt tot een daling in de motivatie om het doel te halen, en daardoor tot een slechtere studieprestatie. Dit is in lijn met literatuur in de psychologie. Deze literatuur laat zien dat mensen vaak gemotiveerder zijn om doelen te halen die ze zelf hebben gezet dan om doelen te halen die anderen voor ze hebben gezet. Tot slot, gevraagd worden om het doel te verhogen in de raise treatment leidt tot een significante afname in prestaties vergeleken met vergelijkbare studenten in de goal treatment.

In hoofdstuk drie hebben we de rol bestudeerd die altruïstische preferenties spelen in baankeuze, inspanningen op het werk, en donaties aan liefdadigheidsorganisaties. We hebben eerst een theoretisch model ontwikkeld. In ons model verschillen mensen in hun altruïstische preferenties en kunnen ze anderen helpen op twee manieren: door het doneren aan een goed doel en door het nemen van een 'publieke service' baan. Mensen maken drie beslissingen: ze kiezen een 'publieke service' baan of een reguliere baan, ze kiezen hoeveel inspanning ze leveren in hun baan, en hoeveel geld ze doneren aan liefdadigheidsorganisaties. Onze theorie voorspelt dat (i) de kans dat iemand een 'publieke service' baan neemt stijgt in zijn/haar altruïstische preferenties, dat (ii) voor een gegeven baan type, donaties aan goede doelen stijgen met mensen hun altruïsme, en dat (iii) voor een gegeven altruïsme en inkomen, mensen die een reguliere baan hebben meer doneren aan goede doelen dan mensen die een 'publieke service' baan hebben. De intuïtie achter de derde predictie is dat mensen met een 'publieke service' baan al bijdragen aan het welzijn van anderen door inspanningen te doen in hun baan, en door substitutie, zullen ze daarom minder doneren.

We hebben vervolgens onze predicties empirisch getest door gebruik te maken van data van de German Socio-Economic Panel Study (SOEP). In lijn met onze theorie vinden we dat werknemers die altruïstischer zijn een grotere kans hebben om een 'publieke service' baan te hebben, en gegeven hun baan, meer doneren aan goede doelen. Verder vinden we dat werknemers met een reguliere baan significant meer doneren aan goede doelen in vergelijking met mensen die even altruïstisch zijn maar een 'publieke service' baan hebben, alhoewel dit verschil insignificant wordt wanneer we ook controleren voor inkomen.

Het vierde hoofdstuk bouwt voort op het derde hoofdstuk. In het vierde hoofdstuk onderzoek ik verder de relatie tussen werknemers' altruïstische voorkeuren, hun mogelijkheden om anderen te helpen in hun baan, en daarbuiten in de vorm van vrijwilligerswerk. Gebaseerd op het theoretische model ontwikkeld in Dur en Van Lent (2016) voorspel ik dat mensen helpen binnen de baan en buiten de werkvloer, in de vorm van vrijwilligerswerk, substituten zijn. Ik onderzocht deze predictie door gebruik te maken van data van het Nederlandse LISS Panel. Ik heb hiervoor gebruik gemaakt van twee bronnen van variatie in werknemers hun mogelijkheden om anderen te helpen binnen hun baan door de tijd en het effect hiervan gemeten op de tijd die mensen spenderen aan vrijwilligerswerk. De eerste bron van variatie was een verandering in de sector waarin iemand werkt. De tweede bron van variatie is een verandering in de match van missie preferenties tussen bureaucraten en hun werkgever. Als een bureaucraat gestemd heeft op één van de politieke partijen die in de regering komt, dan classificeer ik de bureaucraat als iemand met een match in missie preferenties met zijn of haar werkgever. Ik vind enig bewijs voor de predictie die ik getest hebben.

Suggestie voor vervolgonderzoek

In hoofdstuk twee hebben we het effect van het motiveren van studenten om cijferdoelen te zetten op studieprestaties bestudeerd. Een interessante richting voor vervolgonderzoek is om de effecten van niet-cijfermatige doelen op studieprestaties te meten. Clark et al. (2016) hebben al een stap in deze richting gezet door studenten te motiveren om doelen te zetten met betrekking tot een input, om precies te zijn, het aantal online oefententamens dat een student wil maken. Een interessant alternatief zijn doelen die gerelateerd zijn aan het niveau waarop de student het studiemateriaal beheerst. Deze doelen zijn moeilijker te meten, maar de motivatie om deze doelen te halen kan hoger zijn.

Tot onze verrassing vonden we dat een voorstel om de moeilijkheidsgraad van het doel te verhogen leidt tot (insignificant) lagere prestaties als in de controle groep. Een potentiële verklaring voor deze bevinding is dat de motivatie van studenten om hun doel te behalen is verlaagd door het voorstel om het doel te verhogen. Een interessante richting voor vervolgonderzoek is om te bestuderen hoe het veranderen van een doel de motivatie om het doel te bereiken verandert. Lopend onderzoek van mijzelf onderzoekt dit vraagstuk vanuit één mogelijke invalshoek. Door gebruik te maken van een serie vragenlijsten motiveer ik een deel van de studenten om doelen te zetten. Een willekeurig geselecteerd deel van de studenten geef ik expliciet de mogelijkheid om hun doelen aan te passen tijdens de tweede van drie vragenlijsten. In de tweede en derde vragenlijst vraag ik studenten vervolgens hoe gemotiveerd ze zijn om hun doel te behalen. Dit stelt me in staat om te analyseren hoe de motivatie om doelen te behalen verandert wanneer studenten hun doelen aanpassen.

In hoofdstuk drie bestudeerden we de relatie tussen werknemers hun altruïstische voorkeuren, hun baankeuze, en hun mogelijkheden om andere te helpen binnen en buiten hun baan. In ons theoretische model verschilden werknemers op twee manieren, ze verschilden in hun altruïstische preferenties en in hun preferenties voor baanvoorzieningen die specifiek zijn voor 'publieke service' banen, zoals baanbescherming of flexibele werktijden. Het is interessant om verder te onderzoeken hoe deze baanvoorzieningen werknemers hun selectie naar baantypes en werkprikkels beïnvloed.

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