Surviving Calculus

A survival analysis of dropout from calculus at the University of Iceland

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SURVIVING CALCULUS: A SURVIVAL ANALYSIS OF DROPOUT FROM CALCULUS AT THE UNIVERSITY OF ICELAND

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Abstract

The objective of this study was to evaluate the extent of dropout from an introductory course in practical calculus (Calculus IC) at the University of Iceland (UI), the time of dropout and which factors predict whether a student drops out or not. The data used in the study is from the Student registration at UI, the teachers of the course and a diagnostic test held at the beginning of the course. The data includes 484 students who registered for Calculus IC during fall semester 2012. Only half of the registered students completed the course, one-fourth did not start the course even though they were registered, and one-fourth dropped out after starting. The dropout is spread over the duration of the course but about half of the dropout happened in the first third of the course.

Logistic regression was used to analyse which factors predict whether a student started the course or not. A cox proportional hazard model was then used to analyse which factors predict whether students who started the course complete it or not and if they do not complete it, when they drop out. The results indicate that student who do not have proper mathematical foundation are more likely to drop out than students who are have a better foundation. Female students are less likely to start than male students, but if they do, they are less likely to drop out. Students who took Icelandic Matriculation Exams (IME) on time are more likely to start Calculus IC and to complete it than students who delayed IME. Students who entered their major directly after IME are more likely to start the course. First year students are more likely to drop out than students at their second or higher year.

Ágrip

Markmið þessarar rannsóknar var að leggja mat á umfang brottfalls frá inngangsnámskeiði í hagnýtri stærðfræðigreiningu (Calculus IC) við Háskóla Íslands, tímasetningu brottfalls og hvaða þættir spá fyrir hvort nemandi hætti námi eða ekki. Gögnin sem notast var við koma frá Nemendaskrá Háskóla Íslands, kennurum námskeiðsins og stöðuprófi lagt fyrir nemendur við upphaf misseris. Gögnin innihalda alla þá 484 nemendur sem skráðu sig í Calculus IC haustið 2012. Aðeins helmingur nemendanna lauk áfanganum, fjórðungur þeirra hóf ekki nám við áfangann, þrátt fyrir að vera skráðir, og fjórðungur hætti námi. Nemendurnir hættu námi nokkuð jafnt yfir önnina en helmingur brottfallsnemendanna hætti á fyrsta þriðjungi annarinnar.

Lógítísk aðhvarfsgreining var notuð til þess að kanna hvaða þættir spá fyrir um það hvort nemandi hefji nám í áfanganum eða ekki. Cox proportional hazard líkan var síðan notað til þess að kanna hvaða þættir spá fyrir um það hvort nemandi sem hefur nám, ljúki áfanganum eða ekki og ef hann lýkur honum ekki, hvenar hann hætti. Niðurstöðurnar gefa til kynna að nemendur sem eru ekki með nógu góðan stærðfræðiundirbúning eru líklegri til þess að hætta námi en nemendur sem eru betur undirbúnir. Kvenkyns nemendur eru ólíklegri til þess að hefja nám en karlkyns nemendur en ef konur hefja nám eru þær líklegri til þess að ljúka áfanganum. Nemendur sem tóku stúdentspróf á réttum tíma eru líklegri til þess að hefja nám og líklegri til þess að ljúka áfanganum heldur nemendur sem frestuðu stúdentsprófi. Nemendur sem innrituðust í sína námsgrein sama ár og þeir tóku stúdentspróf eru líklegri til að hefja nám í Calculus IC. Fyrsta árs nemar eru líklegri til þess að hætta í áfanganum heldur en nemar á öðru eða hærra ári.

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Abbreviations

AIC = Akaike's Information Criterion
HR = Hazard ratio
IME = Icelandic Matriculation Exams
OECD = Organization for Economic Cooperation and Development
OR = Odds ratio
PL = Practice lesson
SENS = School of Engineering and Natural Sciences
STEM = science, technology, engineering and mathematics
TW = Tutor-web
UI = University of Iceland

Glossary

Entry rates (ísl. innritunarhlutfall)

The estimated proportion of people who are expected to enter university education during their lifetime. The OECD calculates entry rate as "the sum of age-specific entry rates, calculated by dividing the number of entrants of a certain age into a certain education level by the total population of that age." (OECD, 2015, p. 346). The OECD further defines university entry rate as "an estimated probability, based on current entry patterns, that a young adult will enter [university] during his or her lifetime." (OECD, 2015, p. 346). Entry rates provide an indication of the accessibility of university education as well as of the perceived value of attending university (OECD, 2010).

Completion rate (ísl. útskriftarhlutfall)

The proportion of new entrants into a specified level of education who graduate from it within a given number of years after they entered (OECD, 2015). The OECD calculates it as "the ratio of the number of students who graduate from an initial degree during the reference year to the number of new entrants in this degree n years before, n being the number of years of full-time study required to complete the degree" (OECD, 2010, p. 78).

Graduation rate (ísl. brautskráningarhlutfall)

The proportion of the population which has a university degree. Graduation rates correspond to the estimated percentage of an age cohort that is expected to complete university education over their lifetime, based on current patterns of graduation (OECD, 2015).

New entrants (ísl. nýnemar)

Students who enrol in university education for the first time (OECD, 2015). First year students at the first major they register for at university are thus *new entrants*.

Non-starters and no-shows

The term *non-starters* refers here to students who register for a course at a university but do not participate in any part of the course. The term is used in the same way as Haraldsson et al. (2008) used the term *registration dropout* (ísl. skráningarbrottfall). Non-starters can be divided into *resigners*, students who resign from the course before it starts, and *no-shows*, students who are registered for the course at the beginning of the semester but do not participate in any part of the course. The term *no-shows* has also been used to refer to admitted applicants for an university education at a certain institution, who do not register after being admitted (Geiser & Caspary, 2005; Iffert & Clarke, 1965).

Dropouts

Dropouts are usually defined as students who leave a specified level of education without graduating from that level (OECD, 2010). Here the term is also used for student who drop out of an institution, field, major or a course, depending on the context.

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1. Introduction

The extent and reasons for dropout from universities have been researched frequently abroad for the past decades (e.g., Ahlburg, McCall, & Na, 2002; Bahi, Higgins, & Staley, 2015; Bean, 1980; Hovdhaugen, 2009; Smith & Naylor, 2001; Tinto et al., 1993). The topic has been gaining more attention in Iceland recently as the few studies which have been carried out in Iceland indicate high dropout rates from the University of Iceland (UI) (Arnkelsson & Jónsson, 1992; Haraldsson et al., 2008; H. H. Jónsdóttir & Jónsson, 2008; Jónsson, 1989; Ríkisendurskoðun, 2007, 2010; Þórólfsson, Teague, & Jónsson, 2005). UI is the largest public university in the country, open to all students who have finished upper secondary education or the equivalent (Ministry of Education, Science and Culture, 2015).

According to foreign research, the highest dropout rates are among first year students (e.g., Bahi et al., 2015; R. Chen, 2012; Murtaugh, Burns, & Schuster, 1999; Smith & Naylor, 2001), which also seems to be the case in Iceland (Haraldsson et al., 2008). A part of the dropout problem at UI seems to be students registering but never starting their studies. A study found that half of the first year dropouts from UI were students who registered at the school but never attended a single class (H. H. Jónsdóttir & Jónsson, 2008).

Important differences in dropout rates have been found between institutions and programs within universities (Bahi et al., 2015) which makes it crucial to examine dropout from different programs separately. Special attention has been given to dropout and retention rates in science, technology, engineering and mathematic (STEM) programs, where dropout rates are high (X. Chen, 2013; Min, Zhang, Long, Anderson, & Ohland, 2011; Rasmussen & Ellis, 2013), especially among female students (Ellis, Fosdick, & Rasmussen, 2015; Griffith, 2010).

A study showed that in an introductory course in practical calculus (Calculus IC) in UI, taken on the first semester in STEM programs that rely on mathematics, in 2011-2013 less than half of the students who started the course passed it, the others either failed or dropped out (A. H. Jónsdóttir, 2015). In 2012 the teachers of Calculus IC decided to record students attendance and their usage of an online learning system, tutor-web (see A. H. Jónsdóttir, Jakobsdóttir, and Stefánsson (2015)), which was required to use in the course. The data showed that only half of the students who registered for Calculus IC persisted until the final exam. The other half of the students dropped out of the course at some point. This study analyses some of this data to answer the following research questions:

1. Which factors influence whether a registered student starts Calculus IC?

2. What affects whether and when a student drops out from Calculus IC?

High dropout rates are a financial burden for UI as the school receives funding for the number of final exams taken. The unknown number of students who attend classes causes difficulties in the organization of teaching at UI. It is important to estimate the proportion of the registered students who actually start studying to facilitate organization of courses. Knowing which students are most likely to drop out and when they are most likely to do so can help teachers lower the dropout rates by taking timely and appropriate intervention.

Most studies on the dropout of university students use registration data to analyse at which semesters students are most likely to drop out or switch between majors (e.g., Bahi et al., 2015; R. Chen, 2012; DesJardins, Ahlburg, & McCall, 2002; Min et al., 2011; Murtaugh et al., 1999; Smith & Naylor, 2001). Few studies seem to explore at what time of the semester students are most likely to dropout. This study uses student's attendance and online learning in Calculus IC to estimate the end of student's participation in the course. This approach gives a more detailed dropout time from this specific course. The timing of dropout is estimated for each dropout as the last week a student either attends or uses tutor-web. The course lasted fourteen weeks, with a final exam one week later, covering in total fifteen weeks.

The first question is answered with multiple logistic regression, analysing which factors are correlated with increased probability of starting the course, i.e. either attending a lecture or using tutor-web. The second question is answered with structuring a cox proportional hazard model, analysing which factors are correlated with increased probability of dropping out after starting and inspecting the probability of staying in the course at different times during the course. Survival analysis has been used to enrich models of dropout from universities (e.g., R. Chen, 2012; Murtaugh et al., 1999) as well as modelling if and when students switch majors (e.g., Bahi et al., 2015) and graduate (e.g., Zwick & Sklar, 2005). By using survival analysis instead of logistic regression, information of when students are most likely to dropout is gained in addition to know which students are most likely to dropout (Bahi et al., 2015; Willett & Singer, 1991).

The next chapter, chapter 2, reviews the literature on dropout from universities, abroad and in Iceland. In addition, it provides a discussion on how the term *dropout* is used in research and at the University of Iceland as well as an overview of the Icelandic school system, where the research takes place. In chapter 3, the data used in the analysis is described and the subjects of the study are described based on the data. In chapter

3, the analysis carried out in this project is described. Chapter 4 contains preliminary results and the results from the analysis on which type of students are most likely to start the calculus course and which type of students are most likely to drop out after starting, as well as what affects when students drop out. Finally, chapter 5 contains a discussion of the conclusions of this work and a short summary of the results.

2. Literature review

This chapter starts with a section containing a discussion about how the word *dropout* is used in research and how UI keeps track of new entrants and dropouts. The next section, section 2.2, is an overview of the Icelandic school system and common trends. Section 2.3 reviews knowledge of dropout from universities in Iceland and compares the situation in Iceland to other countries. Section 2.4 gives an overview of how age and gender as well as delayed progress through education affect the probability of dropping out of university. Section 2.5 is an overview of research on the timing of university dropout. Finally, section 2.4.3 describes dropout from STEM majors and calculus courses.

2.1. The definitions and usage of the word *dropout*

The basic meaning of the noun *dropout* is a student who has left a specific level of education without graduating from that level (OECD, 2010) or "a student who fails to complete a school or college course" and *to drop out* means "to abandon or withdraw from" (Collins Dictionary, 2016). Dropout rate is "the percentage of students failing to complete a particular school or college course" (Collins Dictionary, 2016). Increasing attention has been given to college and university dropout recently (e.g., R. Chen, 2012; Eggens, Van der Werf, & Bosker, 2008; Hovdhaugen, 2009).

Dropout rates can be measured at different levels, for example: national, institutional, department or program, and at different levels of education. Dropout rates are lower when looking at national levels as students who switch between programs or schools are not included as dropouts. Dropout rates are calculated at a specific time after students enter a specific level of education, often after the theoretical duration of the program. Dropping out of university is not necessarily a permanent state, individuals may drop out, enter again and complete their education later. This, among other factors, results in different dropout rates depending on at what time they are calculated.

The way schools record dropout can differ and is in some cases inadequate. This makes comparison between schools and countries difficult. Depending on registration, it can be difficult to distinguish interruptions of studies from drop out (OECD, 2010). Universities in Iceland do not measure their dropout rates other than information present in administration records and students registries.

The administration at UI has a database of all students who have been registered at the school at some point, called *The Student Registration* (The University of Iceland, 2016). Whenever students register for a program, re-register in the same program or register at a new program, they get a new *career* in the Student Registration. Every time a new career is made, the student gets the status *new entrant*. If students does not register at UI again next year they get the label *quit* and students who interrupt their studies get the same status until they register again. Student who switch majors are thus given the label *new entrant* at their new major and *quit* at their old one. A single student can therefore be registered as *new entrant* and *quit* multiple times, even though the student is still studying at the school. The database does not include information on at what time of the year the student quits their studies, why he quits and whether or not the student continues university education at another school.

This usage of the term *new entrant* is contrary to the definitions the Statistic Iceland and OECD use (OECD, 2010; Statistics Iceland, 2004). As dropout rates among new entrants are often of concern, this can lead to misunderstanding. In addition, the way UI uses the term *quit* makes it impossible to estimate the quantity of dropout from the school in a straightforward way. A report from UI found that 35% of students who had been labelled *new entrants* and then *quit* where in fact, not new entrants according to OECD's definition, but for example students who had extra credits when graduating, students in lifelong learning and exchange students (Haraldsson et al., 2008).

2.2. Overview of the Icelandic school system

2.2.1. Upper secondary education

Compulsory school is 10 years in Iceland, for children aged 6 to 16. After that, 90% of each cohort goes to upper secondary education, which is high compared to other countries (OECD, 2014). However, four years after starting upper secondary education 30% of students in Iceland have dropped out without graduating (Statistics Iceland, 2012). The upper secondary Icelandic school system is currently undertaking a reform to decrease dropout rates (Frumvarp til laga um framhaldsskóla, 2007-2008). One of the main changes is shortening upper secondary school from four years to three years, which has now been implemented in most schools. The secondary school finishes with the Icelandic matriculation examination (IME) which are not standardized but the schools need to follow the Icelandic National Curriculum Guide (Ministry of Education, Science and Culture, 1999).

On average, Icelanders graduate from upper secondary education older than students in other OECD countries. The average graduation age is 23 years old in Iceland, compared to the average age of 19 in the OECD countries (OECD, 2014). In Iceland, nearly 20% of upper secondary graduates are 25 or older, which is by far the highest proportion in OECD countries (OECD, 2014). This is because Iceland and other Nordic countries, have been somewhat more flexible in allowing students to leave the education system and re-enter later on, compared to most other European countries (OECD, 2012a). A number of students use this flexibility to progress slower, but eventually graduate (Jónasson & Blöndal, 2002; Statistics Iceland, 2012). Data from OECD (2014) show that the minority of students who start upper secondary education in Iceland graduates within the theoretical duration of the program while the majority does that in other OECD countries [1].

As a measure to increase the number of students who graduate on time from upper secondary education, a change was made in 2015. Now, students older than 25 years old have more restricted access to upper secondary education and will be directed to other more expensive institutions offering preliminary studies for adults that prepare students for admittance to most universities in Iceland (Harðardóttir, 2014; Ministry of Education, Science and Culture, 2012).

2.2.2. University education

There are seven universities in Iceland, four public and three private (Ministry of Education, Science and Culture, 2015). The biggest university in Iceland is the University of Iceland, a public university. It offers the broadest selection of programs while the other schools offer fewer programs and often focus on specific fields. The private universities charge tuition fees but the public schools only charge registration fees (Ministry of Education, Science and Culture, 2015).

The universities are open to all students holding an IME. However, some universities have restrictions on the number of students or require candidates to take an entrance examination to enter certain programs, for example in medical science, law studies, economy and art programs (Ministry of Education, Science and Culture, 2015). In some

[1] Only 45% of new entrants in 2004 in Iceland graduated within 4 years compared to the average 70% in OECD countries (OECD, 2014).Two years after the theoretical duration, on average 87% of students in OECD countries have graduated compared to only 58% of Icelandic students (OECD, 2014). Of new entrants in 2003 only 44% had graduated after 4 years and 26% were still studying, progressing slower than the theoretical duration of 4 years (Statistics Iceland, 2012). 6 years from entry, over half of the slower progressing students had graduated (Statistics Iceland, 2012). A study of cohorts born in 1969, 1975 and 1985 showed that at age 24, 4 years after the theoretical duration, around 60% had graduated. Of those who had not graduated from the '75 cohort, 16% were still in upper secondary school at age 24 (Jónasson & Blöndal, 2002)

UI programs, a minimum number of credits within natural science (mathematics, physics and chemistry) are required, but exceptions can be made from those prerequisites. In other departments, students are advised on "assumed knowledge" for each study program (The University of Iceland, 2014). The private universities in Iceland are more selective when accepting applicants (Haraldsson et al., 2008; Ríkisendurskoðun, 2007). Evaluation conducted for the European Commission shows that access to universities is only as unrestricted or open in five other European countries; Belgium, France, Italy, Malta and Austria (Eurydice, 2012).

Iceland has a high university graduation rate and in 2012 it was the highest of the OECD countries, or just over 60% (OECD, 2015). Entry rate to universities in Iceland, is among the highest in the OECD countries. The rate in Iceland is 80% whilst the average is 59% in the OECD countries (OECD, 2014). An unusually high proportion of older students contributes to the high entry rate. In the future, the entry rate is anticipated to decrease as the number of older people who do not have university education decreases (Ministry of Education, Science and Culture, 2015).

Students in Iceland graduate from undergraduate education on average older than students in other OECD countries. Over a third of the graduating students are over 30 years old which is the highest proportion in OECD countries (OECD, 2014). On average across OECD countries, students obtain their first university-level degree at the age of 27 but the average age is 31 in Iceland (OECD, 2014). The high graduation age is explained by students starting their university education on average older than in other countries and because UI allows students to interrupt their studies, progress slower and switch majors, which delays graduation. The average age of new entrants was 26 years old in Iceland in 2012 (Ministry of Education, Science and Culture, 2015).

In UI students can finish their undergraduate degree, that is organized as 3 years, in 4 to 6 years maximum, depending on their department, although many departments are not strict on this but rather use this as a guideline (Haraldsson et al., 2008). Students can take a break from their degree for some years and begin again, continuing from where they left off (Haraldsson et al., 2008).

2.3. Dropout from universities in Iceland

Dropout was not considered to be a problem in Iceland or other Nordic universities for a long time (Haraldsson et al., 2008; Hovdhaugen, Frølich, & Aamodt, 2008; Jónsson, 1989) and at UI, some professors even considered high dropout rates a sign of quality of programs (Haraldsson et al., 2008). The view on dropout started to change with new rules on university funding (Haraldsson et al., 2008) and in 2006, UI made it their policy to measure dropout regularly and decrease dropout rates by 50% by 2011 (The

University of Iceland, 2006). Some data has been collected on dropout from UI in the past three decades (Haraldsson et al., 2008) but the collected data has not been measured consistently, which makes it difficult to estimate the extent and trend of the problem. UI is working on establishing indicators to monitor dropout. A committee at UI suggested measuring first-year retention rate (i.e. the proportion of new undergraduate students who continue the following year), measured at university, department and program level, along with 3 and 5 year graduation rates (Haraldsson et al., 2008).

Dropout can be measured at different levels and at different time points (see discussion in section 2.1). These different measurements often show different dropout rates and should be compared carefully. The average completion rate from undergraduate education in the OECD countries is around 70%[2] (OECD, 2010), which indicates a dropout rate of less than 30% because some of the students who have not graduated might graduate later. The completion rates range from 90% in Japan to only 45% in the U.S. (OECD, 2010).

Completion rates from undergraduate education are around 70% in Iceland, 10 years after entry (see table 2.1), which is the same as the average completion rate in the OECD countries which was mentioned above. However, the majority of undergraduate students do not graduate within three years, which is the theoretical duration of undergraduate programs in Iceland. Of new university entrants in 1994, 1996, 1998, 2000 and 2002, only 24 – 32% graduated within three years. The rest of the students progressed slower, interrupted their studies or switched majors, which delayed their graduation. Within 10 years from entry 69-73% had graduated from an undergraduate program (see table 2.1), which indicates that the dropout rate from university education at nation level is less than 30% in the long run.

Even though the dropout rates from university education at the national level in Iceland are not high, the few studies that have been carried out on dropout in Iceland, suggest a high dropout rate from UI. For instance, a study by Þórólfsson et al. (2005) shows that only 45% of students who entered UI in 1982-1988 had graduated in 2000. An additional 15% were still studying and the rest (40%) had dropped out of UI (Þórólfsson et al., 2005). Neither dropout nor completion rates have been estimated at institutional level for other universities but Ríkisendurskoðun (2007) compared dropout at program level for business studies and computer science, in all four universities in Iceland that offer the programs. The results showed that UI had much lower 3 and 5 year completion rates in business studies among new entrants in 1999 and 2005 than other universities (Ríkisendurskoðun, 2007, 2010). In 2003-2005, UI had the highest first year dropout rate in business studies and second highest in computer science (Ríkisendurskoðun, 2007). The private universities had much higher 3 and 5 year completion rates and

[2] OECD uses different timescales for the countries and either cross-section or true cohort. In Iceland, OECD uses new entrants from 1998-9 so it is 10 year completion rates while in some other countries they use new entrants from up to 2005 so that is only 3 year completion rates (OECD, 2010).

Table 2.1: 3, 5 and 10 year completion rates (%) from university level education in Iceland (Statistics Iceland, 2014).

Year of entry	3 year (%)	5 year (%)	10 year (%)
1994	24	52	69
1996	28	55	70
1998	32	57	73
2000	26	53	69
2002	26	55	69

much lower first year dropout rates than the public universities in the two programs (Ríkisendurskoðun, 2007, 2010). Four comparison universities in Norway, Sweden, the Netherlands and U.S. also had much higher completion rates in business studies than UI (Ríkisendurskoðun, 2007).

The high dropout rate in UI has been blamed on the university accepting all students with IME while the private universities in Iceland are more selective (Haraldsson et al., 2008; Ríkisendurskoðun, 2007). According to R. Chen (2012) and Ishitani (2006), dropout rates are higher from public institutions and low-selectivity institutions.

Another commonly stated reason for why the dropout rate is higher in UI than in the private universities are the non-existing tuition fees (Haraldsson et al., 2008). However, the OECD has found no connection between the level of tuition fees charged to students and dropout rates (OECD, 2008, 2010). For example, university tuition fees are greater than 1,500 USD in Australia, Japan, Korea, the Netherlands, New Zealand, the U.K. and the U.S. In New Zealand and the U.S., dropout rates are significantly higher than the OECD average of 30% but the other countries are below it. By contrast, Denmark charges no tuition fees and has a dropout rate of only 18% (OECD, 2010). Furthermore, Ahlburg et al. (2002) found that tuition levels do not affect dropout rates.

Data from Statistics Iceland (2004) revealed that 87% of the students who were registered at university level in 2002 either registered again the following year or graduated in the meantime, which means that dropout from university education was only 13% at national level between the years. This is however not the conventional way of measuring dropout rates as many of the dropouts might actually be interrupting their studies instead of dropping out. A study by UI among students who dropped out of UI in 2003-2006 showed that 75% of the dropouts planned on going back to university in the next two years. Only 20% of the students who planned on re-enter university, were planning on finishing the same program they dropped out of in UI (H. H. Jónsdóttir & Jónsson, 2008). This situation is similar in Norway where more than half of all undergraduate university students left their initial institution before degree completion, but the majority of the dropouts transferred to another higher education institution. Only 17% of the dropouts, dropped out of higher education for good (Hovdhaugen, 2009).

Hovdhaugen (2009) thinks that dropout from universities is mostly a problem for universities but not the society or the individual. A study by H. H. Jónsdóttir and Jónsson (2008) supports this notion, showing that only 22% of the students who dropped out of UI 2003-2006 regret dropping out (H. H. Jónsdóttir & Jónsson, 2008). Another Icelandic study from the 1980s found that students who dropped out of UI were generally satisfied with the decision. The majority had later gone to other universities and, in most instances, graduated (Jónsson, 1989). Studies on dropout from Icelandic universities indicate that dropping out late has a worse effects on student's well-being than dropping out early (Jónsson, 1989; Kjartansdóttir, 2010).

Studies suggest that university students in Iceland are undecided on their choice of major and often try out one or more majors before finishing a degree (Arnkelsson & Jónsson, 1992; Þórólfsson et al., 2005). A study showed that among new entrants at UI in 1987-1992, only around half of the students[3] graduated from the program they originally registered for at UI (Þórólfsson et al., 2005). An additional 5-10% switched majors, one or more times, before graduating and the rest dropped out of UI (Þórólfsson et al., 2005).

Studies show that students who drop out of UI do often not decide what they are going to major in until after they take IME. Results from a recent study on dropouts from UI in 2003-2006, show that the majority of dropouts did not decide on a major until after taking IME and the majority thought it was hard to choose a major (H. H. Jónsdóttir & Jónsson, 2008). An older study of new entrants in 1982, showed that 56% of dropouts and 44% of graduated students, decided on a major after IME (Jónsson, 1989). Furthermore, the study showed that the earlier students decided to attend UI and which major they were going to take, the more likely they were to graduate from that major (Jónsson, 1989). Foreign studies have shown that students who have clear goals with their university education are more likely to finish their degree (e.g., Ozga & Sukhnandan, 1998; Sullivan, Guerra, et al., 2007). Students who are uncertain about their educational choice are less engaged in school (Blöndal, 2014), which increases the likelihood of them dropping out (e.g., Archambault, Janosz, Fallu, & Pagani, 2009; Blöndal, 2014; Finn & Zimmer, 2012; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008).

[3]From 50-59% depending on cohort (Þórólfsson et al., 2005).

2.4. The reasons for dropout

Students may drop out of university for many reasons and it is unrealistic to prevent all dropout. Students may, for example, realise that they have chosen a major that is not a good fit for them; they may fail to meet the educational standards of their program, particularly at low-selective institutions; or they may find attractive employment before completing their program (OECD, 2010). Furthermore, some students who enter university (generally mature students) do not have the intention of graduating, but instead aim to follow only a few courses as part of their lifelong learning (OECD, 2010). Hence, a student who drops out of university education "does not necessarily represent a failure of the individual‘s curriculum" (OECD, 2010, p.73).

Dropout from universities can thus be expected up to a certain level (Ozga & Sukhnandan, 1998). It is important to prevent dropout of students who have interest and abilities to study at university level. To do that it is important to know what groups of students are likely to drop out.

Early research on dropout focused on student's weaknesses or mistakes with little regards to the role and responsibility of the university. In the 1980s, Tinto put forward a theoretical model of student's social and academic integration effect on their persistence in university (Tinto, 1975). Bean later carried out a study where he studied the same, but accounted for various external factors that affect dropout (Bean, 1980, 1982). They both reached the conclusion that university students who do not integrate well into the university community, both socially and academically, are more likely to drop out (Bean, 1980, 1982; Tinto, 1975, 1997; Tinto et al., 1993). Research from past decades on dropout from universities support Tinto's and Bean's theories (e.g., Ishitani & DesJardins, 2002; Nora, Cabrera, Hagedorn, & Pascarella, 1996; Rasmussen & Ellis, 2013; Stratton, O'Toole, & Wetzel, 2007)

Following is an overview of some of the reasons that have been connected with increased probability of dropout from universities that will be researched in this study.

2.4.1. Interrupted studies and older students

Delayed enrolment in university after graduating from upper secondary school not only postpones the economic and social advantages of higher education, but also increases the chances of university dropout (Ahlburg et al., 2002; Johnson, 2006; Jónsson, 1989; Stratton, O'Toole, & Wetzel, 2008; Þórólfsson et al., 2005). The longer an individual takes to enrol in university, the higher the chance of dropout (Ahlburg et al., 2002; Jónsson, 1989; Þórólfsson et al., 2005). Even delaying entry by only one year, dramatically increases the probability of dropping out (Ahlburg et al., 2002; Johnson, 2006), especially in the first year of university education (Johnson, 2006). Furthermore, delaying entry has been shown to have even worse impact on those who got low grades in upper secondary education (Ahlburg et al., 2002).

Taking a break from studies is relatively common among students in some countries (OECD, 2012b). Some of the students who interrupt their studies return quickly to their studies, while others stay away for longer periods of time, which can increase students' risk of not completing the education they started (OECD, 2012b). According to DesJardins, Ahlburg, and McCall (2006), students who interrupt their studies are more likely to drop out of university. Once a student interrupt his studies, he is more likely to do it again (DesJardins et al., 2006; Ishitani, 2006; Johnson, 2006). Interrupting one's studies has also been referred to as *stopout* (e.g., Bahi et al., 2015; DesJardins, Ahlburg, & McCall, 1999; DesJardins et al., 2006; Johnson, 2006; Stratton et al., 2008) and it seems like interrupted study and delayed enrolment in university after matriculation exams are great risk factors in connection with dropout from university.

Students in Iceland do not often enter university directly after taking their IME. For example in 2004 only 39% of first year students at UI took IME the same year (Guðlaugsson, 2012). It seems like delaying entry is becoming more common because in 2011 the portion of first year students taking IME the same year had lowered to 30% (Guðlaugsson, 2012). The minority of students in Iceland graduate from upper secondary education on time (see 2.2.1). As these individuals have interrupted their studies once, they might be more likely to do it again according to DesJardins et al. (2006) and Johnson (2006).

It is common in Iceland to enter university at an older age than in other countries. The average age to enrol in undergraduate education is 26 years old which is the highest age in the OECD countries (Ministry of Education, Science and Culture, 2015). This is partly because many students who go to university graduated from upper secondary education in their twenties (see 2.2.1). It is also common for older individuals to enter university to expand their education and opportunities in the work force. A later start to university education may indicate that students are more confident about what they want to study and are therefore more motivated (OECD, 2014).

Researchers do not completely agree on whether there is a connection between a student's age and dropout from university but it seems like older students are more likely to drop out than younger students (e.g., DesJardins et al., 1999, 2006; Murtaugh et al., 1999; Ozga & Sukhnandan, 1998; Smith & Naylor, 2001). Studies by DesJardins et al. (1999) and Smith and Naylor (2001) suggest that this is especially true among first year students, which may indicate that older students integrate worse into the university environment (Smith & Naylor, 2001). Higher dropout rates for university students older than 24 have been observed in Iceland (Statistics Iceland, 2004).

Older students might be more likely to drop out than younger students because older students are more likely to have a family, financial responsibilities and a job than younger students. Older students may face more difficulties combining work and study and thus may be unable to graduate on time (OECD, 2014). Ozga and Sukhnandan (1998) found that older students might be forced more often to drop out because of external circumstances than younger students. Stratton et al. (2008) findings support this, they found that married individuals are more likely to stop-out than non-married individuals and that mothers are more likely to drop out than other women.

According to a survey of dropouts from UI in 2003-2006, 40% of dropouts, dropped out because it was difficult for them to balance their responsibilities of having a family and staying up to speed with their studies (H. H. Jónsdóttir & Jónsson, 2008). This was especially true for older students (H. H. Jónsdóttir & Jónsson, 2008). Older students were significantly more likely to work while in school and to have a full time job (H. H. Jónsdóttir & Jónsson, 2008). In general, studies agree that working while in university increases the likelihood of dropout (e.g., Astin, 1984; Şimşek, 2013), especially if the student is working over 20 hours per week (Ehrenberg & Sherman, 1987; Vickers, Lamb, & Hinkley, 2003). The majority (63%) of students who drop out of UI work alongside their studies, with one third of those who work alongside their studies, working full time (H. H. Jónsdóttir & Jónsson, 2008).

2.4.2. Gender

University graduates in most fields of study in OECD countries are predominately female, especially in the fields of education, health and welfare, where women were over 70% of graduated students in 2012 (OECD, 2014). However, men dominate the fields of engineering, manufacturing and construction (72% males) and computing (80% males) (OECD, 2014). The proportion of female graduates has grown between 2000 and 2012 but only slightly (from 40% to 41%) in the field of science (life science, physical science, mathematics, statistics and computing) despite many initiatives to promote gender equality in the science field (OECD, 2014). Researchers do not agree on gender differences in correlation with dropout. In some studies, men are more likely to drop out than women (e.g., Blöndal, 2014; Johnson, 2006; Smith & Naylor, 2001; Statistics Iceland, 2004), and in other studies, there is no difference between the genders (Bahi et al., 2015; DesJardins et al., 1999, 2006).

In Iceland there are almost two times as many women than men studying at university level (Statistics Iceland, 2016) and the number of women who graduate from university level each year is close to double the number of men (Statistics Iceland, 2015). The gender ratios are very different between departments and programs as in other OECD countries (see above). The completion rate for university students in Iceland, is slightly higher for women than men[4] (Statistics Iceland, 2014). When Statistics Iceland (2004)

[4]The 10 year completion rate for new entrants in 1994, 1996, 1998, 2000 and 2002 was 5-20%

measured dropout as the proportion of students who were registered at university level in 2002 and neither re-registered the following year nor graduated in the meantime, they found that the dropout rate was 14% for male students and 13% for female students.

Studies on dropout from STEM majors, show that women are more likely to drop out, or switch to another field, than men (Ellis et al., 2015; Rasmussen & Ellis, 2013). A possible reason for this is that women often have lower mathematical confidence than men, even though they have the same mathematical abilities and preparedness (Ellis et al., 2015). Results from a survey among dropouts from UI, showed that a higher percent of women than men think they are not well prepared for studying at university level (H. H. Jónsdóttir & Jónsson, 2008).

2.4.3. Preparedness for university

Precollege characteristics can be useful predictors of student retention. Students have been shown to be less likely to drop out of university if they performed well in secondary education (e.g., Hovdhaugen, 2009; Johnson, 2006; Murtaugh et al., 1999; Smith & Naylor, 2001) and are well prepared for university (Ozga & Sukhnandan, 1998). A study in Iceland from 1989 supported this by showing that students who dropped out of university had on average lower IME grades than students who continued (Jónsson, 1989). Students in STEM programs have been shown to be less likely to persist in a STEM program if they are poorly prepared academically (e.g., X. Chen, 2013; Griffith, 2010; Maltese & Tai, 2011). A study revealed that roughly half of the dropouts from STEM programs switch to a non-STEM field and the other half drops out of university (X. Chen, 2013).

Evidence of decline in mathematical skills of first year students in universities has been detected in some countries (Hunt & Lawson, 1996; Gill, O'Donoghue, Faulkner, & Hannigan, 2010), including Iceland (A. H. Jónsdóttir, 2015). Enrolment to universities has increased substantially the past decade in most OECD countries (OECD, 2013). With increasing enrolment, students with a wider range of academic background are enrolling, changing the profile of the student group (Hoyles, Newman, & Noss, 2001). This could be one of the factors leading to a decline in mathematical performance among first year students (e.g., Mustoe, 2002; Northedge, 2003; Seymour, 2002). Others have proposed that students fail to make the transition from secondary school to university successfully (e.g., Hourigan & O'Donoghue, 2007; Kajander & Lovric, 2005). The transition often presents major difficulties whether students are specializing in mathematics or are in a major where mathematics is an auxiliary subject (Thomas et al., 2015).

In Iceland, the increase in tertiary level enrolment was 40% between 2000 and 2010

higher for male university students than female (Statistics Iceland, 2014).

(OECD, 2013). A study revealed that a large portion of students in SENS lacks basic skills in mathematics and a downward trend in mathematic skills was detected between 2011 and 2014 (A. H. Jónsdóttir, 2015). However, the same study showed that one third of the students who pass Calculus IC are poorly prepared but manage to catch up over the semester (A. H. Jónsdóttir, 2015).

2.5. The timing of dropout

Most of the studies previously discussed focus on causes and factors which can lead to an increased probability of dropout (e.g., Ahlburg et al., 2002; Johnson, 2006; Rasmussen & Ellis, 2013). The studies either ignore the timing of dropout or use a convenient time frame, such as tracking students from fall-to-fall or examining departure before and after an arbitrarily chosen point in time, often 3 or 5 years (e.g., Bahi et al., 2015; R. Chen, 2012; DesJardins et al., 2002; Min et al., 2011; Murtaugh et al., 1999; Smith & Naylor, 2001). However, dropping out of school is not a single event but a process, where the decision to drop out can be seen as the culmination of a process that begins much earlier (Finn, 1989). Thus, it can be useful to know when students are at the greatest risk of dropping out and whether the same factors influence dropout at different times (Willett & Singer, 1991).

Studies suggest that in general, students are most likely to drop out of university, or switch majors, during their first year of university (Bahi et al., 2015; R. Chen, 2012; DesJardins et al., 1999, 2006; Ishitani & DesJardins, 2002; Murtaugh et al., 1999; Smith & Naylor, 2001). Murtaugh et al. (1999) found that 40% of registered students at the Oregon State University, dropped out and half of them did so in the first year. R. Chen (2012) got similar results in his study on students who entered higher education in 1995 in the U.S., 18% of all students dropped out in the first year and the overall dropout rate was 56%. Smith and Naylor (2001) found that the dropout rate in the U.K. was below 10% among students who entered university in 1989, with almost 60% of the dropout occurring during the first year. A Norwegian study found that around 20-40% of new entrants drop out after the first year (Hovdhaugen & Aamodt, 2006). However, the bulk of the dropouts switch to another institution and only 17% quit their studies at university level (Hovdhaugen, 2009).

Students in STEM programs have been found to be most likely to switch their major to a non-STEM major in their first year in university with only 48% of the students who planned to major in a STEM field remaining as STEM majors after the first year (Griffith, 2010). Student's experience in first year mathematic courses, such as calculus, has been linked to student's decisions to leave STEM majors (e.g., Rasmussen & Ellis, 2013).

Dropout rates at universities in Iceland are also highest among first year students (Haraldsson et al., 2008; Jónsson, 1989; Statistics Iceland, 2004). Data from Student Registration at UI, showed that 48% of new entrants at UI in fall 2006, did not continue studying at UI in fall 2007 (Haraldsson et al., 2008). Dropout among new entrants at UI differed between departments from 14-67% (Haraldsson et al., 2008). Variability of student persistence between majors inside the same institutions is common (e.g., Bahi et al., 2015). In UI the dropout rates are highest in the social sciences and humanity departments (51-67%) and lowest in pharmaceutical and medical departments (12-14%) (Haraldsson et al., 2008). According to Ríkisendurskoðun (2007), 48% of first year students in computer science and 57% in business studies, dropped out in 2003-2005. First year dropout rates seem to be much higher in Iceland than in U.S. and U.K. but closer to the dropout rates in Norway, according to the studies discussed above.

There is little information about when during the first year most students drop out of university. Most studies on the timing of educational events, examine at which semester students are most likely to drop out, (e.g., R. Chen, 2012; DesJardins et al., 2002; Murtaugh et al., 1999; Smith & Naylor, 2001), switch between majors (e.g., Bahi et al., 2015), or graduate (e.g., Zwick & Sklar, 2005). Few studies seem to explore in more detail at what time of the semester students are most likely to drop out, but some studies have looked at the proportion of students who enrol but fail to start their studies. According to a survey carried out by UI among dropouts from UI in 2003-2006, around half of the dropouts contacted in the survey, never attended a class (H. H. Jónsdóttir & Jónsson, 2008) (i.e. non-starters). Haraldsson et al. (2008) called this *registration dropout*. A study from 1989 revealed a non-starting rate at UI of 17% (Jónsson, 1989). Foreign studies have also examined the proportion of applying students who are admitted but choose to not enrol (Geiser & Caspary, 2005; Iffert & Clarke, 1965).

2.6. Summary about dropout in Iceland

Dropout rates are high at UI compared to other institutions in Iceland and to other countries. Less than half of the student who enter UI finish an undergraduate degree (Þórólfsson et al., 2005). Most of the dropout happens in the first year when around half of the students who enter UI drop out (Haraldsson et al., 2008; Ríkisendurskoðun, 2007). First year dropout rates might be slightly higher at UI than at other Icelandic (Ríkisendurskoðun, 2007) and foreign universities (e.g., R. Chen, 2012; Hovdhaugen & Aamodt, 2006; Murtaugh et al., 1999; Ríkisendurskoðun, 2007; Smith & Naylor, 2001). Non-starters are around half of all dropout from UI (H. H. Jónsdóttir & Jónsson, 2008). Students in UI take longer time finishing a degree than students in other countries and many switch majors (Jónsson, 1989), delaying graduation.

3. Methods

The School of Engineering and Natural Sciences (SENS) at UI offers three introductory calculus courses for first year students; a theoretical course for students in mathematics or physics, a practical course for students in majors that do not rely heavily on mathematics and a mixed course for engineering students. This thesis focuses on the students who registered for the practical calculus course (Calculus IC) in fall 2012. This chapter describes the data, the students in the course and the analysis carried out.

3.1. Calculus IC

Calculus IC is for first year students in computer science, pharmaceutical science, biochemistry, chemistry and food science and second year students in geology. The students taking Calculus IC do not take another calculus course after Calculus IC but are required to take courses in chemistry or other majors which rely on basic calculus. Calculus IC covers fundamental concepts of calculus like limits and continuous functions, differentiation, integration, linear algebra, vectors and matrix calculations, multivariable functions and differential equations. The course focuses mainly on practical problems. The course starts in the end of August and finishes with a final exam in December, fourteen weeks later. The course consists of lectures twice per week, practical lessons (PL) once per week and assistant lessons twice per week where students could get help with homework. In 2012, attendance was recorded in all PL, but not in the other types of classes.

The final grade constitutes of a final exam (which accounted for 50%), pop quizzes (unannounced tests in lectures) (10%), group projects (20%) and grades from an online educational system called tutor-web (TW) (see A. H. Jónsdóttir et al. (2015)) that contained course materials and quizzes (20%). To qualify for taking the final exam the students were required to attend at least 9 out of 12 practical lessons, turn in 4 group projects, take at least 2 of 3 pop quizzes and answer around 300 questions on TW correctly over the span of the course. Some exceptions were given in special circumstances so some of the students were allowed to take the final exam without meeting all of those requirements.

3.2. The data

The data includes three types of information that were merged together and de-identified prior to analysis. Those variables were included in the data as literature review found them relevant (see chapter 2).

1. Background information for all registered students was collected from the Student Registration at UI.

    - Gender (categorical): female/male. Some studies have found that male students are more likely to drop out from university, while others have found no difference. Studies focused on STEM majors have found female students more likely to drop out (see section 2.4.2).

    - Age (numerical): Centered at 20 years old. Calculated from students' birth year. Students coming straight from secondary school were either 19 or 20 years old (born in 1993 or 1992) if they finished secondary education on time, depending on whether they were in a three or four year upper secondary school. Students at UI are unusually old compared to other countries. Studies have shown that older students might be more likely to drop out of university (see section 2.4.1).

    - IME (categorical): on time/delayed. Calculated from year of IME and birth year. Students are considered to have taken IME on time if they were 20 years old or younger the year they took IME. If not they are considered to have *delayed* IME. Year of IME is missing for 3 students. Studies have observed that students who have interrupted their studies once are more likely to do it again (see section 2.4.1), so students who did not take IME on time are expected to be more likely to drop out.

    - Entry (categorical): direct entry/delayed entry. Calculated from year of IME, which is missing for 3 students, and the year of enrolment into student's major in fall 2012. *Direct entry* is when students entered their major the same year as they took IME and *delayed entry* is when students entered their major one or more years after taking IME. Ahlburg et al. (2002) found that delaying entry to university after graduating from upper secondary education increases the risk of dropping out (see section 2.4.1) so students who enter directly are expected to be less likely to dropout.

    - Year (categorical): first year students/not first year students. Calculated from year of enrolment into current major. Higher year students are either students in geology, who take the course in their second year, or students who are repeating the course as they dropped out or failed the course earlier.

Studies have shown that first year students are more likely to drop out than second year students (see section 2.5). Hence, geology is expected to have lower dropout rates than other majors. Students who are repeating the course are also expected to have lower dropout rates as they would probably not register again if they do not intend to complete the course.

- Career (categorical): first career/not first career. The Student Registration at UI keeps track of how often students register for a new program, or the same program again, with giving the students different *careers* (see section 2.1). Students at their first career in fall 2012 are students who had not been registered at other programs previously. First year students at their first career at UI are called *new entrants* as OECD (2015) uses the term.

- Major (categorical): pharmaceutical science, biochemistry, computer science, chemistry, geology, food science and non-mandatory. Geology, chemistry, food science and non-mandatory majors are together referred to as other majors because there were fewer than 40 students in each major. Non-mandatory refers to students who are in majors where Calculus IC is not a mandatory subject. Studies in Iceland have shown that dropout rates are around 50% in computer science (Ríkisendurskoðun, 2007) while only 12% in pharmacy (Haraldsson et al., 2008). Dropout rates in other subjects have not been estimated but students in non-mandatory majors are expected to be more likely to dropout. In 2012, the geology program was organized with Calculus IC on second year. As dropout rates are highest among first year students (see 2.5), the dropout rate for geology students is expected to be lower than for other majors.

2. Results from a diagnostic test (DT) which the majority of the students in Calculus IC took. Professor Möller, R. G. developed DT to assess students' knowledge in mathematics at the start of their university studies (A. H. Jónsdóttir, 2015). The same test has been administered at UI for first year students in SENS since 2008. It was administered unannounced in the second week of the course in a lecture so only students who attended this particular lecture took the test. The students were also asked to answer a few question related to their preparedness for studying mathematics at university level, performance in upper secondary education and their self-efficacy on their abilities in mathematics. Students who have a performed well in upper secondary education, have good background in mathematics and high self-efficacy are expected to be less likely to dropout (see section 2.4.3).

    - DT grade (numerical): centered at the average grade in Calculus IC 2012. The DT tested knowledge in secondary school mathematics with 20 questions covering basic arithmetic and functions, basic algebra, equations of a straight line, trigonometric functions, differentiation and integration, vectors and complex numbers. The students were graded on the scale from 0 to 10 based on their answers.

- Semesters of math (categorical): number of semesters in mathematics in upper secondary school, less than 6 semesters/6 or more semesters.
- Well prepared (categorical): agree/neutral/disagree. Answers to the question: "I am well prepared for studying mathematics at university level".
- Did well (categorical): agree/neutral/disagree. Answers to the question: "I did well in mathematics in secondary school".
- Like math (categorical): agree/neutral/disagree. Answers to the question: "I like mathematics".

3. Participation data from the calculus course, including information about PL attendance each week, the number of questions answered on TW each week (both wrong and right answers), grades for each group project and pop quizzes and whether students took the final exam or not.

    - Dropout status (categorical): completing/dropping out. Determined based on whether the student took the final exam or not. Student get a dropout status if they did not take the final exam. Students who took the final exam are considered to have completed the course, whether they passed or failed the course. This is a natural division for this study as the event of interest is whether a student drops out or not. Students who take the final exam and fail it have not abandoned or withdrawn from the course and thus not dropped out of the course (see definition of dropout in section 2.1). Students who were sick on the final exam and took a make-up exam instead are treated as having taken the final exam.
    - The timing of dropout: estimated as the number of weeks from the start of the course until the last week the student either attends a PL or uses TW.

3.3. The students

In fall 2012, 484 students registered for Calculus IC. The following terms are used in this research to refer to the registered students:

- Non-starters: Students who registered for Calculus IC in 2012 but neither attended PL nor used TW. The non-starters can be divided into two groups:

  - Resigners: Students who resigned from the course before the course started

  - No-shows: Students who did not resign before the course started and did not show up at PL or use TW.

- Starters: Students who registered for Calculus IC in 2012 and either attended PL or used TW or both. The starters can be divided into two groups:

  - Completers: students who took the final exam, can be further divided into students who passed the course and students who failed it

  - Dropouts: students who either attended PL or used TW but did not take the final exam

At least 18 of the no-shows attended at least one lecture, the lecture when the DT was held. However, there is no way of knowing how many showed up for other lectures or assistant lessons because attendance was only recorded in the PL. Hence, all students who did not attend a PL or use TW are considered to be no-shows even though some of them took the DT.

In the following sections the students who registered for the course will be described based on the variables that are used in this research, which are listed in section 3.2 above.

3.3.1. Background

The students who registered for Calculus IC were from 18 to 54 years old. The mean age was 24 (see table 3.1). Only 23% of the registered students took IME on time and entered their major the same year while 45% took IME on time and then delayed entering their major (see table 3.1). Almost half of the registered students were new entrants at UI and additional 30% were first year students in their major but had been registered at other majors at UI previously (see table 3.1). The 127 students who were not first year students were either geology students, where Calculus IC is organized as a second year course, or students who most likely either dropped out or failed Calculus IC previously.

Table 3.1: Characteristics of registered students and a comparision of male and female students

		Gender	
	Total No. 484	Male No. 275	Female No. 209
Age			
Mean (SD)	$23.6(\pm4.8)$	$24.2(\pm5.0)$	$22.7(\pm4.5)$
IME and Entry			
On time & Direct	112 (23.3%)	50 (18.2%)	62 (30.0%)
On time & Delayed	217 (45.1%)	112 (40.9%)	105 (50.7%)
Delayed & Direct	57 (11.9%)	36 (13.1%)	21 (10.1%)
Delayed & Delayed	95 (19.8%)	76 (27.7%)	19 (9.2%)
Career and Year			
New entrant	213 (44.0%)	105 (38.2%)	108 (51.7%)
1 year, not first major	144 (29.8%)	97 (35.3%)	47 (22.5%)
First major, not 1 year	74 (15.3%)	42 (15.3%)	32 (15.3%)
Not 1 year, not first major	53 (11.0%)	31 (11.3%)	22 (10.5%)
Major			
Pharmacy	86 (17.8%)	27 (9.8%)	59 (28.2%)
Biochemistry	108 (22.3%)	37 (13.5%)	71 (34.0%)
Computer	191 (39.5%)	150 (54.5%)	41 (19.6%)
Other	99 (20.5%)	61 (22.2%)	38 (18.2%)
Took DT			
Took	290 (59.9%)	155 (56.4%)	135 (64.6%)
Did not take	194 (40.1%)	120 (43.6%)	74 (35.4%)
Semesters of math			
6 or more	221 (77.5%)	119 (78.3%)	102 (76.7%)
Less than 6	64 (22.5%)	33 (21.7%)	31 (23.3%)
Well prepared			
Agree	68 (23.8%)	35 (22.9%)	33 (24.8%)
Neutral	122 (42.7%)	67 (43.8%)	55 (41.4%)
Disagree	96 (33.6%)	51 (33.3%)	45 (33.8%)
Did well			
Agree	133 (46.5%)	59 (38.8%)	74 (55.2%)
Neutral	119 (41.6%)	69 (45.4%)	50 (37.3%)
Disagree	34 (11.9%)	24 (15.8%)	10 (7.5%)
Like math			
Agree	160 (56.1%)	77 (50.3%)	83 (62.9%)
Neutral	97 (34.0%)	61 (39.9%)	36 (27.3%)
Disagree	28 (9.8%)	15 (9.8%)	13 (9.8%)
DT grade			
Mean (SD)	$3.2(\pm1.9)$	$3.0(\pm1.7)$	$3.5(\pm2.1)$

Table 3.1: (continued)

	Total	Gender	
		Male	Female
	No. 484	No. 275	No. 209
DT grade C			
[0,2]	95 (32.8%)	55 (35.5%)	40 (29.6%)
(2,5]	142 (49.0%)	77 (49.7%)	65 (48.1%)
(5,10]	53 (18.3%)	23 (14.8%)	30 (22.2%)

3.3.2. Diagnostic test

290 students took the DT in the beginning of the course (see table 3.2) which is 60% of the registered students. The majority of the students who took the DT completed the course but dropouts and no-shows also took it (see table 3.2). Women, new entrants and students who took IME on time were more likely to take the DT (see table 3.3).

Table 3.2: Students who took the diagnostic test at the beginning of Calculus IC in fall 2012

	Took DT	**Did not take DT**	**Total**
Resigners	0	34	34
No-shows	18	60	78
Dropouts	76	44	120
Completers	196	56	252
Total	290	194	484

In general the students got low DT grades. One third of the students got a grade below 2 and only one out of every five students got a grade above 5 (see table 3.1). The majority of the students 78% took 6 or more semesters of mathematics in upper secondary school. Only 24% think they are well prepared for studying mathematics at university level although 12% think they did well in mathematics in upper secondary school and 10% like mathematics (see table 3.1).

Table 3.3: The number and percent of students who took the diagnostic test at the beginning of the semester by gender, time of IME, time of entry, career, year and major and mean age of the students who took the test.

	N (%) took DT
Gender	
Male	155 (56.4%)
Female	135 (64.6%)
Age	
Mean (SD)	$22.8(\pm 4.2)$
IME and Entry	
On time & Direct	76 (67.9%)
On time & Delayed	138 (63.6%)
Delayed & Direct	31 (54.4%)
Delayed & Delayed	44 (46.3%)
Career and Year	
New entrant	157 (73.7%)
1 year, not first major	76 (52.8%)
First major, not 1 year	38 (51.4%)
Not 1 year, not first major	19 (35.8%)
Major	
Pharmacy	61 (70.9%)
Biochemistry	67 (62.0%)
Computer	113 (59.2%)
Other	49 (49.5%)

3.3.3. Gender

A greater number of men than women registered for Calculus IC in 2012 (see table 3.1). The female students were on average younger than the male students, a higher percent of them took IME on time and entered their major directly (see table 3.1). A higher percentage of females were new entrants at UI and a higher percentage of females choose pharmacy or biochemistry while males choose computer science (see table 3.1). A higher percentage of female students thought they did well in mathematics in secondary school but the average DT grade is similar for female and male students (see table 3.1).

3.3.4. Majors

Calculus IC is a mandatory course for computer science, biochemistry, pharmaceutical science, geology, food science and chemistry. 4% of the students that took the course were in majors where Calculus IC is not a mandatory course (see table 3.1).

Computer science had the highest number of students, the highest percentage of males and the lowest percentage of new entrants, with the exception of geology (see table 3.4).

There were more male than female students in all majors except for biochemistry and pharmaceutical science (see table 3.4). The students who registered for biochemistry and pharmaceutical science were on average younger (see table 3.4). A higher percentage of students in pharmacy and biochemistry took the DT (see table 3.4). A higher percentage of students in pharmacy, biochemistry and chemistry took IME on time and entered their major directly (see table 3.4). A higher percentage of students in biochemistry thought they were well prepared for studying mathematics at university level and they got on average higher DT grades than students in other majors (see table 3.4).

More female students took the course as a non-mandatory course (see table 3.4. Students not taking Calculus IC as a mandatory subject were on average older (see table 3.4).

Table 3.4: Characteristics of registered students by major

	Major						
	Computer No. 191	Biochemistry No. 108	Pharmacy No. 86	Geology No. 38	Food science No. 23	Chemistry No. 21	Non-mandatory No. 17
Gender							
Male	150 (78.5%)	37 (34.3%)	27 (31.4%)	25 (65.8%)	16 (69.6%)	13 (61.9%)	7 (41.2%)
Female	41 (21.5%)	71 (65.7%)	59 (68.6%)	13 (34.2%)	7 (30.4%)	8 (38.1%)	10 (58.8%)
Age							
Mean (SD)	$24.2(\pm4.8)$	$21.7(\pm3.0)$	$21.8(\pm3.1)$	$24.4(\pm3.8)$	$26.3(\pm6.1)$	$24.5(\pm8.7)$	$29.5(\pm6.5)$
IME and Entry							
On time & Direct	27 (14.3%)	40 (37.4%)	28 (32.6%)	7 (18.4%)	1 (4.3%)	8 (38.1%)	1 (5.9%)
On time & Delayed	90 (47.6%)	44 (41.1%)	43 (50.0%)	14 (36.8%)	12 (52.2%)	6 (28.6%)	8 (47.1%)
Delayed & Direct	17 (9.0%)	11 (10.3%)	9 (10.5%)	7 (18.4%)	7 (30.4%)	2 (9.5%)	4 (23.5%)
Delayed & Delayed	55 (29.1%)	12 (11.2%)	6 (7.0%)	10 (26.3%)	3 (13.0%)	5 (23.8%)	4 (23.5%)
Career and Year							
New entrant	75 (39.3%)	59 (54.6%)	53 (61.6%)	1 (2.6%)	12 (52.2%)	13 (61.9%)	0 (0.0%)
1 year, not first major	84 (44.0%)	28 (25.9%)	17 (19.8%)	0 (0.0%)	5 (21.7%)	5 (23.8%)	5 (29.4%)
First major, not 1 year	17 (8.9%)	12 (11.1%)	11 (12.8%)	22 (57.9%)	4 (17.4%)	2 (9.5%)	6 (35.3%)
Not 1 year, not first major	15 (7.9%)	9 (8.3%)	5 (5.8%)	15 (39.5%)	2 (8.7%)	1 (4.8%)	6 (35.3%)
Took DT							
Took	113 (59.2%)	67 (62.0%)	61 (70.9%)	21 (55.3%)	12 (52.2%)	10 (47.6%)	6 (35.3%)
Did not take	78 (40.8%)	41 (38.0%)	25 (29.1%)	17 (44.7%)	11 (47.8%)	11 (52.4%)	11 (64.7%)
Semesters of math							
6 or more	80 (73.4%)	56 (83.6%)	45 (73.8%)	18 (85.7%)	8 (66.7%)	9 (90.0%)	5 (100.0%)
Less than 6	29 (26.6%)	11 (16.4%)	16 (26.2%)	3 (14.3%)	4 (33.3%)	1 (10.0%)	0 (0.0%)

Table 3.4: (continued)

	Major						
	Computer No. 191	Biochemistry No. 108	Pharmacy No. 86	Geology No. 38	Food science No. 23	Chemistry No. 21	Non-mandatory No. 17
Well prepared							
Agree	18 (15.9%)	27 (41.5%)	15 (25.0%)	2 (9.5%)	0 (0.0%)	5 (50.0%)	1 (16.7%)
Neutral	52 (46.0%)	23 (35.4%)	24 (40.0%)	11 (52.4%)	5 (45.5%)	4 (40.0%)	3 (50.0%)
Disagree	43 (38.1%)	15 (23.1%)	21 (35.0%)	8 (38.1%)	6 (54.5%)	1 (10.0%)	2 (33.3%)
Did well							
Agree	47 (42.3%)	35 (53.0%)	32 (52.5%)	6 (30.0%)	3 (25.0%)	6 (60.0%)	4 (66.7%)
Neutral	47 (42.3%)	25 (37.9%)	24 (39.3%)	11 (55.0%)	6 (50.0%)	4 (40.0%)	2 (33.3%)
Disagree	17 (15.3%)	6 (9.1%)	5 (8.2%)	3 (15.0%)	3 (25.0%)	0 (0.0%)	0 (0.0%)
Like math							
Agree	66 (58.4%)	37 (59.7%)	32 (52.5%)	8 (38.1%)	5 (41.7%)	8 (80.0%)	4 (66.7%)
Neutral	39 (34.5%)	19 (30.6%)	22 (36.1%)	9 (42.9%)	6 (50.0%)	1 (10.0%)	1 (16.7%)
Disagree	8 (7.1%)	6 (9.7%)	7 (11.5%)	4 (19.0%)	1 (8.3%)	1 (10.0%)	1 (16.7%)
DT grade							
Mean (SD)	$2.7(\pm 1.7)$	$4.4(\pm 2.2)$	$3.3(\pm 1.6)$	$2.6(\pm 1.5)$	$1.7(\pm 1.5)$	$4.8(\pm 2.4)$	$3.2(\pm 1.1)$
DT grade C							
[0,2]	46 (40.7%)	12 (17.9%)	19 (31.1%)	10 (47.6%)	7 (58.3%)	0 (0.0%)	1 (16.7%)
(2,5]	55 (48.7%)	29 (43.3%)	33 (54.1%)	10 (47.6%)	5 (41.7%)	6 (60.0%)	4 (66.7%)
(5,10]	12 (10.6%)	26 (38.8%)	9 (14.8%)	1 (4.8%)	0 (0.0%)	4 (40.0%)	1 (16.7%)

3.4. Analysis

The analysis is divided into three parts, the first is a preliminary analysis and the second and third parts aim to answer the two research questions presented in the introduction. The second and third parts of the analysis begin with unadjusted statistical tests and then adjusted models follow.

3.4.1. Preliminary analysis

Starting and completion rates

The first step is finding out how many students registered for the course and then define what starting studying in the course meant. The conclusion is to define starting student as students who either attended at least one PL or used TW at least once (see discussion in section 3.3). The proportion of starting students is calculated as:

$$\text{starting rate} = \frac{\text{the number of starters}}{\text{the number of registered students}}$$

The next step is finding out how many starters completed the course by taking the final exam and to calculate the completion rate which is the proportion of starters who complete the course:

$$\text{completion rate} = \frac{\text{the number of completers}}{\text{the number of starters}}$$

The odds of starting the course are calculated as:

$$\text{Odds of starting} = \frac{\text{the number of starters}}{\text{the number of non-starters}}$$

and the odds of completing the course given a student started it are:

$$\text{Odds of completing} = \frac{\text{the number of completers}}{\text{the number of dropouts}}$$

The timing of dropout

Most studies on the dropout of university students use registration data to analyse at which semesters students are most likely to drop out or switch between majors (e.g., Bahi et al., 2015; R. Chen, 2012; DesJardins et al., 2002; Min et al., 2011; Murtaugh et al., 1999; Smith & Naylor, 2001). Few studies seem to explore at what time of the semester students are most likely to dropout. This study uses student's attendance in Calculus IC and data from an online learning environment to estimate the end of student's participation in the course. This approach gives a more detailed dropout time from this specific course. The timing of dropout is estimated for each dropout as the last week a student either attends or uses tutor-web. The course lasted fourteen weeks, with a final exam one week later, covering in total fifteen weeks. The measured dropout among starters happened in weeks 2-14 as students could use TW from week 2 up until week 14 and the PL were held in weeks 2-13.

The number of students who have not dropped out each week is referred to as the risk set, i.e. students who are at risk of dropping out. A weekly dropout rate is calculated as the proportion of students who dropped out each week of the risk set. The weekly dropout rates give insight into when most dropout happens and whether there are some observable timepoints with more dropout. The average number of weeks dropouts stayed in the course before dropping out is also calculated.

Participation before dropout

To qualify for taking the final exam, the students had to attend at least 9 PL, answer a certain amount of TW questions, hand in 4 group projects and take 2 pop quizzes. A few students were granted exemptions due to special circumstances and allowed to take the final exam without meeting all of those requirements. The participation of the dropouts is summarised and the average number of weeks dropouts attended PL and used TW is calculated along with the average number of group projects handed in and pop quizzes taken[1].

[1] Very few dropouts took a pop quiz so this is the only part of this thesis which uses data about pop quizzes

3.4.2. Starting or not?

The first part of the analysis aims to answer the question of which students are most likely to start in Calculus IC by analysing background information from the Student Registry at UI (see a list of the background variables in section 3.2). The background characteristics of non-starters are compared to the starters with t-tests, which are used to compare the average of numerical variables for the two groups. χ^2 tests are then used to test whether there is a significant difference in the probability of starting for the subgroups of students based on background characteristics. The data also includes results from the DT for 272 starters and 18 non-starters which are summarised with descriptive statistics.

After the unadjusted comparison of non-starters and starters, a multiple logistic regression model is structured to adjust for confounding between the explanatory variables with the *glm* function in *R* (R Development Core Team, 2015). The outcome is whether a student started the course or not. The following initial model is fitted to the data:

$$ln\left(\frac{p}{1-p}\right) = \beta + \gamma g + \alpha a + \iota i + \omega e + \phi f + \nu c + \eta_m \tag{3.1}$$

where p is the probability of not starting Calculus IC; $\frac{p}{1-p}$ are the odds of not starting Calculus IC; γg is the student gender where g is 0 if male and 1 if female; αa is the student age centered at 20 years old; ιi is IME, where i is 0 if the student took IME on time and 1 if they delayed IME; ωe is entry in current major, where e is 0 if the student entered current major the same year as he took IME and 1 if he did not; ϕf is a first year student where f is 0 if the student is first year student and 1 if they are not; νc is career where c is 0 if first career and 1 if not; and η_m is the student major, where m is 1 for computer science, 2 for pharmaceutical science, 3 for biochemistry and 4 for geology, chemistry, food science or non-mandatory major. β are the log-odds for a 20 year old male student in computer science who took IME on time, entered current major the same year he took IME, is a first year student and a at his first career at UI.

Variables are removed one at a time from the initial model, when their removal results in lower Akaike's Information Criterion (AIC) value. The final model includes non-significant variables if their existence in the model lowers the AIC value. Both crude and adjusted odds ratios (OR) for the variables in the final model will be presented along with 95% confidence intervals. From the confidence intervals it is possible to evaluate which variables are significant. The variable is non-significant if the interval includes 1.

The probability of not starting Calculus IC is predicted by rewriting formula 3.1 into:

$$p = \frac{e^{\beta+\gamma g+\alpha a+\iota i+\omega e+\phi f+\nu c+\eta_m}}{1+e^{\beta+\gamma g+\alpha a+\iota i+\omega e+\phi f+\nu c+\eta_m}} \tag{3.2}$$

The probability of not starting Calculus IC is predicted for female and male students with the characteristics that are the least likely to start the course and the most likely to do so, based on the estimated odds ratios from the final version of the model in equation 3.1.

3.4.3. Completing or dropping out?

The second part of the analysis aims to answer the question of what affects whether and when a student drops out? To do so, the 372 starters are studied. The probability of dropping out is estimated for the subgroups of starters based on the variables used in the study (see section 3.2). Part of the variables come from the DT, which the majority of the starters took at the beginning of the semester, 76 of the students who took it dropped out and 196 completed the course. To begin with, t-tests and χ^2 tests are used to compare the variables (see section 3.4.2). When the background variables are compared, it is done for all students. When the DT variables are compared it is done for just the group of students who took the DT.

To adjust for the confounding between the explanatory variables and to analyse what affects whether and when students drop out, a Cox proportional hazard model is structured. The Cox model is a popular model used for analysing survival data (Kleinbaum & Klein, 2012). Survival analysis has been used to enrich models of dropout from universities (e.g., R. Chen, 2012; Murtaugh et al., 1999) as well as modelling if and when students switch majors (e.g., Bahi et al., 2015) and graduate (e.g., Zwick & Sklar, 2005). By using survival analysis instead of logistic regression, information of when students are most likely to dropout is gained in addition to know which students are most likely to dropout (Bahi et al., 2015; Willett & Singer, 1991).

The Cox model is similar in use to a multiple logistic regression but, instead of giving odds ratios, it gives hazard ratios (HR) for the effect of each variable adjusted for the other variables in the model (Kleinbaum & Klein, 2012). Hazard ratio is defined as "the hazard for one individual divided by the hazard for a different individual" (Kleinbaum & Klein, 2012, p. 114). The model is structured with the *coxph* and *Surv* functions from the *Survival* package (Therneau & Lumley, 2016) for *R* (R Development Core Team, 2015). The outcome is whether a event occurs and if so, the time until it occurs from a specific start time. If an individual does not experience the event, the time is the end of the observation period. The event is often death of a patient receiving certain treatment and from that survival analysis gains its name. Here, the outcome is whether a student completes Calculus IC in fall 2012 or drops out. The time until the event is the number of weeks from the start of the course until a student drops out or, if the student did not drop out, the time is 14 weeks, which is the duration of the course.

The following initial model is fitted to the data for the group of starters who took the DT at the beginning of the semester (n=272):

$$h(t) = h_0(t)e^{\gamma g+\alpha a+\iota i+\omega e+\phi f+\nu c+\eta_m+\delta d+\zeta s+\theta_p+\tau_w+\kappa_k} \tag{3.3}$$

where γg is the student gender where g is 0 if female and 1 if male; αa is the student age centered at 20 years old; ιi is IME, where i is 0 if the student took IME on time and 1 if they delayed IME; ωe is entry in current major, where e is 1 if the student entered current major the same year as he took IME and 0 if he did not; ϕf is a first year student where f is 1 if the student is first year student and 0 if they are not; νc is career where c is 0 if first career and 1 if not; and η_m is the student major, where m is 1 for computer science, 2 for pharmaceutical science, 3 for biochemistry and 4 for geology, chemistry, food science or non-mandatory major; δd is student DT grade, where d is the grade on a scale 0-10, centered at the average grade; ζs is semesters of mathematics in upper secondary school; θ_p is whether the students think they are well prepared for studying mathematics at university level; τ_w is whether the student did well in upper secondary school; and κ_k which is whether the student likes mathematics (see section 3.2 for further information about the DT variables). $h(t)$ is the hazard at time t which is the probability of dropping out at time t given the student has not dropped out already and $h_0(t)$ is the baseline hazard of dropping out at each timepoint t for a 20 year old female student in pharmacy, who took IME on time, delayed entering pharmacy, is not a first year student but is a at her first career at UI, got an average DT grade, took 6 or more semesters of mathematics in upper secondary school, thinks she is well prepared for studying mathematics at university level, thinks she did well in mathematics in upper secondary education and likes mathematics.

Variables are removed one at a time from the initial model when their removal results in lower AIC value for the model. The final model includes non-significant variables, if their existence in the model lowers the AIC value. The final model can only have 14-16 parameters, because there were 76 dropouts from the group of students who took the DT. A well-established rule of thumb states that 10 or more events have to be in the data per parameter in logistic and cox models

(Concato, Peduzzi, Holford, & Feinstein, 1995; Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996). Based on it, the maximum number of parameters is 7-8 for the model, since there were 76 dropouts. Vittinghoff and McCulloch (2007) recently found that this rule might be unnecessarily conservative and can be relaxed. Their results suggest that 5 events per parameter is often enough (Vittinghoff & McCulloch, 2007). That allows up to 14-16 parameters in the model.

The main assumptions of the Cox model are that the hazard ratios have to be proportional over the duration of the study, i.e. the effects of the explanatory variables $\gamma\alpha\iota\omega\phi\nu\eta\delta\zeta\theta\tau\kappa$ have to be the same over the duration of the course (time-independent). The proportionality of the final model is checked with the *cox.zph* function from the *Survival* package (Therneau & Lumley, 2016) for *R* (R Development Core Team, 2015) for each explanatory variable and for the whole model.

Both crude and adjusted hazard ratios for the variables in the final model are presented along with 95% confidence intervals. The probability of completing Calculus IC is predicted by letting $t = 14$, as 14 is the number of weeks in the course, in the equation:

$$S(t) = S_0(t)e^{\gamma g+\alpha a+\iota i+\omega e+\phi f+\nu c+\eta_m+\delta d+\zeta s+\theta_p+\tau_w+\kappa_k} \tag{3.4}$$

where $S(t)$ is the survival function or the probability of not having dropped out. The probability of being still in the course at certain week is predicted similarly by letting t equal the number of week of interest. The probability of completing Calculus IC is predicted for female and male students with the characteristics that are the least likely to complete the course and most likely to do so. Adjusted survival curves based on the final model are presented for the same students.

As the students who took the DT might be different from the rest of the starters who took the course, another model is constructed for all starters (n=372). It includes only the background variables and the initial model is:

$$h(t) = h_0(t)e^{\gamma g+\alpha a+\iota i+\omega e+\phi f+\nu c+\eta_m} \tag{3.5}$$

Variables are removed one at a time from the initial model when their removal results in lower AIC value for the model. The final model includes non-significant variables, if their existence in the model lowers the AIC value. Both crude and adjusted hazard ratios for the variables in the final model are presented along with 95% confidence intervals. The results from this model are then compared to the previous model. The probability of completing Calculus IC is predicted for female and male students with the characteristics that are the least likely to complete the course and most likely to do so. Adjusted survival curves based on the final model are presented for the same students.

4. Results

4.1. Preliminary analysis

4.1.1. Starting and completion rates

484 students registered for Calculus IC in fall 2012, of them 372 were starters and 112 non-starters (see figure 4.1). The starting rate was thus 77%. Of the starters, 120 students dropped out and 252 students completed the course so the completion rate was 68%. The odds of starting the course were 3.3 which means that if we choose a student at random from the data, he is 3.3 times more likely to start the course than not. For a student who started the course, the odds of completing it were 2.1 which means that students who started the course are twice as likely to complete the course as dropping out.

4.1.2. The timing of dropout

The number of starters who dropped out each week of Calculus IC is pretty constant with a dropout rate of 2-4% each week (see table 4.1). Week 5 is the exception with 7% dropout rate or 24 dropouts, over double the number in other weeks (see figure 4.2). On average, the dropouts stayed in Calculus IC for 7 weeks out of the total 14 weeks.

4.1.3. Participation before dropping out

None of the dropouts in Calculus IC during fall 2012 had fulfilled all necessary requirements to take the final exam before they dropped out of the course. However, 23 dropouts had met some of the requirements: 16 dropouts attended 9 or more PL and 11 dropouts handed in 4 group projects (see figure 4.2).

Dropouts attended on average 4 PL, used TW for 4 weeks, handed in 1 group

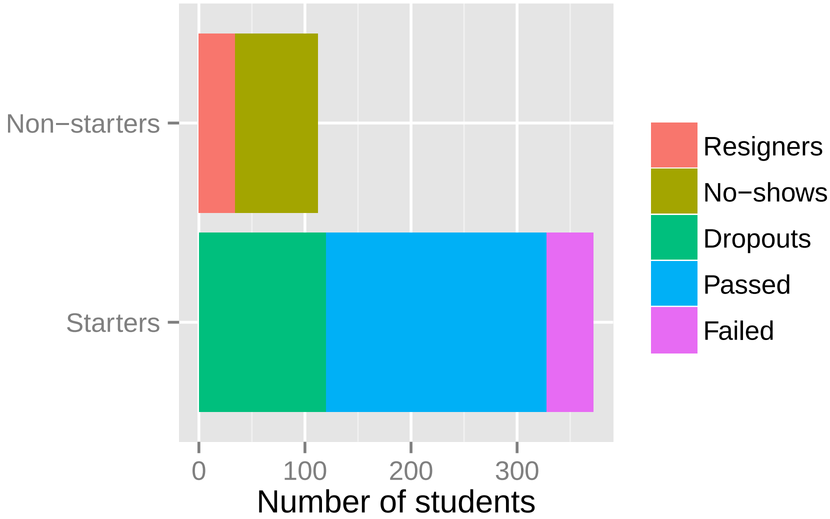

Figure 4.1: The number of students who started Calculus IC in fall 2012 and the number of students who completed the course.

project and did not take any pop quiz. The majority of the dropouts (68%) attended 2 or more PL and used TW for at least 2 weeks. 48% of dropouts handed in one or more projects and 22% took a pop quiz. A part of the dropouts attended 9 or more PL (see figure 4.2).

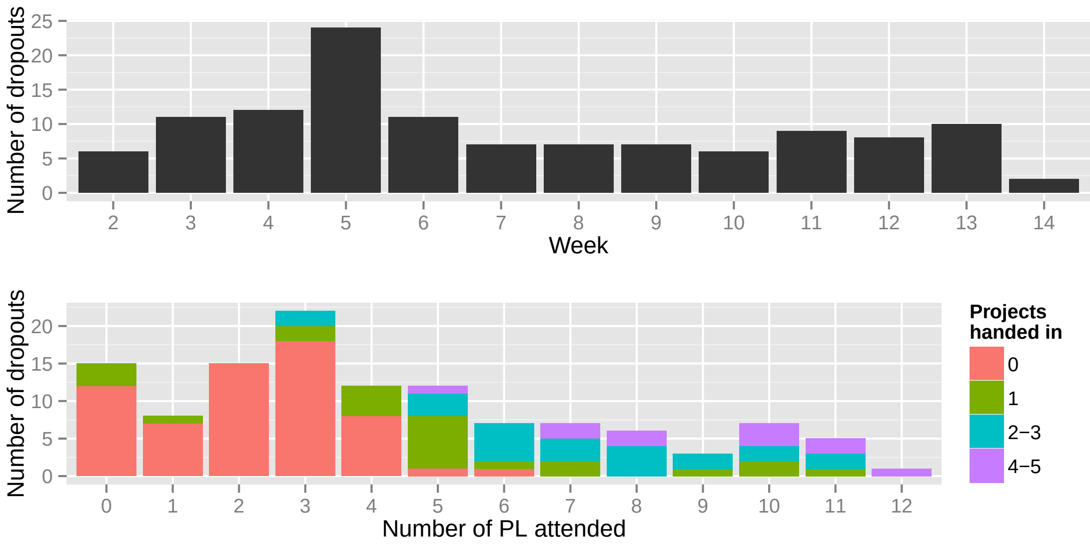

Figure 4.2: The number of students who dropped out each week of Calculus IC in fall 2012 (above). The number of PL dropouts attended and the number of projects they handed in (below).

Week	Risk set	Dropouts	Dropout rate (%)
2	372	6	2
3	366	11	3
4	355	12	3
5	343	24	7
6	319	11	3
7	308	7	2
8	301	7	2
9	294	7	2
10	287	6	2
11	281	9	3
12	272	8	3
13	264	10	4
14	254	2	1

Table 4.1: A survival table. The number of students who are still in Calculus IC each week (Risk set), the number of students who dropped out each week and the weekly dropout rate (%).

4.2. Starting or not?

This section analyses what type of students are most likely to start studying in Calculus IC. The section starts with unadjusted t-tests and χ^2 tests, comparing starters to non-starters. Afterwards follows multiple logistic regression modelling whether or not a student began the course.

4.2.1. Unadjusted results

Similar proportion of female and male students started the course (see table 4.2) but female non-starters were more likely to resign than male non-starters (see table 4.3). The average age of the non-starters was significantly higher than that of the starters (see table 4.2). Students who entered their current major directly after IME were significantly more likely to begin the course than students who delayed entering their major after IME (see table 4.2). Students at their first career were significantly more likely to start the course than students who had registered for other majors before entering their current major (see table 4.2).

Without statistical testing, it can be seen from the proportions in table 4.4 that students who got a DT grade below 2 were less likely to start Calculus IC. The results indicate that studying less mathematics at upper secondary level and/or performing poorly as well as not feeling prepared for studying mathematics at university level, is correlated with lower starting-rate (see table 4.4).

Table 4.2: The probability of starting Calculus IC versus not-starting among registered students by gender, time of IME, time of entry in major, year in major, career at UI and major. Whether the probability of starting is significantly different for the subgroups is tested with χ^2 tests. The average age of starters and non-starters is also calculated and a t-test used to test whether they are significantly different.

	Registered students		
	Starters No. 372	Non-starters No. 112	P-value
Gender			
Male	217 (78.9%)	58 (21.1%)	0.23
Female	155 (74.2%)	54 (25.8%)	
Age			
Mean (SD)	$23.3(\pm 4.7)$	$24.5(\pm 5.3)$	0.002
IME			
On time	259 (78.7%)	70 (21.3%)	0.20
Delayed	111 (73.0%)	41 (27.0%)	
Entry			
Direct	143 (84.6%)	26 (15.4%)	0.003
Delayed	227 (72.8%)	85 (27.2%)	
Year			
First	279 (78.2%)	78 (21.8%)	0.27
Not first	93 (73.2%)	34 (26.8%)	
Career			
First	234 (81.5%)	53 (18.5%)	0.004
Not first	138 (70.1%)	59 (29.9%)	
Major			
Pharmacy	73 (84.9%)	13 (15.1%)	0.17
Biochemistry	84 (77.8%)	24 (22.2%)	
Computer	139 (72.8%)	52 (27.2%)	
Other	76 (76.8%)	23 (23.2%)	

Table 4.3: The probability of not showing up versus resign among non-starters by gender, time of IME, time of entry in major, year in major, career at UI and major. Whether the probability of not showing up is significantly different for the subgroups is tested with χ^2 tests. The average age of no-shows and resigners is also calculated and a t-test used to test whether they are significantly different.

	Non-starters		
	No-shows No. 78	Resigners No. 34	P-value
Gender			
Male	46 (79.3%)	12 (20.7%)	0.025
Female	32 (59.3%)	22 (40.7%)	
Age			
Mean (SD)	$24.6(\pm5.6)$	$24.2(\pm4.5)$	0.97
IME			
On time	48 (68.6%)	22 (31.4%)	0.67
Delayed	30 (73.2%)	11 (26.8%)	
Entry			
Direct	17 (65.4%)	9 (34.6%)	0.63
Delayed	61 (71.8%)	24 (28.2%)	
Year			
First	58 (74.4%)	20 (25.6%)	0.12
Not first	20 (58.8%)	14 (41.2%)	
Career			
First	33 (62.3%)	20 (37.7%)	0.15
Not first	45 (76.3%)	14 (23.7%)	
Major			
Pharmacy	7 (53.8%)	6 (46.2%)	0.20
Biochemistry	15 (62.5%)	9 (37.5%)	
Computer	41 (78.8%)	11 (21.2%)	
Other	15 (65.2%)	8 (34.8%)	

Table 4.4: The probability of starting Calculus IC versus not starting among registered students by semesters of mathematics at upper secondary school, student's preparedness for studying mathematics at university, performance in mathematics at upper secondary school, whether students like mathematics and DT grade. The average DT grade of starters and non-starters is also calculated.

	Registered students	
	Starters No. 372	Non-starters No. 112
Semesters of math		
6 or more	212 (95.9%)	9 (4.1%)
Less than 6	55 (85.9%)	9 (14.1%)
Well prepared		
Agree	67 (98.5%)	1 (1.5%)
Neutral	118 (96.7%)	4 (3.3%)
Disagree	83 (86.5%)	13 (13.5%)
Did well		
Agree	129 (97.0%)	4 (3.0%)
Neutral	109 (91.6%)	10 (8.4%)
Disagree	30 (88.2%)	4 (11.8%)
Like math		
Agree	153 (95.6%)	7 (4.4%)
Neutral	88 (90.7%)	9 (9.3%)
Disagree	26 (92.9%)	2 (7.1%)
DT grade		
Mean (SD)	$3.3(\pm 1.9)$	$1.8(\pm 1.8)$
DT grade C		
[0,2]	82 (86.3%)	13 (13.7%)
(2,5]	138 (97.2%)	4 (2.8%)
(5,10]	52 (98.1%)	1 (1.9%)

4.2.2. Adjusted results

In order to obtain adjusted estimates of each variable effect on whether a student begins the course, a multiple logistic regression model was structured (see section 3.4.2). The initial model is shown in equation 3.1. Students age, major and whether or not a student was a first year student, were found to result in higher AIC value and were thus removed from the model. The variables IME and career are included in the model, even though they are not statistically significant, as including them results in a model with lower AIC value. The resulting model is:

$$ln\left(\frac{p}{1-p}\right) = \beta + \gamma g + \iota i + \omega e + \nu c \tag{4.1}$$

And with the estimated parameters:

$$ln\left(\frac{p}{1-p}\right) = -2.16 + 0.46g + 0.44i + 0.59e + 0.43c \tag{4.2}$$

where g is the student gender, i is whether the student took IME on time, e is whether the student entered current major directly after IME and c is whether the student is at their first career at UI. p is the probability of not starting Calculus IC and $\frac{p}{1-p}$ are the odds of not starting. β is the log-odds of not starting for a male student, who took IME on time, entered current major directly after IME and is at his first career at UI.

The highest odds ratio is between students who entered their major directly after IME, and those who did not. Students who delayed entry are almost twice as likely not to start the course as students who entered directly (see table 4.5). The odds of starting the course, after registering, are greater for first career students and students who took IME on time (see table 4.5).

Without adjusting for time of IME, time of entry and career at UI, there is no significant difference between the odds of a female and male student starting the course (see table 4.2). However after adjusting, a female student who took IME on time, entered her major directly and is at her first career, is 1.6 times more likely to not start the course than the same male student (see table 4.5). The crude odds ratios along with adjusted odds ratios for the variables included in the model can be seen in table 4.5.

The non-starting rate in Calculus IC was 23% (see section 4.1.1). The probability of not starting the course is predicted with:

$$p = \frac{e^{-2.16+0.46g+0.44i+0.59e+0.43c}}{1+e^{-2.16+0.46g+0.44i+0.59e+0.43c}} \tag{4.3}$$

For students who took IME on time, entered their major directly and are at their first career, the predicted probability of not starting is estimated as 15% for females and 10% for males. For students who delayed IME, delayed entering their major and are not at their first career, the predicted probability of not starting the course is substantially higher, or 44% for females and 33% for males.

Table 4.5: Adjusted odds ratios with 95 percent confidence intervals from the model in equation 4.2. The reference in the adjusted model are male students who took IME on time, enrolled directly in their major and are at their first career. Unadjusted odds ratios with 95 percent confidence intervals for each variable and a model with only an intercept are also presented.

	Crude			**Adjusted**		
	OR	Lower	Upper	OR	Lower	Upper
Intercept	0.30	0.24	0.37	0.11	0.06	0.20
Gender						
Female	1.30	0.85	1.99	1.60	1.01	2.52
IME						
Delayed	1.37	0.87	2.13	1.54	0.96	2.46
Entry						
Delayed	2.06	1.28	3.40	1.82	1.07	3.16
Career						
Not first	1.89	1.23	2.90	1.54	0.96	2.49

4.3. Completing or dropping out?

This section analyses which starters are most likely to complete Calculus IC and when those who do not, drop out. It starts with t-tests comparing averages for completers and dropouts and chi-square tests comparing the proportion of students who drop out amongst various subgroups of the starters. Afterwards follows two cox proportional hazard models that analyse what effects whether and when students drop out of the course, one for starters who took the diagnostic test (DT), and the other for all starters.

4.3.1. Unadjusted results

The average age of dropouts is significantly higher than of completers (see table 4.6). Male students are significantly more likely to drop out of Calculus IC than female students (see table 4.6). Students who took IME on time are significantly less likely to drop out, with half of the students who delayed IME dropping out of the course (see table 4.6). First year students are significantly more likely to dropout and students in computer science are significantly more likely to dropout than students in pharmacy and geology (see 4.6).

Students who took the DT are significantly less likely to dropout than students who did not take the DT. Students who think they are well prepared for studying mathematics at university level are significantly less likely to dropout and as students who got a higher DT grade are significantly less likely to dropout (see table 4.6).

Table 4.6: The probability of completing Calculus IC versus dropping out among students who started the course by gender, time of IME, time of entry in major, year in major, career at UI, major, whether students took the DT, semesters of mathematics at upper secondary school, preparedness for studying mathematics at university, mathematic performance at upper secondary school, whether students like mathematics and DT grade. Whether the probability of completing is significantly different for the subgroups is tested with χ^2 tests. The average age and average DT grade of completers and dropouts are also calculated and t-tests used to test whether they are significantly different.

	Starters		
	Complete No. 252	Drop out No. 120	P-value
Gender			
Male	128 (59.0%)	89 (41.0%)	<0.001
Female	124 (80.0%)	31 (20.0%)	
Age			
Mean (SD)	$23.0(\pm4.7)$	$23.8(\pm4.6)$	0.012
IME			
On time	195 (75.3%)	64 (24.7%)	<0.001
Delayed	57 (51.4%)	54 (48.6%)	
Entry			
Direct	93 (65.0%)	50 (35.0%)	0.36
Delayed	159 (70.0%)	68 (30.0%)	
Year			
First	177 (63.4%)	102 (36.6%)	0.002
Not first	75 (80.6%)	18 (19.4%)	
Career			
First	162 (69.2%)	72 (30.8%)	0.42
Not first	90 (65.2%)	48 (34.8%)	
Major			
Pharmacy	59 (80.8%)	14 (19.2%)	<0.001
Biochemistry	58 (69.0%)	26 (31.0%)	
Computer	77 (55.4%)	62 (44.6%)	
Other	58 (76.3%)	18 (23.7%)	
Took DT			
Took	196 (72.1%)	76 (27.9%)	0.004
Did not take	56 (56.0%)	44 (44.0%)	
Semesters of math			
6 or more	159 (75.0%)	53 (25.0%)	0.042
Less than 6	33 (60.0%)	22 (40.0%)	

Table 4.6: (continued)

	Starters		
	Complete No. 252	Drop out No. 120	P-value
Well prepared			
Agree	58 (86.6%)	9 (13.4%)	0.002
Neutral	84 (71.2%)	34 (28.8%)	
Disagree	51 (61.4%)	32 (38.6%)	
Did well			
Agree	100 (77.5%)	29 (22.5%)	0.11
Neutral	72 (66.1%)	37 (33.9%)	
Disagree	20 (66.7%)	10 (33.3%)	
Like math			
Agree	111 (72.5%)	42 (27.5%)	0.65
Neutral	60 (68.2%)	28 (31.8%)	
Disagree	20 (76.9%)	6 (23.1%)	
DT grade			
Mean (SD)	$3.7(\pm 1.9)$	$2.4(\pm 1.6)$	<0.001
DT grade C			
[0,2]	43 (52.4%)	39 (47.6%)	<0.001
(2,5]	106 (76.8%)	32 (23.2%)	
(5,10]	47 (90.4%)	5 (9.6%)	

4.3.2. Adjusted results

In order to obtain adjusted estimates of each variable's effects on whether and when a starting student drops out, a cox proportional hazard model was structured. This section begins with a model for the starters who took the DT and then follows a model for all starters as a comparison. The initial model fitted is shown in equation 3.3. The variables: age, career, whether students think they did well in mathematics in upper secondary school or not, whether students think they are well prepared for studying mathematics at university level, whether students like mathematics or not and the number of semesters of mathematics they took in upper secondary school, were found to result in higher AIC value and were thus removed from the model. Taking IME on time and being a first year student, are included in the model even though they are not statistically significant as including them results in a model with lower AIC value. The resulting model is:

$$h(t) = h_0(t)e^{\gamma g+\iota i+\omega e+\phi f+\eta_m+\delta d} \tag{4.4}$$

And with the estimated parameters:

$$h(t) = h_0(t)e^{0.92g+0.38i+0.52e+0.65f+\eta_m-0.43d} \tag{4.5}$$

where g is student's gender; i is whether the student took IME on time; e is whether the student entered their major the same year as he took IM; f is whether the student is a first year student or not; $\eta_1 = 1.63$ which is biochemistry, $\eta_2 = 1.09$ is computer science and $\eta_3 = 0.38$ is other majors; and d is a increase of DT grade by 1 on a scale 0-10. $h_0(t)$ is the hazard at time t, for a female student in pharmacy, who took IME on time, did not enter pharmacy the same year as she took IME, is not a first year student and got an average DT grade. The estimated hazard ratios along with crude hazard ratios are presented in table 4.7 in columns *Crude* and *Adjusted 1*. Table 4.7 also presents estimated hazard ratios from the same model but without the DT grade (*Adjusted 2*) as adding the grade has great effect on the hazard ratios.

Table 4.7: Crude and adjusted hazard ratios with 95 percent confidence interval for the model in equation 4.5 (Adjusted 1) and the same model without DT grade (Adjusted 2). The reference is a female student in pharmaceutical science who took IME on time, delayed entry in pharmaceutical science, is not a first year student and got an average DT grade. The models in both Adjusted 1 and 2 apply only to the students who started the course and took the DT (n=272).

	Crude			**Adjusted 1**			**Adjusted 2**		
	HR	Lower	Upper	HR	Lower	Upper	HR	Lower	Upper
Gender									
Male	2.5	1.5	4.1	2.5	1.4	4.6	1.9	1.0	3.3
IME									
Delayed	2.2	1.4	3.5	1.5	0.9	2.4	1.9	1.2	3.2
Year									
First	2.2	1.1	4.6	1.9	0.9	4.3	2.0	0.9	4.4
Entry									
Direct	1.2	0.7	1.8	1.7	1.0	2.7	1.3	0.8	2.2
Major									
Biochemistry	3.5	1.4	8.8	5.1	2.0	13.2	3.1	1.2	7.7
Computer	4.7	2.0	11.0	3.0	1.2	7.4	3.3	1.3	8.1
Other	1.8	0.6	5.2	1.5	0.5	4.5	1.5	0.5	4.7
DT grade									
Grade	0.7	0.6	0.8	0.7	0.6	0.8	–	–	–

Male students are significantly more likely to drop out than female students if they start the course (see table 4.7). A male student who has not yet dropped out at certain week of the course has a 2.5 times higher chance of dropping out that week than a female student with the same values in the other variables in model in equation 4.5 (see table 4.7). The results indicate that first year students are two times more likely to drop out every week than other students, although the differences is not significant (see table 4.7).

According to the adjusted model without DT grade (*Adjusted 2*), students who delayed IME are 1.9 times more likely to drop out each week than students who took IME on time (see table 4.7) but as students who took IME on time perform on average better on the DT than students who delayed IME, the difference lowers down to 50% in the adjusted model with the DT grade. Hence, students who delayed IME are only 50% more likely to drop out every week than students who took IME on time, given they have the same mathematical preparedness.

Students who did not enter their major the same year as they took IME are less likely to drop out each week than other students, all else being equal. It should however, be noted that without DT grade in the model (see *Adjusted 2* in table 4.7), the effect of the time of entry is less prominent as students who delay entering their major score on average lower DT grade (see appendix A.1).

Students who score a high DT grade are less likely to drop out; the probability of dropping out each week, given a student has not dropped out yet, lowers by 30% for each point in DT grade on a scale 0-10 (see table 4.7). Students who score DT grade of 2 or lower have around 50% probability of completing Calculus IC while students who score above 2 have at least 75% percent chance of completing the course (see figure 4.3). Students who take IME on time, enter their major directly score on average higher DT grade than students who either delay IME or delay entry (see appendix A.1).

The difference in the probability of dropping out is considerable between the majors. According to the unadjusted results, students in computer science have the highest probability of dropping out (see *Crude* in table 4.7 and figure 4.4). However, the adjusted results with the DT grade indicate that students in biochemistry are most likely to drop out, and students in computer science second (see *Adjusted 1* in table 4.7 and figure 4.4). This is because students in biochemistry score on average higher DT grade than students in the other majors (see appendix A.1). In the adjusted model without DT grade, students in biochemistry and computer science have similar hazard of dropping out (see *Adjusted 2* in table 4.7 and figure 4.4).

The type of student which is most likely to drop out, according to the model in equation 4.5, is a first year student in biochemistry who delayed IME, entered directly and scored a DT grade 2 or lower. If the student is male he only has a 7% probability of completing the course but if the student is female the probability

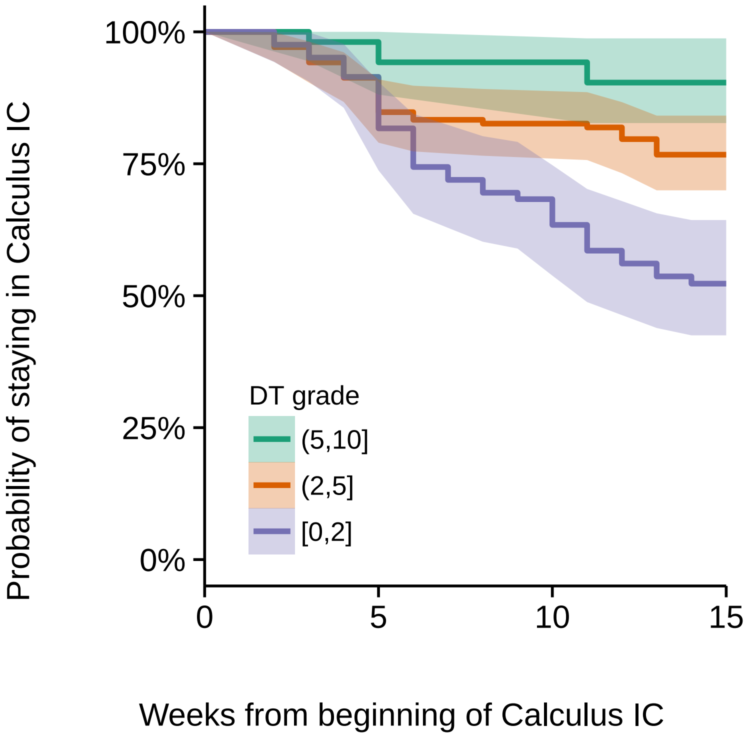

Figure 4.3: The probability of staying in Calculus IC during the course based on DT grade. A Kaplan-Meier survival curve for the students who took the DT.

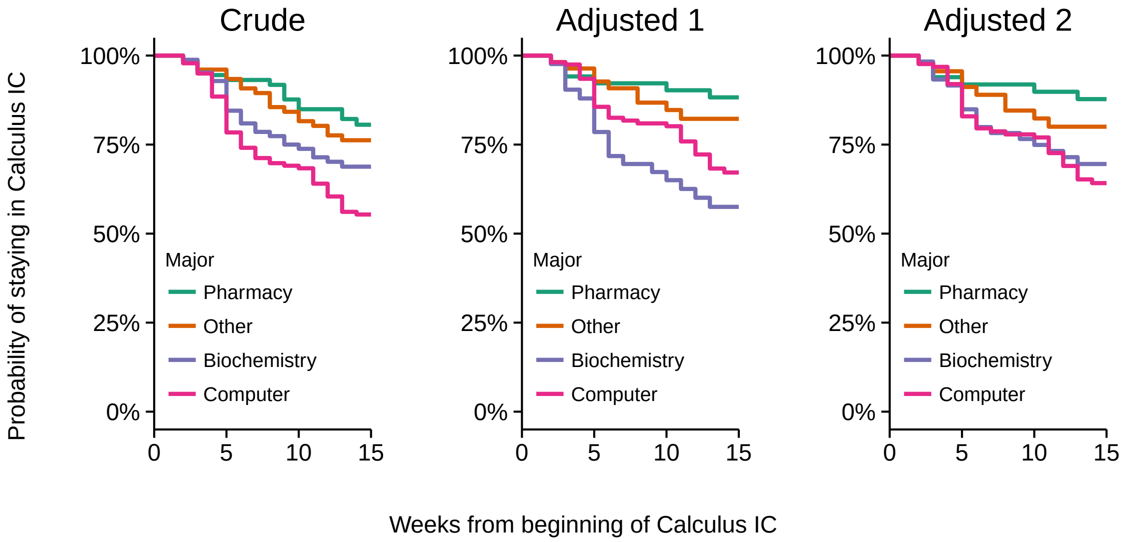

Figure 4.4: The probability of staying in Calculus IC during the course based on major, crude and adjusted based on the cox model in equation 4.5 and the same model without DT grade. The left graph is a Kaplan Meier survival curve based on the data. The middle graph shows 1. year students who took IME on time, entered directly and adjusted for gender and DT grade. The right graph shows the same student without adjusting for DT grade.

is 28%. The probability of completing the course would be similar for a student in computer science with the same characteristics but higher for a student in pharmacy or other majors with the same characteristics.

The type of student which is the least likely to drop out, according to the model in equation 4.5, is a second year student in pharmacy who took IME on time and scored a DT grade of 5 or higher. If the student is male they have a 99% probability of completing the course but if the student is female the probability is 99%. If the a student with the same characteristics would be instead in computer science or biochemistry the student would be slightly less likely to complete the course.

Male students who delay IME are considerable less likely to complete the course than female students who took IME on time. This can be seen in figure 4.5 which presents the effect of gender and time of IME for first year students who entered their major directly after IME on the probability of dropping out over the duration of the course. It shows that at week 10, a male student who delays IME has about 50% probability of still being in the course while a female student who took IME on time has a about 80% probability. The three graphs below show how great effect the DT grade has on the probability of dropping out. Students who score a low grade are much more likely to drop out than students who score a high

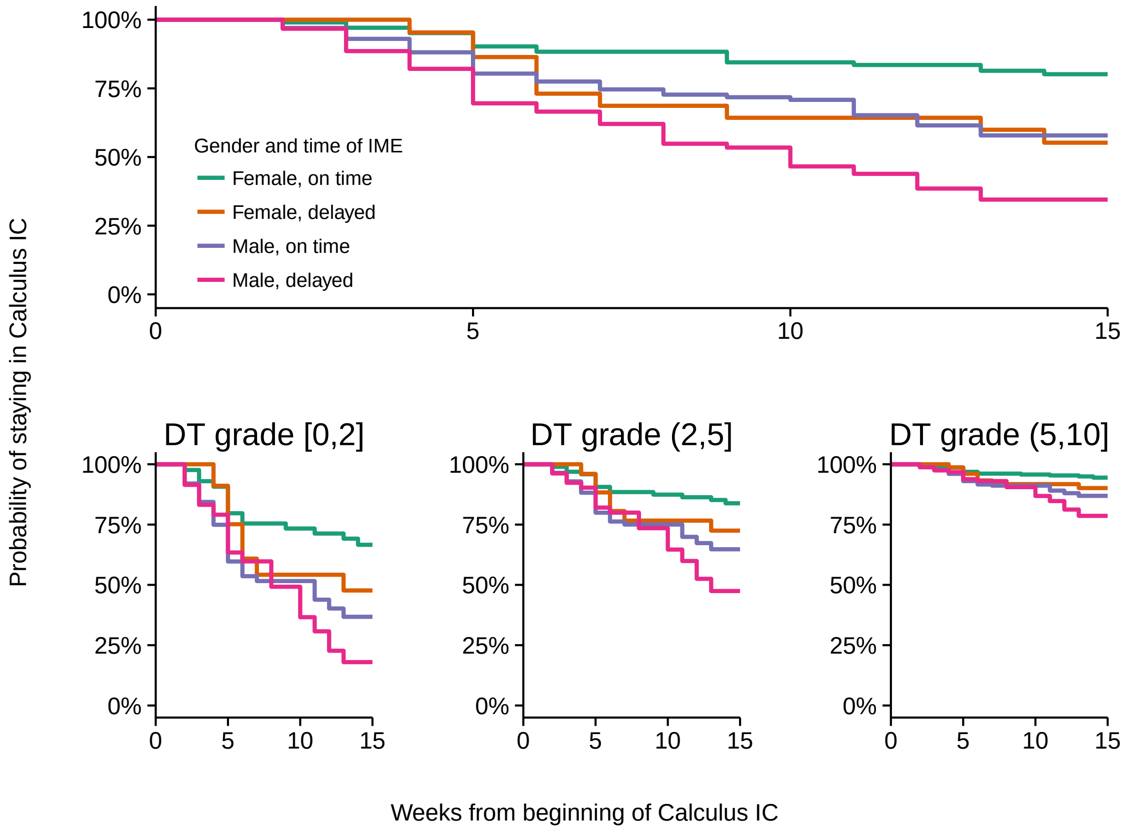

Figure 4.5: The probability of staying in Calculus IC during the course for a first year student who entered their major directly based on gender, time of IME and DT grade. The top graph is based on the model in equation 4.7. The graphs below are based on the model in equation 4.5.

grade. A student who is either male or delayed IME and scores a DT grade of 2 or lower has just over 50% probability of still being in the course at the 5th week (see figure 4.5) and a 25-50% probability of completing the course. On the other hand, a female student who took IME on time and scores a DT grade of 2 or lower has about 75% probability of still being in the course at week 5 and about 70% probability of completing the course.

A cox model was also structured for all starters, without DT grade and the other variables from the DT. The initial model is shown in equation 3.5. The variables: student age, major, time of entry and career resulted in higher AIC values and were subsequently removed from the model. The resulting model is:

$$h(t) = h_0(t)e^{\gamma g + \iota i + \phi f} \tag{4.6}$$

And with the estimated parameters:

$$h(t) = h_0(t)e^{0.78g+0.75i+0.92f} \tag{4.7}$$

where g is student gender, i is whether or not the students took IME on time and f is whether or not the students are first year students. $h_0(t)$ is the hazard at time t for a female student who took IME on time and is not a first year student. The estimated hazard ratios along with crude hazard ratios are presented in table 4.8 in columns *Crude* and *Adjusted 2*. Table 4.8 also presents estimated hazard ratios from the same model but with the variables *Time of entry* and *Major* (*Adjusted 1*) to allow for comparison to the models for students who took the DT as the students who took the DT might be different from the students who did not take it.

When adjusting for gender and year in major, the hazard for students who did not take IME on time is around 2 times the hazard for students who took IME on time (see table 4.8). The adjusted hazard for male students is also around 2 times the adjusted hazard for female students (see table 4.8). This model supports the findings in the first model but it has narrower confidence intervals, indicating more reliable results. Figure 4.6 shows adjusted survival curves based on the model in equation 4.7 for gender, timing of IME and year in major separately.

This model shows that students who enter their major directly after IME might be slightly more likely to drop out (HR=1.3) (see column *Adjusted 1* in table 4.8) but this is not significant just as in the model for the DT students without the DT grade (see column *Adjusted 2* in table 4.7). This model indicates that students in biochemistry and computer science are more likely to drop out than students in pharmacy, like the previous model did.

The type of student which is most likely to drop out according to the model in equation 4.7 is a first year student who delayed IME. If the student is in addition male, the probability of completing the course is only 38% but if the student is female it is 64%. The type of student who is least likely to drop out is a second or higher year student who took IME on time. If the student is male, the probability of completing is 83% but if they are female it is 92%. For a first year student who took IME on time the probability of completing the course is 81% for a female student and 63% for a male student. Adjusted survival curves based on the model in equation 4.7 for gender and timing of IME are presented in figure 4.5.

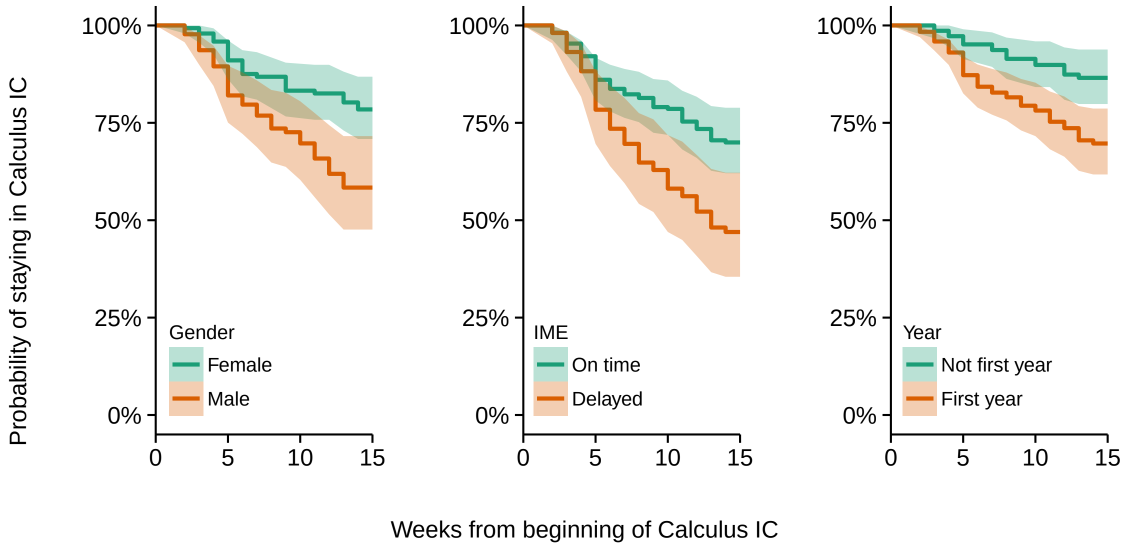

Figure 4.6: The probability of staying in Calculus IC during the course, based on gender, timing of IME and year in major, adjusted based on the cox model in equation 4.7. The left graph shows 1. year students who took IME on time. The middle graph shows 1. year students, adjusted for gender. The right graph shows students who took IME on time, adjusted for gender

Table 4.8: Crude and adjusted hazard ratios and 95 percent confidence interval for model in equation 4.7 (Adjusted 2) and the same model with Entry and Major (Adjusted 1). The reference is a female student in pharmacy who took IME on time, delayed entry and is not a first year student.

	Crude			Adjusted 1			Adjusted 2		
	HR	Lower	Upper	HR	Lower	Upper	HR	Lower	Upper
Gender									
Male	2.4	1.6	3.6	1.9	1.2	3.1	2.2	1.4	3.3
IME									
Delayed	2.3	1.6	3.3	2.0	1.4	3.0	2.1	1.4	3.0
Year									
First	1.2	0.8	1.7	2.2	1.3	3.8	2.5	1.5	4.1
Entry									
Direct	2.1	1.3	3.4	1.3	0.9	1.9	–	–	–
Major									
Biochemistry	1.7	0.9	3.3	1.6	0.8	3.1	–	–	–
Computer	2.8	1.5	4.9	1.9	1.0	3.5	–	–	–
Other	1.3	0.6	2.6	1.1	0.5	2.4	–	–	–

5. Discussion

In fall 2012, 484 students registered for Calculus IC. Only half of the registered students took the final exam, resulting in a total dropout rate of 48%, which is similar to the first-year dropout rate that was found at UI in 2006 (Haraldsson et al., 2008) but much higher than the observed dropout rate in foreign studies on university dropout (R. Chen, 2012; Haraldsson et al., 2008; Murtaugh et al., 1999; Ríkisendurskoðun, 2007; Smith & Naylor, 2001). However, about one out of every four registered students in Calculus IC, did not start the course which means that the non-starters were almost half of the dropouts. This is similar to the findings of a survey by UI, which found that around half of the dropouts never showed up in class (H. H. Jónsdóttir & Jónsson, 2008).

The exact non-start rate was 23% which is just above what Jónsson (1989) observed among new entrants at UI in 1982. However, the non-start rate in this study is slightly overestimated because students who attended lectures but neither attended a practice lesson nor used tutor-web are counted as non-starters because attendance was not recorded in the lectures.

The dropout rate from Calculus IC was 32%, excluding the non-starters. This is still higher than the dropout rates observed in other studies on university dropout (R. Chen, 2012; Murtaugh et al., 1999; Smith & Naylor, 2001) but it is worth mentioning that this is dropout rate at the course level while the dropout rates in the other studies are at a program or an institution level. The dropouts stayed in Calculus IC 7.2 weeks on average before dropping out and the mode was week 5. A few dropouts stayed in the course up until the end but dropped out less than two weeks before the final exam.

This study suggests that students gender, time of IME, time of entry in major and career number affect the probability of starting Calculus IC and students gender, mathematical preparation, time of IME, major, year in major and time of entry in major affect the probability of completing the course for students who start it.

5.1. Non-starters

Students who delay IME and delay entering their major are significantly less likely to start the course than students who took IME on time and entered their major directly. Male students are significantly more likely to start the course than female students and students at their first career are more likely to start the course than other students.

Students who took IME on time and entered their major directly are almost 3 times more likely to start Calculus IC than students who delayed IME and delayed entering their major. Students who took IME on time but delayed entering their major are more likely to start the course than students who delayed IME and delayed entering their major, but they are still almost two times more likely not to start the course than students who took IME on time and entered their major directly. This suggests that interrupting one's studies at upper secondary level affects the probability of starting university education after registering.

Older students are less likely to start the course than younger students. However, after adjusting for the time of IME and time of university entry, age is not significant. The data shows that older students, who delayed IME but entered their major directly are more likely to start the course than younger students who took IME on time but delayed entry to university.

Unadjusted, there is no significant difference in the probability of starting in Calculus IC after registering, between female and male students. However, after adjusting for the time of IME and time of entering major, male students are 60% more likely to start the course than female students.

The data from the diagnostic test suggests that non-starters might be less prepared for studying mathematics at university level than starters. This indicates that students who are poorly prepared for studying mathematics at university level are less likely to start studying in Calculus IC after registering, than students who are better prepared. So students who are poorly prepared might not only be more likely to drop out of university, they might also be less likely to attend a course they register for. But further research is needed to explore this relationship.

The minority of the non-starters resigned from the course before it started, while the majority simply did not show up (i.e. no-shows). Female non-starters were more likely to resign rather than not show up than male non-starters.

The type of student which is least likely to start Calculus IC after registering for the course is a female student who delayed IME, delayed entering her major and is not at her first career at UI. This type of student only has a 56% probability of starting the course. On the other hand, a female student who took IME on time, entered her major directly and is at her first career at UI has a 85% probability of starting the course.

5.2. Dropouts

The variables which significantly affect the probability of dropping out of Calculus IC are mathematical preparation, gender, time of IME, major and year in major. In addition, the data indicates that time of entry in major might affect the probability of dropping out. The worse that a student's mathematical preparation is, then the more likely they are to drop out. Male students are significantly more likely to drop out than female students. Students who delayed IME are more likely to drop out than students who took IME on time. Students in biochemistry and computer science are significantly more likely to drop out than students in pharmaceutical science. First year students are more likely to drop out than other students. The results suggest that students who entered their major directly might be slightly more likely to drop out than students who delayed entry.

The results show that male students who start Calculus IC are 2.5 times more likely to drop out than female students who start Calculus IC. This is in accordance with the results of some studies on dropout from universities (Johnson, 2006; Smith & Naylor, 2001). However, other studies have found that in STEM programs, female students are more likely to drop out (Ellis et al., 2015; Rasmussen & Ellis, 2013).

Students who delayed IME are around 1.5-2 times more likely to drop out of Calculus IC than students who took IME on time. This suggests that interrupting one's studies at upper secondary level effects the probability of dropping out of university education. This is in accordance with studies which have shown that students who have once interrupted their studies are more likely to do so again (DesJardins et al., 2006; Johnson, 2006; OECD, 2012b).

First year students are more likely to drop out of Calculus IC than students in their second or higher year in their major. This result is in line with numerous other studies on the timing of dropout which have found that students are most likely to drop out in the first year (e.g., Bahi et al., 2015; Bean, 1980, 1982; R. Chen, 2012; DesJardins et al., 1999, 2006; Haraldsson et al., 2008; Jónsson, 1989; Murtaugh et al., 1999; Smith & Naylor, 2001; Tinto et al., 1993; Þórólfsson et al., 2005).

Students who scored a low DT grade at the beginning of the course are more likely to drop out of the course than students who scored a higher grade. The DT grade measures student's mathematical knowledge and the grade is highly correlated with how the students conceive their preparedness for studying mathematics at university level (see appendix A.1). Other studies have also found that students who are well prepared are less likely to drop out of university (Ozga & Sukhnandan, 1998; Smith & Naylor, 2001) although poorly prepared students often manage to catch up in Calculus IC at UI if they choose to stay (A. H. Jónsdóttir, 2015).

The proportion of dropouts varied between majors The lowest dropout rate was in pharmaceutical science where only 19% of the starters dropped out. This is comparable to what has been recorded before (Haraldsson et al., 2008). The highest proportion of dropouts was in computer science where 45% of the starters dropped out. This is similar to what Ríkisendurskoðun (2007) measured among first year students in computer science in 2003-2006 at UI. Students in both computer science and biochemistry are more likely to drop out than students in pharmaceutical studies. Students mathematical knowledge varies between majors, with students in biochemistry noticeable better prepared than students in the other majors. Even after adjusting for mathematical preparation, students in biochemistry and computer science are still significantly more likely to drop out of Calculus IC than students in pharmaceutical science and other programs.

A similar proportion of students who entered their major directly and students who delayed entry dropped out of Calculus IC in fall 2012. Students who entered their major directly were, on average, better prepared for studying mathematics at university level (see appendix A.1). Surprisingly, they were slightly more likely to drop out than students who delayed entry, given they scored the same DT grade. This result is contrary to other studies on the effect of delaying entering university after matriculation on the probability of dropping out of university. Studies have found that students who delay entering university after upper secondary education are more likely to drop out than students who enter directly (Ahlburg et al., 2002; Johnson, 2006; Jónsson, 1989; Þórólfsson et al., 2005). Students who enter their major directly after matriculation might be less sure of their career choice and thus more likely to drop out of Calculus IC and switching to another major later. Studies at UI have shown that Icelandic students often try out more than one major before graduating (Þórólfsson et al., 2005) and mature students are often more sure of their choice of major (OECD, 2012b).

The type of student which is most likely to drop out of Calculus IC after starting the course is a first year male student in computer science or biochemistry who delayed IME and is poorly prepared (scored 2 or less on the DT). This type of student has a 50% probability of dropping out before week 5 of the course and less than 20% probability of completing the course.

5.3. Summary

Half of the dropout from Calculus IC results from a high proportion of registered students not starting the course. Without the non-starters, the dropout rate is only 32% instead of 48% with the non-starters. Almost half of the dropout happens in the first 5 weeks of the course.

The main findings from the study are that students who have low mathematical knowledge are less likely to start the course, and given they started the course, they are more likely to drop out of the course than students who are better prepared. Female students are less likely to start the course than male students, but if they start the course, they are less likely to drop out than male students. Students who enter their major directly after IME are more likely to start the Calculus IC than students who delay entry. However, given that they have the same mathematical knowledge as students who delay entry, they are more likely to drop out after starting. Students who took IME on time are more likely to start the course and complete it, than students who delayed IME. Students at their first career are more likely to start the course than other students. First year students are more likely to drop out than students at their second or higher year. Students in computer science and biochemistry are more likely to drop out than students in pharmacy.

To lower the dropout rates from Calculus IC it is important to focus on students who are poorly prepared mathematically, especially male students and students who delayed IME. Those groups seem to drop out early, with only around half of them staying past the fifth week of the course. Poorly prepared female students who took IME on time do not drop out as early and are more likely to complete the course. It is important to remember that students in Calculus IC are dropping out right until the end of the course so it seems like intervention has to happen at multiple times during the course.

This study shows that different characteristics are correlated with on one hand the probability of starting a university course after registering for it and on the other hand the probability of completing a university course after starting. It is thus important to study the events of starting and dropping out separately as is done in this research. It is also crucial for UI to distinguish between dropout and not starting in its records to better facilitate appropriate intervention. In order to gain a better understanding of which groups of students are at the greatest risk of not starting, and which are at the greatest risk of dropping out, a study on a larger scale should be carried out including students in other majors.

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A. Additional analysis

This appendix contains results from additional analysis on the data.

A.1. DT grade

A multiple linear regression was carried out to find out what factors are connected with a high DT grade amongst students in Calculus IC. Getting a low DT grade dramatically increases the probability of dropping out of the course (see section 4.3) so it is important to know which students are likely to have a poor mathematical preparation. The following initial model is fitted to the data for the group of students who took the DT at the beginning of the semester (n=290):

$$y = \gamma g + \alpha a + \iota i + \omega e + \phi f + \nu c + \eta_m \tag{A.1}$$

where γg is the student gender where g is 0 if female and 1 if male; αa is the student age centered at 20 years old; ιi is IME, where i is 0 if the student took IME on time and 1 if they delayed IME; ωe is entry in current major, where e is 0 if the student entered current major the same year as he took IME and 1 if he did not; ϕf is a first year student where f is 0 if the student is first year student and 1 if they are not; νc is career where c is 0 if the student is at their first career at UI and c is 1 if not; and η_m is the student major, where m is 0 for computer science, 1 for pharmaceutical science, 2 for biochemistry and 3 for geology, chemistry, food science or non-mandatory major. y is the average DT grade for a 20 year old female student in pharmacy, who took IME on time, entered pharmacy directly, is a first year student and at her first career.

Non-significant variables were removed one at a time from the initial model, resulting in the following final model:

$$y = 3.3 + \eta_m - 0.5e - 0.7i \tag{A.2}$$

where $\eta_0 = 0$, $\eta_1 = 0.4$, $\eta_2 = 1.4$ and $\eta_3 = 0.2$.

According to the model, students in computer science who took IME on time and entered computer science the same year score on average 3.3 DT grade. If they delayed IME they score on average 0.7 lower DT grade and if they delayed entry they score on average 0.5 lower DT grade. Students in other majors score on average higher DT grade than students in computer science. Biochemistry students score on average the highest DT grade of the majors, 1.4 points higher than computer science students on average.

If variables from the DT are added to the model, the only significant variables are major and how the students think they are prepared for studying mathematics at university level. This is because students who delay entering their major and students who delay IME are more likely to feel they are not well prepared than other students. A model with major and how the students think they are prepared shows that students who think they are well prepared score on average 2.8 higher DT grade than students who think they are not well prepared when adjusted for major.

The DT seems to measure well how the students are prepared for studying mathematics at university level. The results suggest that students in computer science are worse prepared than other students and students in biochemistry are best prepared.

Table A.1: Results from a multiple linear regression on DT grade. The table shows the average DT grade crude and adjusted with 95 percent confidence intervals. The crude intercept is the average DT grade for the group of students who took the DT while the adjusted intercept is the average DT grade for a student in computer science who took IME on time and entered his major directly.

	Crude			Adjusted		
	DT grade	Lower	Upper	DT grade	Lower	Upper
Intercept	3.2	3.0	3.5	3.3	2.8	3.8
Major						
Pharmacy	0.6	0.0	1.2	0.4	−0.2	0.9
Biochemistry	1.7	1.1	2.2	1.4	0.8	1.9
Other	0.2	−0.4	0.8	0.2	−0.4	0.8
Entry						
Neutral	−0.7	−1.2	−0.3	−0.5	−1.0	−0.1
IME						
Disagree	−0.9	−1.4	−0.4	−0.7	−1.2	−0.2

A.2. Handing in group project 1

To be allowed to take the final exam, students in Calculus IC were required to hand in all group projects assigned to them. The bulk of the students who did not hand in group project 1 did thus drop out during the course. This was 90% of those who did not hand it in or 69 students. The rest of the students who did not hand in group project 1 were allowed to get an exemption and take the final exam without handing in all group projects. Students who turned in group project 1 were much less likely to drop out with only 17% of them dropping out (see figure A.1).

As turning in group project 1 is thus a similar decision as deciding to complete the course it is interesting to see which characteristics are connected with turning in group project 1 a logistic regression was carried out. One model with all starters and one with starters who took the DT were structured. The following initial model is fitted to the data:

$$ln\left(\frac{p}{1-p}\right) = \beta + \gamma g + \alpha a + \iota i + \omega e + \phi f + \nu c + \eta_m \tag{A.3}$$

where p is the probability of not handing in P1; $\frac{p}{1-p}$ are the odds of not handing in P1; γg is the student gender where g is 1 if male and 0 if female; αa is the student age centered at 20 years old; ιi is IME, where i is 0 if the student took IME on time and 1 if they delayed IME; ωe is entry in current major, where e is 0 if the student entered current major the same year as he took IME and 1 if he did not; ϕf is a first year student where f is 1 if the student is first year student and 0 if they are not; νc is career where c is 0 if the student is at their first career at UI and 1 if they are not; and η_m is the student major, where m is 0 for computer science, 1 for pharmaceutical science, 2 for biochemistry and 3 for geology, chemistry, food science or non-mandatory major. β are the log-odds of not handing in P1, for a 20 year old female student in computer science who took IME on time, entered current major the same year she took IME, is a first year student and at her first career at UI.

Non-significant variables were removed one at a time from the initial model, resulting in the following final model:

$$ln\left(\frac{p}{1-p}\right) = -3.1 + 1.4g + 0.7i + 0.7f \tag{A.4}$$

Males are 4 times less likely to turn in project 1 than females. Students who delayed IME are 2 times less likely to turn in project 1 and 1. year students are 2 times less likely to turn in project 1 than other students (see table A.2).

The only significant variable from the DT is the DT grade. After adding it only gender is significant, resulting in the following model:

$$ln\left(\frac{p}{1-p}\right) = -2.3 + 1.0g - 0.2d \quad (A.5)$$

where d is the grade from the DT on a scale 0-10, centered at the average grade which was 3.3.

According to this second model (equation A.5) males are 3 times less likely to turn in project 1 than females. The higher DT grade students score, the more likely they are to hand in project 1.

Table A.2: The odds of not handing in P1 based on model in equation A.4. Crude and adjusted odds ratios with 95 percent confidence intervals are presented. The reference is a female student who took IME on time and is not a first year student.

	Crude			**Adjusted**		
	OR	Lower	Upper	OR	Lower	Upper
Intercept	0.26	0.20	0.33	0.04	0.02	0.10
Gender						
Male	4.12	2.27	7.95	4.05	2.16	8.09
IME						
Delayed	2.35	1.39	3.96	1.92	1.10	3.33
Year						
1. year	1.65	0.90	3.21	2.01	1.06	4.04

On figure A.1 is a Kaplan-Meier graph for the survival of the starters depending on whether they turned in P1 or not. The graph shows that the vast majority of the students who did not turn in P1, drop out of the course which is to be expected as turning in P1 is one of the requirements for taking the final exam. The surprising fact here is that even though P1 was due in week 3 of the course, the majority of the students who did not turn in P1 do not drop out until at least two weeks later.

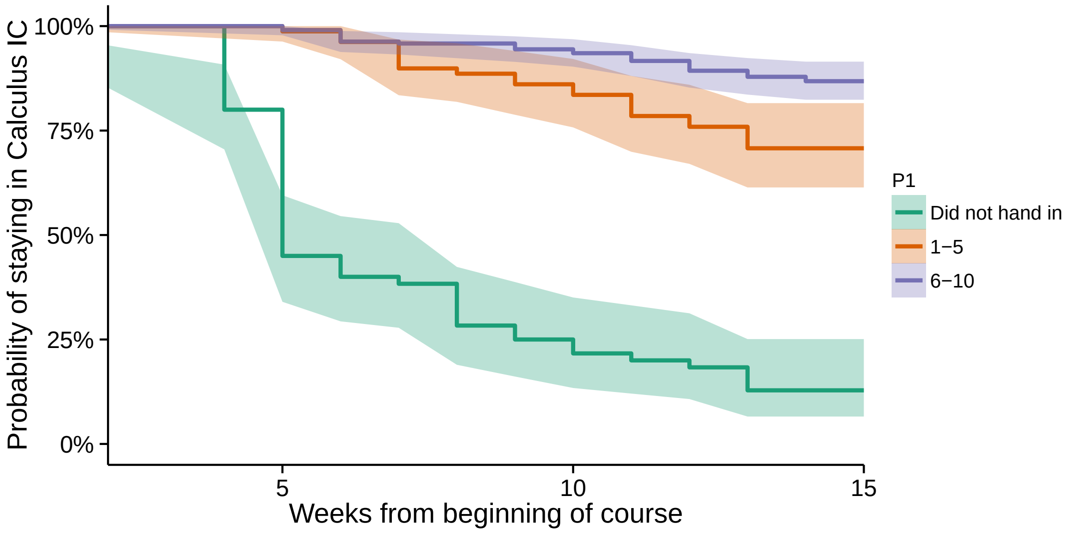

Figure A.1: The probability of staying in Calculus IC for students who did not hand in project 1, students who did and scored a grade of 5 or less and students who scored a grade higher than 5.