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Essays in Social Finance

by

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Committee in charge:

Professor Brett Green, Chair
Professor Ulrike Malmendier
Professor Christine Parlour
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Abstract

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This dissertation consists of three chapters centered on the idea of social finance. Social finance is a burgeoning field in finance that asks questions about how social motives and social concerns influence the actions of economic agents. Although economics and finance tend to model agents as purely self-interested, psychology and self-reflection are clear that humans value the concerns of others. Often such concerns are reflected in government policy. These policies can have interesting and often unintended effects.

In my first chapter "A Harming Hand: The Predatory Implications of Government Backed Student Loans," I consider the impact that government intervention in the student loan market has on student welfare showing that the welfare impact may not always be obvious. Although economic research is near unanimous finding that college is a good investment, there is growing concern about the impact that student debt and defaults have on student borrowers. Using the Department of Education's College Scorecard, I document a new stylized fact about cross-sectional return heterogeneity across schools. Motivated by this fact, I then construct a basic informed lending model to study the optimal way to encourage greater college attendance via loan policies. I show that under a socially optimal guarantee scheme, a social planner will want to pool all students at a single, uniform rate. This optimal policy, however, will result in weak students accepting predatory offers.

In my second chapter, "Paying to Stay Motivated: The Impact of University Gym Fees on Student Usage," I ask if making gym memberships costly always discourage usage of gyms? In many health-related settings, it has been documented that consumers choose expensive sub-optimal contracts. It has been suggested that such choices are a result of projection bias. Using a natural experiment with gym membership fees, I show that costly gym membership fees, may actually serve to encourage some users to go to the gym more because of the sunk-cost fallacy. In effect, gym usage fees may act as a commitment device improving consumer welfare.

In my third and final chapter, "Looking Good: Charitable Giving as a Signaling Mechanism," I explore the motivations for corporations to engage in pro-social behavior (i.e. corporate social responsibility programs). Traditional research into corporate social responsibility

(CSR) programs has argued that these CSR programs are a result of positive investment opportunities, agency costs, or investors' pro-social motives. I, however, advance a new explanation: that CSR programs act as a signal of future firm strength. Using information on corporate donations, I show that firms who donate more perform better both in terms of their real performance and their stock returns. Both the investment hypothesis and my signaling hypothesis could plausibly explain such results. To differentiate between the two hypothesis, I examine the difference in giving and firm performance between firms with a short-term and a long-term focused CEO. I find that the relationship between giving and firm performance is much weaker in firms with a short-term CEO. Only my signaling hypothesis can account for this difference.

To
my wife, Erica Schwartz,
my mother, Leslie Schwartz,
and
my late grandmother, Rose Harris

Contents

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Chapter 1

A Harming Hand: The Predatory Implications of Government Backed Student Loans

1.1 Introduction

In 2010, student loans passed credit card debt to become the second largest source of consumer debt in the United States. By March, 2018 the total outstanding balance on student loans had surpassed 1.5 trillion dollars. Nearly 90% of these loans involve the federal government as either the ultimate lender or guarantor of the debt. The government's intervention, however, has not reduced concern regarding the real and negative effects this debt has on student borrowers. In recent polling, 57% of Americans indicated that student debt for young people is a major problem. Further research has also found that student debt has impacted real consumer behavior (Rothstein & Rouse, 2011; Thompson & Bricker, 2016; Sieg & Wang, 2017).

Despite the growing concern regarding student debt, the economic literature is nearly unanimous: higher education is an excellent investment (Avery & Turner, 2012; Oreopoulous & Petronijevic, 2013). Summing up this literature, the Council of Economic Advisers (2016) found that "college remains an excellent an investment overall ... [funding] investments with large returns to student borrowers and the economy." At the same time that college is becoming an increasingly important and valuable investment, student debt is becoming a growing issue both for economists and for policy makers. If student loans were always worth it, they should not unduly burden student borrowers.

The purpose of this paper is two-fold. First, I show that the returns to higher education may not be uniformly distributed and some students, especially students at for-profit colleges, may not benefit. Second, I use this observation of return heterogeneity to motivate an informed lending model of the student loan market. Since risk-based pricing is not permitted on federal student loans, students are unable to learn the value of their education. This has negative consequences for students.

I begin by presenting evidence that, in contrast to popular perception, many students do not appear to benefit from a college education. To show this, I use the Department of Education's new College Scorecard to estimate the percent of students at a school-level who realized a negative return on their investment in higher education. The College Scorecard provides detailed data on wage outcomes, regardless of graduation status, and the net cost of attendance at each school; this data allows me to calculate the present value of the benefits and direct costs of education. To calculate the opportunity cost of not going to college, I use state-level wage data for recent high school graduates. While selection effects will likely result in an underestimate of the opportunity cost for college students, such selection effects would overstate the value of education working against me.

Based on this NPV analysis, I find that one-third of students realize a negative return from their investment in higher-education. These results confirm the large literature showing that for the average student college is a good investment (Card, 1995; Kane & Rouse, 1995; Hoekstra, 2009; Zimmerman, 2014; Ost et al., 2018). At many schools, however, students do not appear to be benefiting. Such schools tend to be for-profit colleges offering short-term training programs. Although these programs are short (meaning the cost is relatively low), they tend not to produce a significant wage premium for their students. Despite the existence of such poor performing institutions, students still display a willingness to attend them.

Next, I show that institutions can predict their students' outcomes. Colleges and universities that receive access to federal student loan programs must ensure that no more than 30% of their students default on federal loans; schools with default rates greater than 30% risk losing access to federal financial aid programs. As these programs are a vital source of revenue for schools (sometimes exceeding 80% of total revenue), losing access would likely result in bankruptcy for the institution. Hence, institutions near the 30% threshold have a strong incentive to control their admissions processes. Using federal data on school-level default rates, I show that schools near the 30% threshold experience large declines in their year-over-year default rates that can be explained by either reversion to the mean effects or macroeconomic conditions. These results suggest that schools can predict students' outcomes.

In addition to the evidence that schools can predict outcomes, students seem particularly poor at estimating the value of their education (Jensen, 2010; Bettinger et al., 2012; Scott-Clayton, 2013; Bleemer & Zafar, 2017; Wiswall & Zafar, 2015). Young students have also had few opportunities to gain financial literacy (Lusardi & Mitchell, 2014), learn about their readiness for college (Stinebrickner & Stinebrickner, 2012), or gauge their suitability for specific fields of study (Stinebricker & Stinebrickner, 2013). In contrast, schools and lenders have been able to learn from experience how certain student characteristics will likely map to post-college performance. Increasing information available to students does seem to improve their ability to estimate the value of their education (Fryer, 2016). Hence, students plausibly face information deficits when they make the decision to accept a student loan.

A final unique element of the student loan market is the single interest rate that prevails in the market. Approximately 90% of all student loans are part of various federal lending programs. Under these federal loan programs, lenders are not allowed to vary the rates that students are charged based on any observables or underwriting procedures. The rate set annually by the federal government is the rate that prevails for everyone. In traditional consumer credit markets, stronger borrowers will likely get better interest rates. With student loans, however, there is virtually no variation in prices based on risk.

Combining these three elements (seemingly uniformed students, informed schools/lenders, and a mandated uniform interest rate) can limit student borrowers' ability to learn the value of their education. In a laissez-faire market, interest rates would have conveyed the information lenders possessed about expected outcomes. In the student loan market, however, students cannot learn from interest rates because of the government's uniform rate requirement. To examine the impact that this information loss has on students, I construct a simple model of informed lending.

Under an informed lending model, lenders are able to observe borrowers' type; borrowers, however, are less informed and must attempt to infer their types from the lenders' actions. Security design and lending in the face of informed principals has been well studied in relations to venture capitalists and the financing of new enterprises (Habib & Johnsen, 2000; Axelson, 2007; Biais & Perotti, 2008; Casamatta & Haritchabalet, 2013) but have received less attention in the context of household finance. Two notable exceptions are Bond, et al. (2009) and Inderst (2008). In these informed lending models, not only can lenders be too conservative in their provision of capital, but they can also become too aggressive (Inderst & Mueller, 2006). Even when borrowers are partially informed, informed lenders can still generate valuable information helping both borrowers and lenders avoid negative NPV loans (Manove et al., 2001).

My model of informed lending is based on a canonical 1-period risky project financing model. There is a borrower who is seeking to finance a 1-period risky project (e.g. going to college). A group of competitive, identical lenders exist who are able to extend credit to the borrower. If the borrower agrees to terms with a lender the project is undertaken. At the end of the project, the borrower repays the loan, to the extent possible, and keeps the remainder of the project's output. In contrast to traditional models, however, borrowers only have some information about their type, whereas the lenders' have superior information[1].

When interest rates are allowed to vary based on risk, the borrower's information deficit is irrelevant. Because of the competition between lenders, the lenders' information is fully conveyed via interest rates. Hence, as long as risk-based interest rates are allowed, the first-best equilibrium will prevail, and all agents act as though they started with full information.

Under a uniform interest rate mandate, however, the borrower is unable to learn her true type. As long as a borrower is "good enough," she will be offered a loan at the mandated, prevailing rate. Upon seeing a loan offer, the borrower is now only able to learn that she is

[1]Explicitly, I assume that lenders know the borrower's type perfectly, whereas the borrower only knows the distribution that her type is drawn from.

in a pool of borrowers. This means that a borrower will face an information deficit opening the possibility for negative borrower outcomes.

Even though interest rate pooling creates an information deficit for student borrowers, interest rate pooling is still the mandated government policy. I extend my model to consider the social planner's welfare function showing that, despite the information loss, interest rate pooling may be socially optimal. To justify intervention in the first place, suppose that higher education generates a positive externality. Numerous studies have found significant positive externalities associated with higher education: improved health outcomes at both the individual and societal level (Currie & Enrico, 2003; Lleras–Muney, 2005; Grimard & Parent, 2007), improved civic engagement (Dee, 2004; Lance, 2011), reductions in crime (Fella & Gallipoli, 2014), productivity spillovers (Moretti, 2004; Iranzo & Peri, 2009), etc. Without government intervention, too few students would go to college.

Intervening and subsidizing loans in the higher education market, however, is costly. The social planner is able to both guarantee loans as well as mandate a uniform interest rate. With loan guarantees, a lender will be willing to lend at lower interest rates and to more borrowers. The government, however, will have to fund guarantee payouts from somewhere (e.g. higher taxes, crowding out other funding priorities, etc.). Hence, the social planner will want to balance the benefits of loan guarantees with their cost.

Interest rate pooling can be used to reduce the cost of a guarantee program. If the social planner wants to ensure that a student will go to school if and only if her type exceeds some threshold this could be done with or without using a uniform rate policy. Under risk-based interest rates, the student will be able to infer her true type. Hence, the threshold student will learn that she is relatively weak. This student will accept the loan if she is offered a very low interest rate; the lender would only be willing to lend at such a low interest rate if the credit guarantee was large.

With uniform rates, however, the student does not learn her true type. The student only learns that her type is in the pool of types at or above the threshold type. Since the expected strength of the pool is always strictly higher than the marginal type, the student will be willing to accept a loan at a higher interest rate. Given that the marginal borrower is willing to accept a loan at a higher interest rate, the government can offer lower credit guarantees to the lender. Under a uniform interest rate scheme, the social planner is able to induce the same level of lending but at a lower cost.

Although a uniform rate scheme can be socially optimal, it comes at a cost to students. With such a policy students may be induced to accept "predatory admissions" offers. Under the socially optimal policy the social planner will want some students to accept a loan with a negative value for the student. Because of interest rate pooling, the marginal student is not able to learn her true type. The marginal student will, unknowingly, accept a loan that decreases her utility. If the borrower had full information, she would never accept such a loan.

Traditionally, negative NPV consumer loans have been justified via behavior explanations (e.g. Della Vigna & Malmendier, 2004; Morgan, 2007; Bertrand & Morse, 2011). Most policy prescriptions have also tried to tackle predatory lending from this behavior perspective

(Stango & Zinman, 2011; Agarwal et al., 2014; Fritzdixon et al., 2014). In contrast, Bond, et al. (2009) considers rational predatory lending in the context of mortgage refinancing. Rational predatory lending can also arise in markets with imperfect competition (Inderst, 2008). To the best of my knowledge, this is the first paper to consider rational predatory behavior in the context of the student loan market.

As a robustness check, I extend the model along two dimensions: two-sided private information and direct government lending. Under two-sided private information, the lender must also consider selection effects when choosing who should be offered credit. Even with these selection effects predatory admissions will still arise under a uniform rate regime. The direct government lending extension is inspired by changes to the structure of federal student loan programs in the aftermath of the financial crisis; after the financial crisis most student loan origination shifted from private lenders to the federal government with screening still occurring at the school-level via admissions decisions. Even with direct lending, under reasonable conditions the socially optimal scheme will pool all students at a uniform rate. This uniform rate requirement will still result in predatory admissions.

The remainder of this chapter is organized as follows: Section 1.2 discusses the institutional details of federal student loan programs. Section 1.3 documents cross-sectional heterogeneity in the returns to college education and the existance of negative NPV institutions. In section 1.4, I discuss the role of colleges in the student loan market showing that it appears that schools have private information about students' expected outcomes. Section 1.5 discuss how government intervention in the student loan market impacts equilibrium behavior, while in 1.6 the government intervention is made endogenous. In section 1.7, I consider the implications for borrower welfare of the optimal intervention. Section 1.8 contains extensions to the base model showing the key results are robust to alternative market structures. Section 1.9 concludes the chapter.

1.2 The Working of Federal Student Loan Programs

The student loan market is unique in that 90% of loans are through various federal student loan programs. One of the key features of all of these programs is a uniform interest rate requirement: all loans must be issued at the same interest rate regardless of school or student quality. Such a rule severely limits the ability of risk to be considered when deciding who gets a loan.

With the exponential growth in both college costs and college enrollments, the federal government has played an ever increasing role in helping students finance their educations. Of the three major forms of federal assistance (loans, grants, and tax credits), federal loans are by far the largest. During the 2015-16 academic year, federal loans represented over 60% of all federal financial aid.

Federal loan programs first became widely available in the 1960s with the passage of the Higher Education Act of 1965 (HEA). Prior to that time, student loans were only available to students in specific majors without regard to student need. The HEA, however, opened up federal loans to all students so long as they were at an accredited institution of higher education.

Over the past 20 years, the averaged sticker price of a 4-year education has increased approximately 80%[2]. Over the same time period, total student borrowing has grown by nearly 150%. Much of this growth in student borrowing has been driven by increases in the four major federal student loan programs: unsubsidized[3], subsidized, Perkins, and PLUS loans. Figure 1.1 documents the growth in these four programs over time as well as the growth in overall student borrowing.

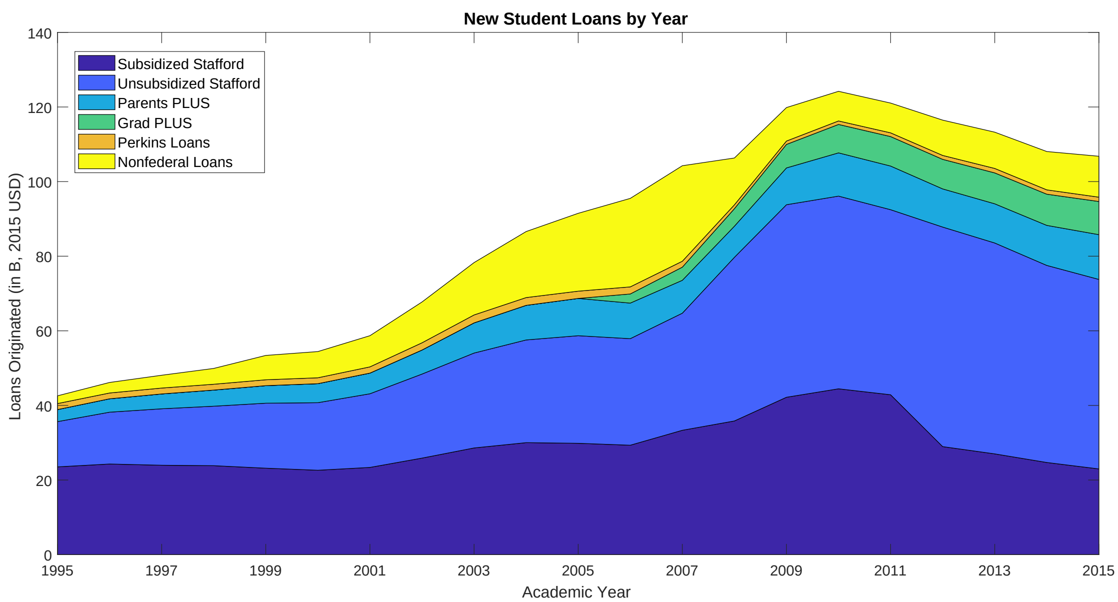


Figure 1.1: New student loans originated by year from 1995-96 to 2015-16 in 2015 dollars. Other than the nonfederal loan piece, all loans were originated under a federal loan program.
Data Source: The College Board

Traditionally, these programs operated as federal loan guarantee programs. Under the guarantee system, the federal government would pay upto 99% of the principal and accrued

[2]Due to the increasing use of tuition grants and other forms of grant aid, the average net cost of a 4-year education has only grown by approximately 40% since 1995-1996.

[3]Although officially known as "unsubsidized" loans. Such loans have still historically been guaranteed by the federal government at rates similar to the other programs. The main difference between unsubsidized and subsidized loans is how interest accrues while the student is still in school. With subsidized loans, the government pays the interest on the loan so long as the student is still enrolled in a qualifying degree program. In contrast, interest begins accruing immediately on unsubsidized loans; if the student does not make any payments towards the loan while in school, this accrued interest is capitalized into the loan after the student leaves school.

interest upon default. In 1994, a direct loan program was instituted with the federal government serving as the lender. Under the direct loan program, the federal government would directly issue loans to students and then pay servicers a fixed fee to service these loans. Until the financial crisis, however, direct loans made up only a small portion of the total student loan market. Further, from the student's prospective direct loans were indistinguishable from guaranteed loans. After the financial crisis, growing concern about the ability of private lenders to finance student loans prompted the elimination of guaranteed loans in 2010-2011. To students, however, this change had only a limited impact.

Of the four types of federal student loans, only the PLUS loan is not targeted at undergraduate students. The other three programs are all primarily focused on student borrowers. Although all three programs have some differences, the basic structure of the programs are all the same[4]. While students are enrolled at least half-time in an accredited program, students are not obliged to make any payments towards these loans. The unsubsidized loan program is offered to almost all US citizens or permanent residents whereas the subsidized and Perkins loans are only offered to those students with demonstrated financial need. For all three student facing programs, neither students' ability to repay nor their credit history are considered.

Once accepted into a program students are able to borrow up to their estimated cost of attendance (less any grant aid) or legislatively established limits. In addition to the annual borrowing limits, federal law also fixes the interest rate for each type of loan; once a loan has been originated, the interest rate is fixed for the life of the loan. The interest rate does vary on an annual basis and across program; however, within a given borrowing cohort, the offered interest rate is the same for all borrowers. For example, all undergraduate unsubsidized and subsidized Stafford loans issued during the 2017-18 academic year have been issued with an interest rate of 4.45%. Critically, this interest rate does not vary based on the student's field of study or school. Although selection effects make a direct comparison impossible, this rate compares favorably with non-federal loan rates[5].

After leaving school, students typically have between six and nine months to begin making payments towards their loans. In addition to the standard 10-year repayment program, students can also opt into various extended income-based repayment programs that give students up to 25 years to repay their loans; after 25 years, any remaining balance would be forgiven.

In spite of such flexible repayment terms, over 15% of former students are in default on their student loans, and a further 25% are not currently making payments towards their loans. Furthermore, student loan debt cannot be discharged in bankruptcy. Wages can also be garnished without a court order when former students are behind on their loan repayments. The inability to discharge student loans combined with easy wage garnishment

[4]For instance, the main difference between the unsubsidized and subsidized program is that students are not charged interest on subsidized loans while still in school.

[5]For fixed rate loans, Sallie Mae currently charges between 5.74% and 11.85%.

makes default on student loans especially costly. With so many students in default, it seems plausible that many students might, at least ex-post, not be benefiting from their loans.

1.3 A Positive NPV Investment? Cross-Sectional Evidence

Using the Department of Education's College Scorecard, I present evidence that there is significant heterogeneity in outcomes across schools. In particular, I find that at some colleges, especially some for-profit colleges, the median student actually realizes a negative return on their investment in higher education. Despite this, students still choose to enroll in such colleges.

Data

College Scorecard

My main data comes from the U.S. Department of Education's College Scorecard. This scorecard contains data collected from all institutions of higher education with at least one student who receives federal financial aid. The College Scorecard provides a wage distribution at the school level for students 6 and 10 years after initial enrollment. A student is included in the wage distribution regardless of whether they successfully graduated. Hence, the data includes both students who complete and those who only attempt college. Having both groups included in the wage distribution is important as ex-ante students will not know whether they will actually get their degree.

The most recent available wage data is pooled data for students who first entered college between 2005-2007. To construct the wage distribution, the College Scorecard matches students who received federal financial aid with administrative tax records. Wage data is then aggregated to the school level where the mean and standard deviation of wages is reported. The College Scorecard also reports various wage quantiles for almost all schools.

The administrative wage data only captures students who at sometime during the enrollment received Title IV aid (federal financial aid). Hence, a school's complete distribution of post-enrollment wages may differ from that reported in the College Scorecard. Although the complete distribution may not exactly match what I calculate, this is not a major limitation for our specific analysis. Since I am concerned with the impact of student loan policies on student outcomes, limiting the data to only those students receiving federal financial aid may in fact allow a better focus the analysis on the relevant population.

In addition to wage data, the College Scorecard provides information on costs, student demographics, and information on degree programs. The cost data includes both the sticker price the college publicly states as well as the average net price students pay. Due to significant grant and tuition waiver programs, even at for-profit universities there is often

Table 1.1: Summary Statistics

Panel A: Unweighted						
	Mean	SD	p25	p50	p75	N
Public	0.475	0.499	0	0	1	3,221
For-Profit	0.178	0.382	0	0	0	3,221
4-Year	0.636	0.481	0	1	1	3,221
Log(Income)	10.94	0.19	10.80	10.95	11.08	3,137
First Gen	0.416	0.123	0.335	0.432	0.506	3,136
Part-Time	0.267	0.229	0.064	0.210	0.447	3,221
Average Cost	14,493	9,110	7,464	13,130	19,984	3,221
Average Debt	13,088	6,063	8,000	12,920	17,989	3,084
Earnings (6-Years)	31,902	8,959	26,100	30,600	35,700	3,221
Earnings (10-Years)	40,273	12,244	32,100	38,300	45,600	3,221
Panel B: Weighted by # of Students						
	Mean	SD	p25	p50	p75	N
Public	0.792	0.406	1	1	1	3,221
For-Profit	0.038	0.190	0	0	0	3,221
4-Year	0.633	0.482	0	1	1	3,221
Log(Income)	10.98	0.19	10.87	10.99	11.12	3,136
First Gen	0.406	0.121	0.319	0.420	0.500	3,136
Part-Time	0.324	0.250	0.090	0.254	0.582	3,221
Average Cost	11,590	7,487	6,142	9,960	14,725	3,221
Average Debt	11,964	5,983	6,000	12,316	16,500	3,084
Earnings (6-Years)	34,096	8,666	27,900	32,500	38,000	3,221
Earnings (10-Years)	43,975	12,444	35,000	41,200	49,800	3,220

a substantial difference between the sticker price and the average net price. For all of my calculations, I use the average net price as the base cost of tuition and fees.

The unit of observation is each individual institution of higher education. In total, the College Scorecard has data for 5,328 schools. Due to privacy concerns, the College Scorecard censors data from very small schools. Further, missing data prevents me from calculating the expected net cost of attendance at all schools over the 2005-2007 period. After removing schools with missing data, 3,221 institutions remained. Table 1 provides summary statistics[6].

[6]Panel A presents the unweighted summary statistics and Panel B presents summary statistics weighted by the number of students enrolled at each institution.

American Community Survey

In order to calculate the NPV of a college education, I must establish the opportunity cost of going to college. To do this I use wage data from the American Community Survey to estimate the amount a student could have earned had they entered the workforce immediately after high school in a given state[7]

To calculate the opportunity cost using the American Community Survey I take, by state, the average wage for adults age 18-22 who graduated high school but have not attended college. Hence, the opportunity cost will be constant for every school located in a given state. Between 2007 and 2008, there was a large increase in the average wage for employed adults age 18-22 with only a high school education which can be attributed to increases in the minimum wage under the Fair Minimum Wage Act of 2007. Hence, I will use the average high school only wage by year for the period 2005-2009 and then model post-2009 wages as a growing annuity to estimate the expected wages from 2009 on-wards.

I suspect the counter-factual is lower than the true opportunity wage for two reasons. First, selection effects would mean the pool of no-college wage earners will be weaker than the pool of potential college students. Hence, the marginal student who went to college likely would have been able to receive a wage higher than the no-college average had they foregone college attendance. Second, not attending college today would not preclude future investments in higher education. If it becomes clear that as an employee, the individual needs further education he/she can still pursue that education. In contrast, once the student has spent time in college he/she can never recover those sunk costs.

The estimate for the no-college wage is also substantially lower than the $25,000 annual earnings for high-school only, young adults the Department of Education publicizes on the College Scorecard's public facing interface. Since higher no-college wages will increase the opportunity cost of attending college, our deliberately low estimate will bias us away from finding negative economic benefits to education.

Estimating the Return of a College's Education

To estimate the value of a college education consider the case of a student graduating high school with the choice of either attending college or entering the workforce directly. The benefits of college are (hopefully) higher exepcted wages. The cost of higher education are both direct (tutition and fees) and indirect (the opportunity cost of not entering the workforce right away). The financial NPV of a given student's choice to enter college is then given by NPV(College)=PV(Post-College Earnings)-PV(Cost of Attendance)-PV(No-College Earnings).

The College Scorecard provides the data to estimate the post-college earnings and the cost of attendance. Using the American Community Survey, I can construct a conservative estimate of the no-college earnings that a student could have made had they entered the

[7]In 2014, 72% of students attending traditional 4-year residential colleges remained in state and very few students at 2-year or other non-traditional colleges would be classified as out-of-state students.

workforce directly from high school.[8]. Even with a conservative assumption, a substantial fraction of students college is a negative NPV financial investment.

In order to calculate the present values, I use the average 10-year Treasury notes rate over the period from 2005-2011, 3.81%. The 10-year note was chosen as the default repayment plan for student loans is 10 years. Further, by choosing the Treasury notes as the discount rates, I use a risk-free discount rate. Since there is systemic variability in wages, it is likely that the true discount rate students should use is higher than this estimate. Here a low discount rate will bias the results towards finding positive returns to education. Since the benefits are realized in future years while the costs are realized today, low interest rates would increase the present value of the benefits while holding the costs constant. Recent research on the returns to higher education has used much higher discount rates on the order of 6% (Zimmerman, 2014).

Having established the direct and opportunity costs of post-secondary education, I can then calculate what wage a student at each college would need to earn to break even. I then match this break even wage to that college's wage distribution to determine what percent of students from each particular school earn a negative return on their investment in higher education. This *NegativeReturnRate* will be the primary measure of the aggregate performance of each college. To find the *NegativeReturnRate* I proceed in four steps:

1. Calculate the PV of No College Earnings and Cost of Attendance:

$$PV(\text{No-College Earnings}) = \frac{W_{05}^{NC}}{1+r} + \frac{W_{06}^{NC}}{(1+r)^2} + \frac{W_{07}^{NC}}{(1+r)^3} + \frac{W_{08}^{NC}}{(1+r)^3} + \frac{W_{09}^{NC}}{(1+r)^4} \frac{1+\left(\frac{1+g^{NC}}{1+r}\right)^{n-4}}{r-g^{NC}}$$

$$PV(\text{Cost of Attendance}) = \text{Avg. Net Annual Cost} \frac{1-(1+r)^{-\text{Program Length}}}{r}$$

2. Calculate a school level annuity factor by school (to account for difference in early career wage growth by school):

$$\text{Annuity Factor} = \frac{\frac{1-\left(\frac{1+g_{early}^{C}}{1+r}\right)^{10}}{r-g_{early}^{C}} + \left(\frac{1+g_{early}^{C}}{1+r}\right)^{10} \frac{1-\left(\frac{1+g_{late}^{C}}{1+r}\right)^{n-\text{Program Length}-10}}{r-g_{late}^{C}}}{(1+r)^{-\text{Program Length}}}$$

3. Find the break even wage for each school:

$$\text{Break Even Wage} = \frac{PV(\text{No-College Earnings}) + PV(\text{Cost of Attendance})}{\text{Annuity Factor}}$$

[8] In traditional papers studying the return to educations, assumptions are usually made conservative by biasing the results against positive returns to education. In our paper, however, I argue that too many students are choosing to go to college. Hence, the conservative assumptions will bias the results towards finding a positive value in further education.

Table 1.2: Percent of Students Realizing a Negative Return by School

	Schools		Students	
NegativeReturnRate	Number	%	Number	%
$X < 0.10$	116	3.60%	480,890	3.32%
$0.10 \leq X < 0.20$	392	12.17%	2,341,871	16.18%
$0.20 \leq X < 0.30$	612	18.99%	3,910,343	27.02%
$0.30 \leq X < 0.40$	801	24.86%	3,941,242	27.24%
$0.40 \leq X < 0.50$	743	23.06%	2,925,067	20.21%
$0.50 \leq X < 0.60$	358	11.11%	708,591	4.90%
$0.60 \leq X < 0.70$	154	4.78%	142,105	0.98%
$0.70 \leq X < 0.80$	36	1.12%	17,592	0.12%
$0.80 \leq X < 0.90$	10	0.31%	2,727	0.02%
$0.90 \leq X$	0	0.00%	0	0.00%
TOTAL	3,222	100.00%	14,470,428	100.00%

*NegativeReturnRate*is our calculation for the percent of students at each school who will realize a negative financial return for having attended that college. *NegativeReturnRate*=0 corresponds to no students realizing negative returns, whereas *NegativeReturnRate*=1 implies that all students at that school will realize a negative return. The Schools columns are the number of institutions that fall into eachh *NegativeReturnRate* bucket. The Students columns correspond to the total number of students enrolled in institutions in each *NegativeReturnRate* bucket.

4. Using the mean and standard deviation of ex-post school wages calculate where in a school's wage CDF, a student would need to fall to break even[9]

The *NegativeReturnRate* measure will capture the percent of students at a given school who realized a negative financial return on their investment in higher education. I can then aggregate this rate across schools to calculate the total percent of students who realized a negative financial return on their investment in higher education.

Analysis of the Returns to Higher Education

Overall, I find that 31% of students fall below their school's break even threshold. This translates to nearly 5 million students currently in college who realize a negative return on their investment in higher education. While the median student is better off, a surprisingly high proportion of students will realize a negative financial return.

6% of students are enrolled in schools where over half of the students realize a negative return. Most students, however, seem to be concentrated in schools where approximately a

[9] I assume that school-level wages follow a log-normal distribution.

third of students realize a negative return. When considering which schools have high *NegativeReturnRate* value, clear differences emerge. Table 1.3 presents the *NegativeReturnRate* across school type (e.g. 2-year, inclusive 4-year, etc.) and ownership structure (e.g. public).

As schools become more selective, the percent of students realizing a negative return on their investment declines dramatically. While this result may not be surprising, recall that the estimate of the opportunity cost was made at a state level. If students attending more selective institutions had better outside options, then the *NegativeReturnRate* variable would be biased downward for students at these selective universities. Also, note that within each classification category the for-profit schools tend to perform worse than their public or non-profit counterparts. Even within the public and non-profits, however, a high number of students will still realize a negative return from their education.

In figure 1.2 I estimate the empirical PDF of the outcome measure *NegativeReturnRate*. I also break out the empirical PDF by ownership type (public, private non-profit, and private for-profit. There are substantial differences in the outcomes between different ownership structures. On average for-profits exhibit much worse outcomes than either public colleges or non-profits. The average *NegativeReturnRate* for private for-profits is over 46% indicating that nearly half of all for-profit students will realize a negative return from their education. In contrast, for public schools the mean *NegativeReturnRate* value is 32%; private non-profits are even lower with a mean *NegativeReturnRate* of only 24%.

As over three-quarter of students in our sample are enrolled in public schools, when the results are weighted for school size the overall empirical PDF closely matches the public school PDF. The for-profits schools also appear marginally better when weighting for school size. It appears that some of the very worst performing schools are very small. Even when I exclude the smallest schools, however, for-profit colleges have significantly higher *NegativeReturnRate* values than either the public or non-profit colleges.

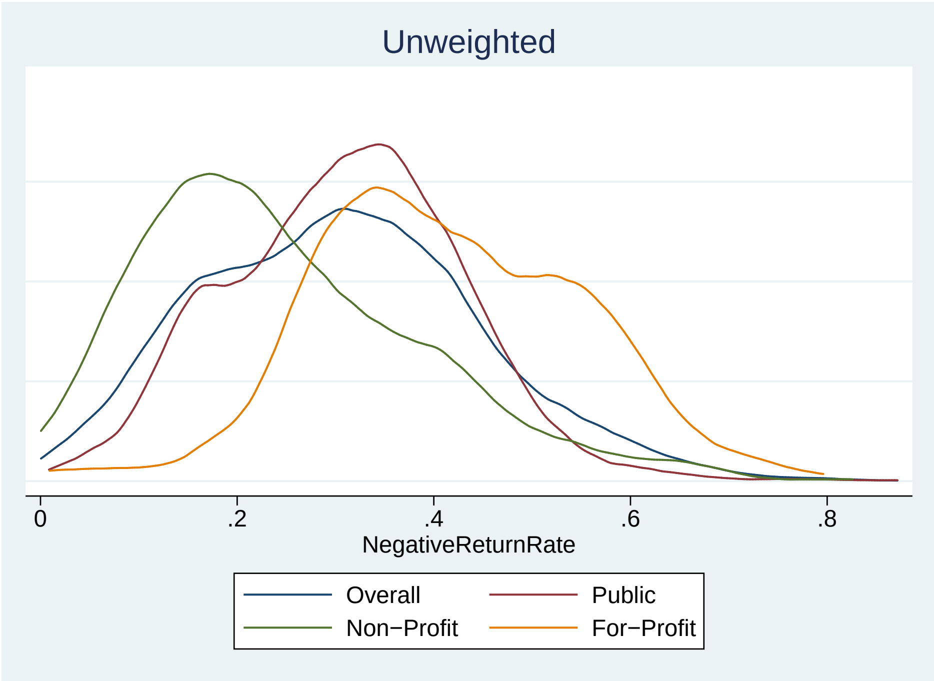
Although the median student is better off going to college, there is substantial heterogeneity across institutions with regard to the value of their education. Students, however, are still obviously willing to enroll in the poorest performing schools. In spite of this heterogeneity, government policy does not differentiate between such colleges. Students are able to get student loans at the same terms as their peers at much stronger colleges.

1.4 The Role of Colleges in the Student Loan Market

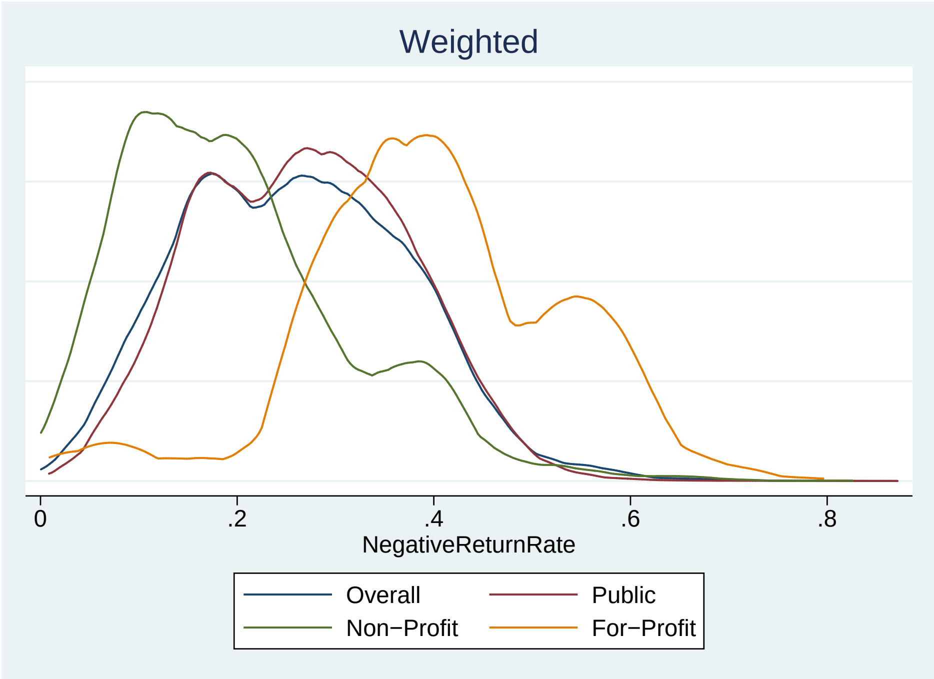
A unique element of the student loan market is that all students who get into college are eligible for federal student loans. This makes school admissions officers the effective lending officers in the student loan market. Given the importance of access to federal aid programs, school admissions officers have strong incentives to evaluate the riskiness of students when

Table 1.3: *NegativeReturnRate* by College Classification and Ownership Structure

Panel A: Unweighted					
College Type		Public	Non-Profit	For-Profit	Overall
	Mean	0.375	0.264	0.475	0.399
Unclassified	SD	0.183	0.286	0.174	0.215
	N	26	14	33	73
	Mean	0.426	0.367	0.503	.0.437
2-Year	SD	0.090	0.200	0.141	0.111
	N	871	40	192	1,103
	Mean	0.355	0.379	0.462	0.400
4-Year (Inclusive)	SD	0.122	0.153	0.127	0.144
	N	276	418	344	1,038
	Mean	0.258	0.280	0.337	0.272
4-Year (Selective)	SD	0.081	0.106	0.096	0.097
	N	245	358	2	605
	Mean	0.185	0.183	0.054	0.183
4-Year (Most Selective)	SD	0.080	0.099	N\A	0.094
	N	112	289	1	402
	Mean	0.367	0.295	0.475	0.361
Overall	SD	0.125	0.153	0.137	0.151
	N	1,530	1,119	572	3,221
Panel B: Weighted by # of Students					
College Type		Public	Non-Profit	For-Profit	Overall
	Mean	0.377	0.234	0.479	0.394
Unclassified	SD	0.142	0.240	0.152	0.171
	N	26	14	33	73
	Mean	0.400	0.392	0.492	0.401
2-Year	SD	0.074	0.160	0.132	0.0.77
	N	871	40	192	1,103
	Mean	0.342	0.349	0.450	0.361
4-Year (Inclusive)	SD	0.095	0.132	0.134	0.118
	N	276	418	344	1,038
	Mean	0.246	0.262	0.391	0.250
4-Year (Selective)	SD	0.069	0.094	0.059	0.76
	N	245	358	2	605
	Mean	0.191	0.163	0.054	0.181
4-Year (Most Selective)	SD	0.070	0.082	N\A	0.075
	N	112	289	1	402
	Mean	0.321	0.244	0.456	0.313
Overall	SD	0.113	0.128	0.135	0.124
	N	1,530	1,119	572	3,221



(a)



(b)

Figure 1.2: Here I present the empirical PDFs of the *NegativeReturnRate* measure by college. The empirical PDFs were estimated using kernel density estimation. The x-axis represents the percent of students at a given school who realize a negative return. I show the density estimates for the complete sample of schools and broken out by ownership type. Panel (a) presents the unweighted results, and panel (b) presents the results weighted by number of students.

deciding to admit them. Further, I present evidence that admissions officers have private information that they use to ensure the pool of students they admit is not too risky.

Admissions Officers as Lending Officers

In the student loan market, all students who get admitted to and enroll are able to access federal student loans. Thus, whether a student gets admitted is the determining factor in whether or not they are issued a loan. This puts admissions officers in a unique position, whether or not a student can obtain student loans is up to the admissions officer.

While admissions officers may not have the exact same value function as a bank lending officer, it is still a useful abstraction to think of admissions officers as lending officers in this market. For most institutions, a substantial part of their revenue is derived from student loan programs. Especially at for-profit colleges access to student loans is vital for their survival. Hence, ensuring that the pool of student borrowers admitted to the school is not too risky must be a key component of admissions officers' jobs.

Admissions Officers and Private Information: Evidence for Informed Lending

One possible explanation for the large number of students who take out negative NPV student loans is that they simply do not know the true value of their investment in higher education. Colleges on the other hand have a strong incentive to gauge expected student outcomes, if at all possible. Under federal law, if a school's default rate exceeds 30% for a three year period, the school will no longer be able to participate in federal finance aid programs. Since these programs often make up a large portion of a institution's revenues, participation in the program is necessary for a school's survival. Hence, there is a large incentive for schools near the 30% threshold to engage in screening to reduce their default rates. I proceed to show that schools with default rates near the 30% threshold are much more likely to see significant improvements in the default rates in following years; this suggest that schools can predict their students' outcomes.

Using the Department of Educatin's FY2014 Cohort Default Rate Report, I calculate the year-over-year changes in default rates. This report contains data on the default rates for all institutions of higher education in 2012, 2013, and 2014. Schools with a small pool of borrowers are susceptible to large, random variations in their default rates on a year-to-year basis. To prevent these small schools from biasing any conclusions, I limit the default rate analysis to schools with at least 500 active borrowers in each year. After dropping these small schools, there are default rates for 1,829 institutions.

I compare school-level default rates from 2012 with school-level default rates in 2013 and 2014. The main variables of analysis is $change_{i,t}$ and $better_{i,t}$. $change_{i,t}$ measures the change in school i's default rate from 2012 to year t. To prevent large swings in default rate's from influencing our results, I winsorize $change_{i,t}$ at the 1% and 99% level. $better_{i,t}$ is an indicator variable equal to 1 if and only if school i's default rate has improved from 2012 to year t.

Table 1.4: Changes in Default Rates

	Mean	SD	p25	p50	p75	N
$change_{i,13}$	-0.0025	0.0194	-0.0120	-0.0020	0.0070	1,829
$change_{i,14}$	-0.0002	0.0272	-0.0120	0.0000	0.0120	1,829
$better_{i,13}$	0.5648	0.4959	0	1	1	1,829
$better_{i,14}$	0.4740	0.4995	0	0	1	1,829

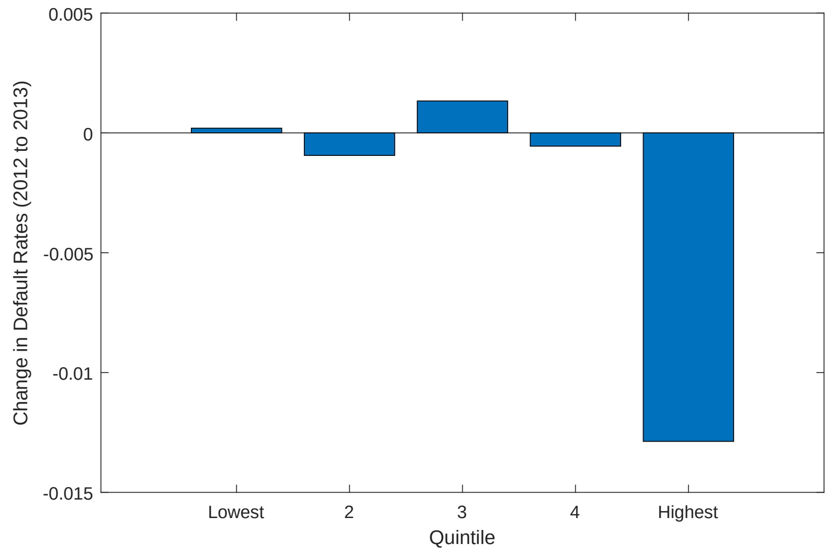
Table 1.4 presents the average change in default rate across all schools and the percent of schools with improved default rates in each year. Overall, the mean change in default rates in each year is almost exactly zero suggesting that the macro-environment is not driving changes in the default rates for individual colleges.

I then divide schools into quntiles by their 2012 default rates. In table 1.5, I compare the mean change in default rates and the proportion of schools improving by quintile. Other than the highest quintile (i.e. the schools with the highest default rate),there is little evidence that default rates improved at schools. If anything, default rates got slightly worse at most schools between 2012 and 2014. For those in the highest quintile, however, there is a dramatic improvement in default rates.

Since schools in the highest quintile are in the greatest danger of losing access to federal loan programs, these schools have the largest incentive to engage in increased monitoring and screening of students. Regression to the mean and systemic factors may explain part of the change in default rates among schools in the highest quintile. As, changes in default rates in the other quintiles, however, appear random it is unlikely that regression to the mean and systemic factors explains all of the improvement. While not conclusive, this is suggestive that schools can predict student outcomes

1.5 Lending with an Exogenous Government Intervention

In the previous sections, I documented that some students appear to take out loans that even ex-ante appear to have a negative NPV. In this section, I construct a model that takes as given the government's mandate that all student loans be issued at a uniform interest rate. When students face an ex-ante information disadvantage, this uniform interest rate mandate results in students not being able to infer the true value of their education. Not being able to infer the true value of education will make the student vulnerable to facing negative NPV loans.



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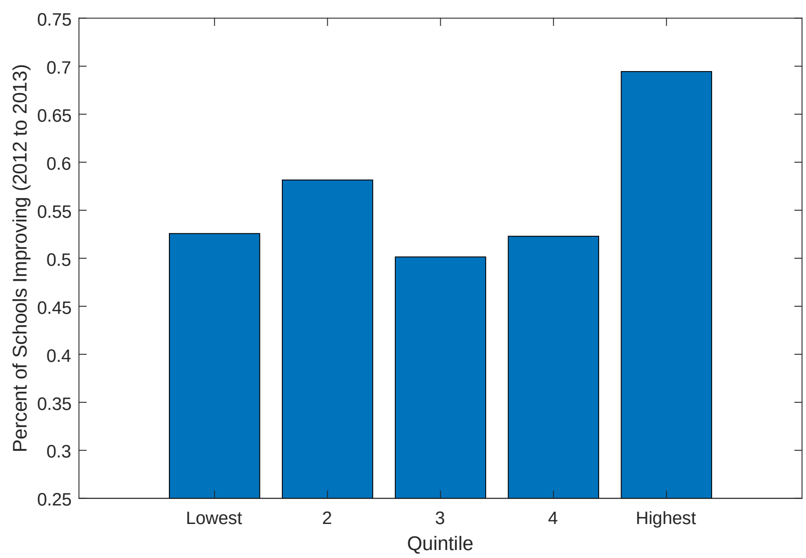

(b)

Figure 1.3: In Panel (a), I calculate the mean change in default rates between 2012 and 2013 by quintile. Only schools in the highest quintile (i.e. those with the worst 2012 defualt rates) saw a significant improvement between 2012 and 2013. In Panel (b), I caclulate the proprotion of schools in each quintile whose default rates improved between 2012 and 2013. By far, the largest proportion of schools improving was in the highest quintile.

Table 1.5: Change in Default Rates by Quntile

Panel A: Change in Default Rates						
		2013			2014	
Quintile	Mean	SD	t-score	Mean	SD	t-Score
Lowest	0.0002	0.0080	0.477	0.0025	0.0097	4.944***
2	-0.0009	0.0117	-1.535	0.0020	0.0134	2.853**
3	0.0013	0.0186	1.363	0.0044	0.0268	3.124**
4	-0.0006	0.0011	-0.481	0.0052	0.0301	3.302***
Highest	-0.0129	0.0267	-9.133***	-0.0156	0.0390	-7.573***
Panel B: Improvement in Default Rate?						
		2013			2014	
Quintile	Mean	SE	z-score	Mean	SE	z-Score
Lowest	0.526	0.026	0.989	0.379	0.025	-4.633***
2	0.582	0.026	3.123**	0.435	0.026	-2.502**
3	0.501	0.026	0.053	0.452	0.026	-1.842*
4	0.523	0.026	0.883	0.426	0.026	-2.856**
Highest	0.694	0.024	7.379***	0.683	0.025	6.957***

I divide schools into 5 quintiles based on their 2012 default rates. In Panel A, I calculate the average change in default rate by quintile and then run a t-test comparing the average change by quintile to 0 (i.e. no pattern to changes in default rates). In Panel B, I calculate the proportion of schools in each school who saw an improvement in their year-over-year default rates. I then run a test of proportion on each quintile comparing the percent of schools seeing an improvement to 50%.
$*p < 0.1, \; **p < 0.05, \; ***p < 0.01$

Model Setup

A single borrower or student wants to finance a risky project. Multiple competitive and identical lenders exist who are willing to provide the necessary financing. Time is discrete with two periods: $t \in \{0, 1\}$. For simplicty, I assume that all agents are risk-neutral and do not discount between periods. Neither of these assumptions have any qualitative impact on our results.

Borrowers

At $t = 0$, the borrower is faced with a potential risky investment opportunity, defined by its quality, θ, with a non-zero upfront investment cost. Project output is distributed according to $F(w|\theta)$ with support over the interval $[0, \bar{w}]$, where $0 < \bar{w} \leq \infty$. Without loss, let $\theta \in [0, 1]$. I make the following assumptions on $F(\cdot|\theta)$:

Assumption 1. *$F(\cdot|\theta)$ displays strict first-order stochastic dominance in θ*

Assumption 2. *The partial derivative $f_\theta(w|\theta)$ exists and is continuous in θ*

The first assumption ensures that θ is a valid measure of project quality as borrowers with higher θ's will always generate a higher expected profit regardless of the interest rate charged. The second assumption is purely technical.

In addition to θ, which determines the project's quality, there is a public signal, $\sigma \in (0,1)$. This signal, σ, determines the distribution of θ. Let $G(\theta|\sigma)$ be the distribution of θ given σ. Higher σ's correspond to a better signal regarding the project's true quality (i.e. as $\sigma \to 1$, $\mathbb{E}[w|\sigma]$ increases). To ensure that σ is a valid signal, I place the following assumptions on $G(\cdot|\sigma)$:

Assumption 3. *The distribution $G(\cdot|\sigma)$ statisifes the following properties:*

1. *$G(\cdot|\sigma)$ has the monotone likelihood ratio property.*
2. *For all σ, $G(\cdot|\sigma)$ has full support on the interval $[0,1]$.*
3. *For all σ, The partial derivative $g_\sigma(\cdot|\sigma)$ exists almost everywhere.*

The first assumption is the standard assumption that σ is a useful signal and provides valuable information. The second and third assumptions are both purely technical assumptions.

The payoff of any project is verifiable, and lenders can enforce repayment upto the project's total output.

Although the project's expected payoff is governed by θ, the borrower is unable to observe her individual type, θ, directly at $t = 0$. This is in contrast to traditional lending models where the borrower is privately informed. The public signal σ, the distribution of types given σ, $G(\cdot|\sigma)$, and $F(w|\theta)$, however, is common knowledge at $t = 0$.

The borrower has a reservation wage given by $c > 0$. The loan contract is a standard one period loan, with a required gross repayment R at $t = 1$. If a loan R is accepted by a borrower of type θ, the borrower's net expected payoff is given by,

$$V_B(R;\theta) = \int_R^{\bar{w}} (w - R) dF(w|\theta) - c. \tag{1.1}$$

Lenders

Multiple identical, competitive lenders exist in the market with the ability to extend the necessary credit to the borrower. All lenders are able to perfectly observe the borrower's type, θ, at $t = 0$. The ability of lenders to observe the borrower's type is common knowledge. Knowing that lenders observe her type, a borrower can use the offered contract to try to infer her type. After observing θ, all lenders simultaneously choose whether to offer a loan to the borrower and if so the contract, R, to offer.

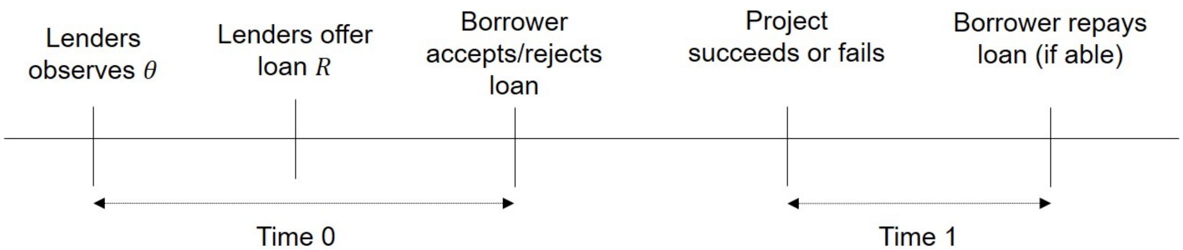

Figure 1.4: Timeline

In order to provide the loan to the borrower, a chosen lender must pay a cost, which is normalized to 1. The cost includes both the cost of funds to provide the necessary investment capital as well as any servicing and origination costs associated with the loan. This cost is paid regardless of whether the borrower repays the loan. For simplicity, assume that the loan cost is paid at $t = 1$. Although in the practice, much of this lending cost would likely be borne at the time of loan origination, the cost 1 could just represent the total cost of the loan, compounded at the lender's cost of capital.

I also assume that the possible payoffs of the project are such that the lending and borrowing decisions are non-trivial:

Assumption 4. *There exists some valuable projects: There exists* $\theta \in (0,1)$ *such that* $\mathbb{E}_w[w|\theta] = 1 + c$

Assumption 5. *There exists some projects that will surely be worthless:* $P(w < 1|\theta = 0) = 1$

Assumption 6. $\mathbb{E}[w|\theta] < \infty \ \forall\theta$

These assumptions guarantee that the information asymmetry problem matters to the agents. Under the first-best, there will both be loans accepted and loans rejected.

If the borrower accepts an offer of R, the expected payoff to the lender is given by,

$$V_L(R;\theta) = \int_0^R w dF(w|\theta) + R[1 - F(R|\theta)] - 1.$$

The Intervention

In addition to the borrower and the lenders, there also exists a social planner who can intervene, indirectly, in the credit market to alter the equilibrium lending outcomes. The social planner has a technology that allows for an intervention in two ways:

1. The social planner may introduce loan subsidies or credit guarantees, s, that compensate the lender in cases where the borrower defaults. I also allow the social planner to impose additional costs on the lender if the borrower defaults[10] Hence, the guarantee need not be positive.

2. The social planner can also restrict the interest rate that can be charged for a given loan so that all borrowers must receive the same interest rate. Although the government can mandate a uniform interest rate across all loans, lending cannot be compelled to a particular borrower. Hence, the choice of whether to offer a loan is always up to the lender.

These tools are used in various government programs. Many programs exist that cover lenders in case of default such as student loans, FHA loans, and SBA loans. Further, some programs, most notably student loans, require that all borrowers in a given cohort receive the exact same interest rate.

In setting the intervention, the social planner cannot observe θ or σ. To motivate this assumption, consider that the lenders' long-term survival depends on their ability to assess and screen potential borrowers; they will need to invest in superior models and data in order to analyze the chances of success of a given project. The government, however, does not depend on assessing individual investments; hence a social planner would have little incentive to invest in the costly capabilities necessary to evaluate the exact riskiness of inherently risky projects.

Given these restrictions on the social planner's information set, the intervention must be constant across all borrowers. Let s be the guarantee rate that the government sets. The guarantee will cover $s\%$ of any principal losses suffered by the lender. Thus, a guarantee payment will be transferred from the government to the lender if and only if the project fails to produce an output of at least 1, the lender's upfront cost.

The social planner can always perfectly observe the project's outcome implying that the guarantee is paid out if and only if the project fails to cover the lender's cost (i.e. $w < 1$).

A positive guarantee, when it is paid out, represents a transfer from the social planner to the lender. This changes the lenders' expected profits to,

$$V_L(R, s; \theta) = \int_0^1 s(1-w)dF(w|\theta) + \int_0^R wdF(w|\theta) + R[1 - F(R|\theta)]. \tag{1.2}$$

The subsidy decreases potential losses in cases of default and reduces the lender's downside risk. Such a risk reduction will increase the lender's willingness to extend credit to weaker borrowers.

If the subsidy were too large, however, the social planner could destroy any incentive for the lenders to engage in screening of credit applicants. Suppose the social planner set a credit guarantee such that $s > 1$. Such a scenario would create severe moral hazard

[10]For example, if too many borrowers default the government may restrict a lender's ability to access the program.

problems. Further if the subsidy was more than enough to cover losses, no lender would invest in screening capabilities as it would be profitable to finance projects that are certain to fail. To prevent this, I will impose the condition that credit guarantees can't be too large to completely subvert the incentives to engage in screening.

Assumption 7. *No credit guarantees are larger than the lenders' costs:* $s < 1$

This is a relatively mild restriction as it doesn't prevent the government from providing very large credit guarantees. It also prevents a severe moral hazard problem where the lenders purposely give loans to borrowers with no chance of repayment in order to receive the high guarantee payment when the borrower defaults, thereby making a positive profit.

From the borrower's perspective, her utility does not change directly by the introduction of credit guarantees. Any impact on the borrower must enter through the interest rate channel. Since borrowers prefer low interest rates, borrowers should benefit from the lower interest rates induced by positive credit guarantees.

Equilibrium Under Risk-Based Interest Rates

If the government allows lenders to set interest rates based on risk, a fully separating equilibrium will arise and borrowers will learn the true value of their project. Under an equilibrium where interest rates are not set by government policy, borrowers will only accept useful loans. Although borrowers begin at an information disadvantage, competition between the lenders via interest rates will ensure that the borrower ends up acting as though she began with complete information.

For the construction of the equilibrium, I will use a perfect Bayesian equilibrium concept with the minor refinement that the borrower must exhibit monotonicity of beliefs.

Definition. *A borrower is said to exhibit* ***monotonic beliefs*** *if for any* $R_i' < R_i$ *sent by lender* i*, the borrower's expected type conditional on* R_i' *is (weakly) higher than the expected type conditional on* R_i*:* $\mathbb{E}[\theta|(R_i', R_{-i})] \geq \mathbb{E}[\theta|(R_i, R_{-i})]$ $\forall R_i' < R_i$*.*

The imposition of monotonic beliefs is both minor and intuitive. Without monotonic beliefs, pooling equilibria could be constructed. These equilibrium, however, would have the unnatural property that upon observing a low, but off-equilibrium, interest rate the borrower assumes she must have a very low type. Intuitively, interest rates should be at least non-increasing in the borrower's type.

I will now establish several standard but useful facts regarding the lending equilibrium. Since all the lenders have the same information set and move simultaneously, it must be that for any given borrower type, θ, the lenders must, in expectation, make zero profit.

Lemma 1. *For any type* θ*, all lenders must, in expectation, make zero profit.*

Since all lenders act the same, throughout the remainder of the paper I will refer to "the lender." The presence of other potential lenders who could skim some types if the lender made a strictly positive profit constrains the interest rate that the lender is willing to offer.

Corollary 1. *The lender's offer will not be a function of* σ

Although the signal σ is public information, the lender will never use it in setting the interest rate, since the lender is constrained to making zero-profit on each type θ.

Lemma 2. *There exists a threshold* $\underline{\theta_s} \in (0, 1)$ *such that only types* $\theta \geq \underline{\theta_s}$ *receive a loan offer.*

Since some projects will surely fail to cover the lender's cost, these projects will never be funded. If no loan is offered, the borrower has no choice to make. Without loss, I can restrict our attention to the interval of borrower types $[\underline{\theta}, 1]$ as only these borrowers will have a loan to evaluate.

For projects with types above $\underline{\theta}$, the lender will be willing to extend credit at some interest rate. Per lemma 1, the lender's expected profit, (1.2), must be zero. Hence, $R(\theta)$ will solve $V_L(R(\theta, s), s; \theta) = 0$.

Lemma 3. *The interest rate offer,* $R(\theta, s)$*, is a strictly decreasing function of* θ*.*

The higher θ, the higher the expected output of a project. This reduces the likelihood that the lender will suffer losses. As the downside risk decreases, the lender can offer a lower interest rate and still break-even in expectation.

In this environment, low interest rates are good for the borrower for two reasons. First, there is the direct channel; low interest rates mean that the borrower is able to keep more of the profit's a project generates. Second, thre is an information channel; low interest rates also provide an additional positive signal about project quality.

As lemma 3 indicates that $R(\theta)$ is a strictly monotonic function, $R(\theta)$ must also be an invertible function. As long as interest rates are allowed to vary based on risk, interest rates will provide enough information for an uninformed borrower to perfectly infer her type.

Proposition 1. *There exists* $\hat{\theta}_s \in (\underline{\theta_s}, 1)$ *such that the borrower accepts the loan if and only if* $\theta \geq \hat{\theta}_s$*.*

Since the borrower will always perfectly learn θ, the borrower's action can be conditioned on θ. When θ is above the threshold, $\hat{\theta}_s$, the borrower will get a good interest rate and be willing to accept the loan. When θ is not high enough, the borrower will either not get a loan or will get a loan with a very high interest rate that she rejects. Hence, if interest rates are allowed to vary based on risk in equilibrium there will be there regions:

1. If $\theta < \underline{\theta_s}$, then no loan will be offered.

2. If $\underline{\theta_s} \leq \theta < \hat{\theta}_s$, the lender will offer a loan, $R(\theta)$, but that offer will be rejected.

3. If $\hat{\theta}_s \leq \theta$, then the lender will offer loan $R(\theta)$, and the borrower will accept that offer.

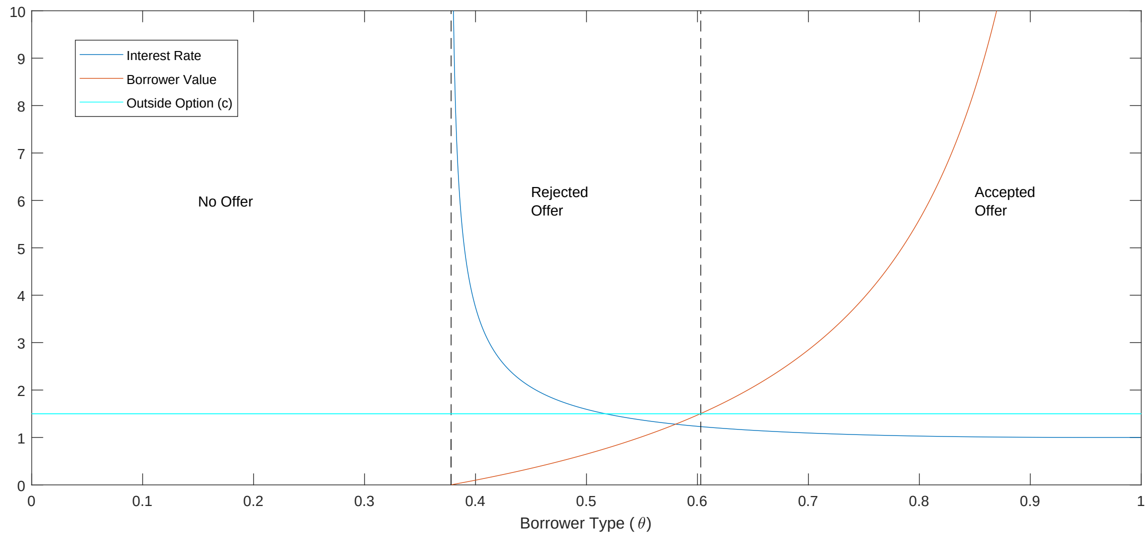

Figure 1.5: I present the borrower's expected utility and the interest rate, if any, offered to each type. There are 3 regions of behavior. First, the weakest types receive no loan offer. Second, there exists an intermediate group who are offered loans, but reject them as the interest rate is too high. Finally, the strongest borrowers will accept a loan offer as these borrowers have a positive expected value from the loan.

Although the borrower is uninformed, the lender's equilibrium behavior reveals the borrower's type. Thus, the initial information disadvantage has no adverse consequences under risk-based interest rates.

Equilibrium Under Interest Rate Pooling

If instead of allowing interest rates to vary based on risk, the government forces all loans to be issued at the same interest rate, the lender will lend to a borrower as long as she is "good enough." Since all of these good enough borrowers get the exact same loan, the borrower is no longer able to perfectly infer her type. Now she is only able to estimate the project's true value.

Suppose that the social planner now restricts the interest rate that can be charged to R^U. The social planner cannot require the lender to lend to a borrower, but is mandating that if the lender wants to lend it must be done at rate R^U.

With risk-based interest rate, the lender needs to choose both whether to offer a loan and if so what interest rate to charge. If the social planner mandates an interest rate, however, the second choice no longer exists. Instead, all a lender needs to decide is if a loan should be offer; government policy is fixing the offer to R^U. Since the social planner cannot force the lender to violate its IR constraint, a loan will be offered if and only if $V_L(R^U, s; \theta) \geq 0$. In order to ensure that there exists some type who gets a loan, $R^U \geq 1$. If $R^U < 1$ then the lender would lose money for all types and would never be willing to offer a loan.

Lemma 4. *For each $R^U > 1$, there exists some $\theta' \in (0, 1)$ such that a loan is offered if and only if $\theta \geq \theta'$.*

To determine who should receive a loan, the lender can use a cutoff rule. A loan will be given to a borrower if and only if her type is at least some threshold θ'. Given the assumptions placed on $F(\cdot|\theta)$ it is trivial to show that $V_L(R^U, s; \theta)$ must be an increasing function in θ. Hence, for all $\theta \geq \theta'$ it must be the case that $V_L(R^U, s; \theta) \geq 0$.

The cutoff type creates an interval $\Theta' = [\theta', 1]$ such that the borrower is offered a loan if and only if the borrower's type is in Θ'. In contrast to the risk-based interest rate environment, now the borrower has less information. When a loan is issued the borrower no longer learns her true type, but only that her true type is in the interval Θ'.

Conditional on getting a loan the borrower knows $\theta \geq \theta'$ and her public signal, σ. Using these two pieces of information, the borrower can estimate the value from accepting a loan:

$$\overline{V_B(\theta', \sigma)} := \mathbb{E}[V_B|\theta \geq \theta', \sigma] = \int_{\theta'}^{1} V_B(R^U; \theta) \frac{dG(\theta|\sigma)}{1 - G(\theta'|\sigma)} \tag{1.3}$$

Using (1.3), the borrower can calculate whether the expected NPV of the loan is non-negative. The borrower's IR constraint implies that she will accept a loan if and only if $\overline{V_B(\theta', \sigma)}$ is non-negative. Given that $G(\cdot|\sigma)$ has the MLRP in σ, $\overline{V_B(\theta', \sigma)}$ must be increasing in σ. Hence, the equilibrium with uniform rates can be characterized as a pair (θ', σ') where θ' is the weakest type offered a loan and σ' is the weakest signal the borrower can have and still accept the loan. In equilibrium (θ', σ') will satisfy:

$$\begin{cases} V_L(R^U, s; \theta') = 0 \\ \overline{V_B(\theta', \sigma')} \geq 0 \end{cases} \tag{1.4}$$

.

Whenever $\sigma' > 0$, the inequality in (1.4) can be replaced by an equality (otherwise there would exist some signal $\sigma < \sigma'$ which would result in the borrower accepting her loan).

The information the borrower gets now, however, is not enough to determine, perfectly, the true value of the loan. With a uniform interest rate policy, the borrower only learns that her type is among a (potentially) large continuum of types. This lack of learning presents the possibility that a weak borrower will accept a loan because she is unable to infer the true probability of success. Although the uniform interest rate policy prevents discrimination on prices, such a policy prevents learning. This lack of learning can be costly for borrowers.

1.6 Endogenizing the Intervention: The Optimal Guarantee Program

In the previous section, the social planner's intervention was exogenous. In this section, I establish the social planner's value and determine the optimal guarantee program. If the funds are costly, then the social planner will want to use a uniform interest rate policy even though this depress the information available to borrowers.

Social Planner's Problem

From the borrower's and lender's perspective the government's guarantees represent an exogenous infusion of cash into the credit market. The social planner, however, will have to raise the costly funds necessary to provide such subsidies. Let $\alpha > 0$ be the social planner's cost of funds to provide the credit guarantee. α could represent the government's borrowing costs or the distortionary impact of taxes. Alternatively, α can be viewed as the Pareto weighting the social planner places on taxpayers versus the private credit market.

To motivate the social planner's desire to intervene in the lending market, suppose that all accepted projects generate some positive social externality $e > 0$[11]. For example, higher education can reduce the likelihood that a student will require future government assistance (e.g. unemployment benefits), which is costly to society at-large. Since the borrower and lender would not value these externalities in a laissez-faire credit market, without government intervention some positive social projects may be rejected.

The social planner's objective is to maximize the total expected utility in the credit market. The planner's expected value, for an accepted loan is given by

$$V_{SP}(R,s;\theta) = \underbrace{V_B(R;\theta) + V_L(R,s;\theta)}_{\text{Private Loan Value}} + \underbrace{e}_{\text{Externality Value}} - \underbrace{\alpha \int_0^1 s(1-w)dF(w|\theta)}_{\text{Guarantee Cost}}. \tag{1.5}$$

If the loan is rejected, the social planner's utility is simply zero. The first two terms of (1.5) represent the value of the project to the borrower and the lender respectively. The third term captures the externality generated by the project (i.e. the reason for the intervention). The final term represents the social cost of the externality to the planner.

Using the definitions of V_B and V_L I can simplify (1.5) to

$$V_{SP}(R,s;\theta) = \underbrace{\mathbb{E}[w|\theta] + e}_{\text{Expected Social Value}} - \underbrace{\left[1 + c + (\alpha - 1)\int_0^1 s(1-w)dF(w|\theta)\right]}_{\text{Expected Social Cost}}. \tag{1.6}$$

The first term of (1.6) is the expected social value of the risky investment. The remaining terms captures the expected social cost of the investment, both the lender's and the borrower's private cost as well as the net cost of any credit guarantees that may be paid out.

[11]Without loss, assume that the externality is valued from the social planner's perspective.

The social planner's objective is to set the guarantees in such a way as to maximize total social welfare. In addition the social planner is able to choose which type of guarantee scheme to implement: risk-based interest rates or uniform interest rates.

Choosing Between Risk-Based Interest Rates and Uniform Interest Rates

Suppose the social planner wants to create a program such that some arbitrary type θ' is the cutoff type so that a borrower will go to college if and only if her type is at least θ'. Under risk-based interest rates, the marginal borrower will learn her type is exactly θ'. Since this weak borrower knows she is a weak borrower, she will demand a very low interest rate if she is to accept the loan.

In contrast under a uniform interest rate scheme, the marginal borrower never learns her exact type. Hence, a borrower can only estimate the expected value of the loan. Consider the marginal borrower with the weakest signal ($\theta = \theta', \sigma = 0$). With risk-based interest rates, this borrower will go to school so long as $V_B(R^U;\theta') \geq 0$; if rates are uniform, however, this borrower will go to school so long as $\mathbb{E}[V_B(R^U;\theta)|\theta \geq \theta', \sigma = 0] \geq 0$. The latter inequality can be satisfied with higher interest rates. When interest rates can be higher, the social planner need not provide guarantees that are as high.

Proposition 2. *When $\alpha \geq 1$ it is the socially optimal policy to pool all borrowers at a uniform interest rate.*

By restricting the interest rate that can be charged, the social planner obscures the borrower's true type. When the true type is hidden, the marginal borrower will require a lower interest rate. This fact can then be leveraged by the social planner to reduce the cost of a guarantee program and increase total social utility.

1.7 The Implications for Borrower Welfare

In the previous section, I showed that under reasonable conditions the optimal social policy will pool all loans at a uniform interest rate. In this section, I show that this optimal policy has two negative impacts on borrower welfare: it leads to predatory admissions or negative NPV loans being accepted, and it results in a transfer of surplus value from borrowers to lenders.

Predatory Admissions

Recall, that in practice admissions officers function as loan offers. By admitting a student, college admissions officers allow students to access student loans at the uniform interest rate. If the students are not independently wealthy, then enrolling requires students to accept the loan. If the loan turns out to be a negative NPV loan, I can call the college enrollment decision a negative NPV decision. I use the term "Predatory Admissions" to describe these cases.

Definition. ***Predatory Admissions*** *occurs when a student is admitted and offered a student loan that the lender knows will be accepted even though the student's private value will be negative.*

In the case of risk-based interest rates, no predatory admissions can occur. The student is able to perfectly infer her type. Knowing exactly her type, the student will only accept the admissions offer and corresponding loan if the value of the loan is non-negative. Without the lender maintaining some information advantage over the borrower, no predatory admissions can occur.

Whenever a pooling equilibrium is mandated (i.e. uniform interest rates), some borrowers may face predatory admissions. The lender knows that negative NPV loans are being offered but has no incentive to alert the borrower to these predatory offers as the lender is not losing money on any loan they offer.

In the previous section, I showed that the optimal social policy is to pool all loans at a uniform interest rate whenever funds are costly ($\alpha > 1$). Under this pooling regime the social planner will institute a scheme that has negative consequences to students. Here the optimal policy will result in students accepting negative NPV loans.

Proposition 3. *Let $\alpha > 1$. Under the socially optimal guarantee policy, predatory admissions will occur.*

To institute the socially optimal policy guarantee policy, the social planner wants to insure that for at least some student borrower their IR constraint holds with equality, $V_B^{\sigma}(\sigma) = 0$. As this student breaks-even in expectation she will accept the loan. Since the student is only breaking-even in expectation, it must further be the case that $V_B(R^U; \theta') < 0 < V_B(R^U; 1)$. For this marginal student, the lack of information means she may accept a negative NPV loan. If the student knew that the true type was θ' the project would have been rejected.

As can be seen from figure 1.6 a significant percentage of potential borrowers may accept a predatory admissions offer. In a full information environment (i.e. risk-based interest rates), no borrower with a negative utility would have accepted such an offer. Uniform interest rates, however, results in a significant number of students accepting bad offers.

Although uniform interest rates might induce a socially optimal level of enrollment, from a student's perspective too much credit is available. Students know that on average they won't be worse off, but the weakest will be. Without the government's intervention these students would have had their applications rejected and avoided a negative NPV loan. It is only because of the intervention that they face predatory admissions at all.

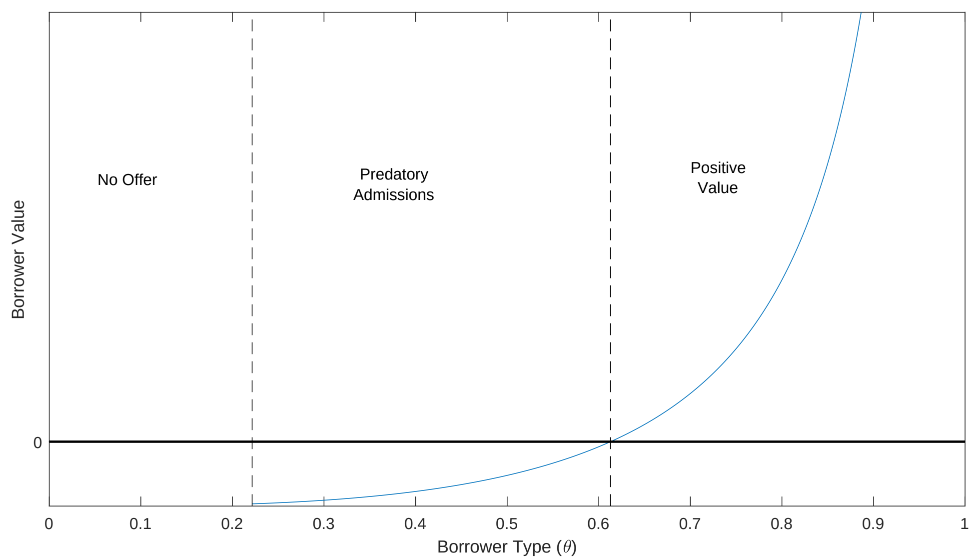

Figure 1.6: I construct a pool of student borrowers who are offered admissions. The plot shows the borrower's value versus her type. Here the student borrower's expected value from the loan is non-negative, so the borrower will accept the loan when offered. For the weakest students, however, the value of the loan is negative. For these borrowers they will accept a predatory admissions offer. The strongest students, however, take out a positive-NPV loan.

Surplus Transfer

In addition to predatory admissions, uniform interest rates also result in a surplus transfer to lenders. Although government policy is ostensibly to have student loan portfolios net no profits (Cox, 2017), profits are still common in the student loan industry. By fixing a uniform interest rate across borrower quality, the lender no longer faces interest rate competition. This lack of competition means that the lender is able to charge higher interest rates and capture more of the project's surplus value.

Proposition 4. *Let $\alpha > 1$. Under the socially optimal guarantee scheme, the lenders make a positive profit on all borrowers.*

Under some conditions a uniform interest rates scheme may be socially beneficial. Borrowers, however, are not necessarily beneficiaries of these policies. Being a better credit risk no longer translates to getting lower interest rates. Even the strongest borrower gets the same interest rate as the marginal borrower.

Without the government's intervention competition would force profits down to zero. A mandate that a uniform interest rate must be used, however, results in positive profits. The uniform interest rate scheme may be good for lenders, but such a policy comes at a cost to

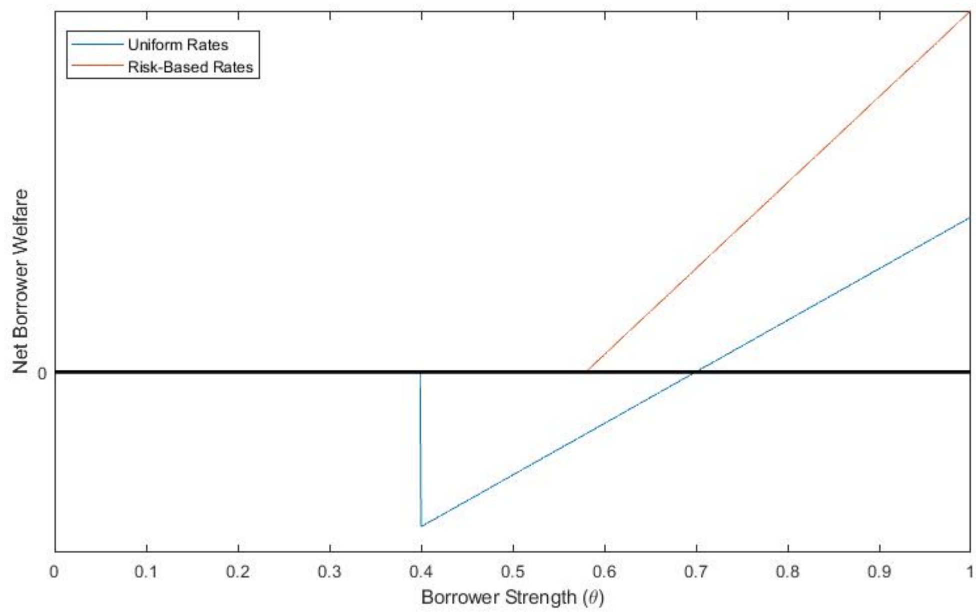

Figure 1.7: I plot borrower strength versus borrower welfare under both the risk-based interest rate and uniform interest rate schemes. For all borrower types θ, borrowers who accept a loan are strictly better off under the risk-based interest rate scheme. Further, under a uniform interest rate scheme some borrowers accept a predatory admissions offer.

borrower welfare. All borrowers who receive a loan would have been better off if rates had been allowed to vary across borrowers based on their risk.

This surprising result shows that when the government tries to induce a socially optimal level of enrollment by offering credit guarantees and mandating interest rates, the agents the government appears to help (i.e. weak borrowers) may actually be harmed. Uniform interest rates provide lenders an opportunity to profit off of students. Further, fixed rates exacerbate information disadvantages that reduce student welfare. If students knew as much as the lender, they could have avoided both the predatory offer and a transfer of surplus to the lender. Despite these negative consequences to student welfare, if guarantee programs are costly, a uniform interest rate scheme is still socially optimal.

1.8 Model Robustness

In this section I consider two extensions to the base model presented in the previous sections: direct government lending and two-sided private information. I show that most of my main results are robust to these different model specifications suggesting that my results are driven by interest rate pooling. As long as students cannot infer schools private information from interest rates, some students will face predatory admissions. For simplicity in this section, I turn-off the public signal σ.

Two-Sided Private Information

In many situations, students may possess some private information that colleges and lenders cannot accurately infer. For example, students entering college may misreport their intended major in order to increase their chances of gaining admissions to a particular college. In this subsection, I extend our analysis to an environment where both the lender and the borrower have private information.

Let the payoff distribution $F(w|\theta_L, \theta_B)$ now be a function of both the lender's private information, θ_L, and the borrower's private information, θ_B. Assume that $\theta_L \sim U[0,1]$ and $\theta_B \sim U[0,1]$. Further to focus our attention on interest rate pooling, I will consider the impact of a fixed government policy of mandated interest rate R and guarantee rate s. Let $V_L(R, s; \theta_L, \theta_B)$ and $V_B(R, s; \theta_L \theta_B)$ be the value functions for the lender and the borrower respectively when the (θ_L, θ_B) borrower accepts a loan. To ensure that some lending occurs I place the following restrictions on the distribution function F.

Assumption 8. *The payoff distribution $F(\cdot|\theta_L, \theta_B)$ has the following properties:*

1. *$F(\cdot|\theta_L, \theta_B)$ displays strict FOSD in both θ_L and θ_B*
2. *For all θ_B, $V_L(R, s; 0, \theta_B) < 0 < V_L(R, s; 1, \theta_B)$*
3. *For all θ_L, $V_B(R, s; \theta_L, 0) < 0 < V_B(R, s; \theta_L, 1)$*
4. *$f_{\theta_L}(\cdot|\theta_L, \theta_B)$ and $f_{\theta_B}(\cdot|\theta_L, \theta_B)$ are continuous in θ_L and θ_B almost everywhere*

Similar to before, our equilibrium result will be in the form of a threshold strategy whereby a lender extends credit if and only if its private information is above some endogenously chosen threshold, and the borrower accepts the loan if and only if her private information is above some endogenously chosen threshold.

Lemma 5. *There exists an equilibrium of the form $(\tilde{\tilde{\theta}}_L, \tilde{\tilde{\theta}}_B)$ such that the lender offers a loan if and only if $\theta_L \geq \tilde{\tilde{\theta}}_L$, and the borrower accepts an offered loan if and only if $\theta_B \geq \tilde{\tilde{\theta}}_B$.*

There will now be two thresholds: one based on the lender's private information which defines when the lender is willing to offer a loan and the other where the borrower is willing to accept an offered loan. At the borrower's cutoff, the borrower breaks even in expectation. As the borrower is strictly better off when the lender has better private information, the only way the borrower can break even in expectation is if the borrower is sometimes worse off having accepted a loan.

Proposition 5. *In a two-sided private information market, predatory admissions will occur.*

Conditional on being offered admissions and the corresponding loan, the student knows the lender's private information is in the interval $[\tilde{\tilde{\theta}}_L, 1]$. At the borrower's threshold $\tilde{\tilde{\theta}}_B$, the student's expected value is zero. Given multiple types all receive the same loan offer, the only way that the student's expected value can be zero is if at least some student's are strictly worse off having accepted that loan. Thus, predatory behavior still occurs as some students would have rejected the loan if they possessed the lender's private information.

Direct Lending

After the Health Care and Education Reconciliation Act of 2010, almost all new federal student loans have been originated by the federal government rather than independent lenders. The primary loan eligibility criteria, however, remained unchanged. In order to be eligible for a federal student loan, the student must be enrolled in an accredited post-secondary educational program. Schools that do not perform well, however, can be dropped from the program. Under this setup schools function as screeners ensuring that only the right mix of students are admitted and receive federal loans.

Setup

Under our extension, a social planner is considering offering loans directly to borrowers. As before, however, the social planner is unable to observe a borrower's type, either ex-ante or ex-post. A school exists who can observe the borrower's type ex-ante. As schools profit from enrolling students, the social planner must pay an additional rent $\zeta > 0$ to the school for all accepted borrowers. As schools are able to observe and screen (i.e. accept) students based on their type, I will also refer to schools as "screeners" to reflect this additional service preformed by colleges.

As the screener is paid only when they accept a borrower, the screeners have an incentive to accept all borrowers. The social planner will need to use a discipline device to ensure that the right number of borrowers are accepted. Since the social planner is unable to observe θ, either ex-ante or ex-post, the social planner must use ex-post wages in the disciplining device. To reflect the current setup of the direct lending program I use the following disciplining device: in order to continue in the program, the average wage of students accepted by the screener must be at least $\underline{w}$. If the average wage is less than $\underline{w}$ the screener is permanently dropped from the program and unable to capture any further rents.

In this setup the admissions officer functions similarly to our base model. The admissions officer is still functioning as the screening agent and determining, by his admissions decision, whether a student should be offered a loan. Now, however, the admissions officer's objective function is not to ensure the lender makes a non-negative profit; instead, the admissions officer is ensuring his students' ex-post outcomes meet some government target.

Analysis

Since the screener is only paid for accepted students, the screener wants to accept as many students as possible subject to the constraint that the expected average wage is at least $\underline{w}$. The screener's optimal policy will be to use a cutoff rule where they only accept students whose type exceeds some threshold θ'.

Lemma 6. *In equilibrium, the screener will approve a borrower if and only if $\theta \geq \theta'(\underline{w})$.*

From the student's prospective this cutoff rule functions analogously to the base model. If a students is offered admissions, she knows that she must be at or above some endogenously determined threshold. The social planner is able to determine what threshold will be used by changing the required average wage level.

Lemma 7. *$\theta'(\underline{w})$ is a strictly increasing function in $\underline{w}$ over the interval $(\mathbb{E}[w|\theta = 0], \mathbb{E}[w|\theta = 1])$.*

Since $\theta'(\underline{w})$ is a strictly monotonic function, each required average wage level will induce a unique threshold. From the social planner's prospective, two choices can be made: what interest rate to charge all students and what cutoff type to set. As before, the interest rate and cutoff type will need to be set so that the borrower's IR constraint is not violated. If the interest rate were too high, the borrower would reject the loan. If the borrower's IR constraint holds with equality, however, our predatory admissions result, proposition 3, will still apply. In order for the IR constraint to hold with equality, it must be the case that the weakest accepted students are worse off.

Proposition 6. *Suppose $\alpha > 1$. If ζ is sufficiently small, the social planner will want to use a direct lending program with the borrower's IR constraint holding with equality.*

When all students receive the same interest rate, the lender (i.e. the government) will receive positive profits on loans issued. When funds are costly, the social planner is able to use fixed interest rates loan as a way to raise funds while financing projects with a positive social value. Whether this is the optimal way to achieve the socially optimal level of lending will depend on how much the social planner must pay screeners. When ζ is relatively small, the additional screening cost is negligible making it better to lend through the direct lending channel.

1.9 Conclusion

Although higher education has been shown to be, on average, a good investment for students even if financed via student loans, concern has grown over the impact that student debt has on student borrowers. To explain these divergent results, I construct a novel measure to capture heterogeneity in returns to college attendance across schools. My results confirm the large prior literature that, on average, attending college is a positive NPV investment; however, nearly a third of students appear to realize a negative return. Much of this poor performance is constrained in for-profit colleges. In spite of such negative results, students are still willing to attend such schools.

To explain why students are willing to go to poor performing schools, I consider the impact that the structure of the student loan market has on borrower behavior. When students face information asymmetries, current policies mandating uniform interest rates on all federal student loans can have dire consequences for students.

Since students cannot learn from interest rates, students cannot learn the true value of their education. As college is worth it for the average student, students are most often willing to take the risk and go to college. With better information, however, weaker students may realize that, for them, going to a poor performing college would not be worth it.

Even though the current structure of the student loan market may not be optimal for borrowers, this structure may still be socially optimal. By mandating a uniform interest rate for all student loans, a social planner is able to achieve an optimal level of enrollment at a lower cost to the social planner. The programs and policies that are best for society as a whole may in fact create a cost for the students policy makers claim to be helping. Lending programs may not always help weak borrowers access credit; instead, they may facilitate the creation of predatory behavior harming those the programs appear to be helping.

Chapter 2

Paying to Stay Motivated: The Impact of University Gym Fees on Student Usage

2.1 Introduction

What encourage people to go to the gym, and how do we get people to go more often? Gym attendance behavior has become a relevant setting for economists to study. Not only does understanding gym attendance help economists recommend better health policies, but the setting also allows us to empirically examine consumer choice theory in relatively controlled settings. In this paper, I study the impact that the sunk-cost fallacy has on gym user's desire to regularly attend the gym.

Early work on gym attendance demonstrated that consumers seem to often choose sub-optimal contracts (DellaVigna & Malmendier, 2004; DellaVigna & Malmendier, 2006). Often consumers seemed to overestimate their propensity to workout, selecting contracts with high flat-rate fees rather than what, in hindsight, would have been a cheaper pay-per-visit option. It is well known that individual agents are prone to projection bias and may not accurately predict the behavior of their future selves (Strotz, 1955; Loewenstein et al., 2003); when gym users suffer from projection bias they overestimate the likelihood they will go to the gym (Acland & Levy, 2013; Garon et al., 2015). To overcome this problem, consumers seem willing to pay to create commitment devices (Fudenberg & Levine, 2006; Ashraf et al., 2006) especially at the gym (Milkman et al., 2013; Royer et al., 2015).

While the value of commitment devices for consumers is well known, the use of the sunk-cost fallacy as a possible commitment device has received less attention. From a purely financial standpoint, decision makers should ignore sunk costs since those costs are irrelevant to any future decisions. Behavioral economics and psychology, however, have long recognized the importance of sunk costs in various settings both experimental and in the field (Arkes & Blumer, 1985; Just & Wansink, 2011; Ketel et al., 2015; Augenblick, 2016; Ho et al., 2018). Although a few notable exceptions exist (Friedman et al., 2007, Ashraf, 2010), in many situations the sunk-cost fallacy will have a substantial impact on consumers' actual choices. Given the relevance of the sunk-cost fallacy, it stands to reason that consumers may actively use the sunk-cost fallacy to nudge their future selves to future actions.

In this paper, I exploit a natural experiment at a university health fitness center to explore the role that the sunk-cost fallacy plays in users' decisions to access the gym. In previous papers, consumers' sub-optimal contracting choices have often been suggested to be the result of behavioral biases. Here, I argue that agents may factor these behavioral biases into their decision making. The choice of a seemingly sub-optimal contract may, in fact, be the agent leveraging their biases to commit their future selves to attend the gym more.

To illustrate whether the sunk-cost fallacy factors into gym users' decision to go to the gym, I construct a simple model of gym usage. When users have standard preferences, high membership fees discourage users from purchasing a membership and thus going to the gym. When users suffer from the sunk-cost fallacy, however, the impact of membership fees on usage is more ambiguous. The fees discourage users from purchasing a membership but conditional on having already purchased a membership these fees help motivate a user to go to the gym more regularly.

The model provides three testable predictions on how users will respond to the decrease in membership fees. First, membership purchases should increase when costs go down even if users recognize they have non-standard preferences (i.e. suffer from the sunk-cost fallacy). Second under non-standard preferences, the conditional probability of going to the gym will be lower when membership fees are decreased. The change in the conditional probability, however, will be lower the longer an individual has been a member. Right after purchasing a membership, the sunk cost will be especially salient, motivating attendance; however, as time goes on the sunk cost will be less salient and less of a motivator. Third, with standard preferences the change in usage probability is strictly monotonic over time, but under non-standard preferences the change in usage probability need not be monotonic. These three predictions will allow for a test of whether the sunk-cost fallacy influences users' decisions to access the gym.

To test the model, I exploit a unique natural experiment where costs for gym membership fees were eliminated for student users at a university health fitness center. Both students and faculty/staff are eligible to acquire membership at the university gym. Prior to Fall 2015, both groups had to purchase memberships. In Fall 2015, the student membership fee was bundled into the university's required tuition and fees. Hence, for student users the membership fee was effectively eliminated as the fee became incidental to university enrollment. For faculty/staff users, however, the terms of membership did not change. Hence, the faculty/staff group can serve as a control to test the impact of the elimination of membership fees on gym usage.

Using administrative records of gym entry, I observe each of the 6 million entries into the university gym from August, 2012 to November, 2017 which allow for direct observation of the impact of the elimination of the discretionary student membership fee. All students and faculty/staff were eligible to use the gym each day in my sample period. Since the administrative records of entry includes ID numbers, I can construct a dataset that tracks usage patterns over time.

Applying a difference-in-differences framework, I use the student membership fee change to test the importance of the sunk-cost fallacy on usage behaviors. First, I test the impact that the membership fee change had on membership purchases. Although the student fee was small its elimination increased student membership by approximately 7% over the course of a semester, this translates to nearly 3,000 more student members. Despite the increase in membership numbers, the impact on daily usage is much more ambiguous. In the next test, I consider the probability of daily usage conditional on membership. While conditional usage probabilities decay over time, without the sunk-cost fallacy the policy change should have no impact on the rate of this decay. The results, however, indicated that after the elimination of the discretionary membership fee the daily usage probability decayed at a 15% slower rate.

As the key test of non-standard preference, I calculate the aggregate probability a user accesses the gym over time. In order to access the gym a user must both have purchased a membership and then choose to go to the gym on a given day. Under non-standard preferences the impact of eliminating the membership fee on aggregate usage probabilities will be ambiguous. The high fee will reduce the likelihood of purchasing a membership but will encourage users to go to the gym more once they've purchased the membership. At the beginning of the semester, the relative probability of gym usage declines over time. Without the sunk cost of membership fees, it is harder to motivate students to go to the gym on a regular basis. As time goes on, however, usage probability begins to increase again as more low propensity users decide to acquire membership. While the late semester uptick in usage may occur under standard preferences, only the sunk-cost fallacy can explain the relative decrease in early semester usage. Early on in the semester the sunk-cost fallacy would likely have played a large role in motivating users to go to the gym. Hence, it appears that the sunk-cost fallacy is a substantial motivator in agents' decisions to go to the gym on a given day.

The remainder of the chapter is organized as follows: Section 2.2 discusses my model of gym usage. Section 2.3 presents the institutional details surrounding the policy change and the dataset. Section 2.4 is my main results, and section 2.5 concludes the chapter.

2.2 Model

To illustrate how gym membership fees may serve as a commitment device, I construct a simple model of gym usage with membership fees. Under standard preferences, reducing fees will increase usage throughout the membership period. When preferences include the sunk-cost fallacy, however, the model predicts that usage may not increase during the middle of the membership period as the reduction in costs also reduces the sunk costs agents face. If agents suffer from the sunk-cost fallacy then membership fees may serve as a commitment device.

Gym Usage under Standard Preferences

Given the unique setting of the experiment, I construct a simple multi-period model that captures the key features of gym membership contracts at the university gym. Each membership period has T periods or days. A member can purchase a membership at a fixed and exogenous cost $c \geq 0$ at any time between day 1 and day T. Once purchased, the member would have the right to go to the gym in each day upto day T. Note that in contrast to a traditional gym membership, a user would only get a full T days of membership if they purchased the membership at time 1[1].

After purchasing a membership, the user would then have the option of attending the gym each day. The daily net utility of gym attendance is given by $u_t = x + \epsilon_t$. x represents the known benefits and costs of going to the gym each period. On day 1, the agent knows the value x for all periods. ϵ_t is the random component of the agent's daily utility. Let ϵ_t be an iid continuous random variable with distribution $F(\cdot)$. Assume that $F(\cdot)$ has full support in $\mathbb{R}$ and the PDF, $f(\cdot)$, is a continuous function. The agent only learns of ϵ_t in period t. Hence, the decision to attend the gym in period t will be random from the perspective of all periods $s < t$.

As the membership fee is a sunk cost, gym users with standard preferences will ignore the fee when determining their daily net utility. Hence, a rational user will go to the gym on day t if and only if $u_t \geq 0$. The total expected utility an agent gets from purchasing a membership at time t will be

$$U_t = \sum_{s=t}^{T} \mathbb{E}[\max(u_s, 0)] - c. \tag{2.1}$$

As potential members will only purchase a membership when their expected usage utility exceeds the membership cost, it is trivial to show that the conditional probability a user acquires a membership in any given period t is decreasing in c. Hence, if gym users ignore sunk costs eliminating gym membership fees should have the unambiguous effect of increasing gym usage on any given day.

Usage under the Sunk-Cost Fallacy

If agents suffer from the sunk-cost fallacy, the impact of eliminating gym membership fees may no longer be unambiguous. Conditional on purchasing a membership, high membership fees actually increase the daily value of attending the gym. Because of the sunk-cost fallacy, users want to "get their monies worth" and become more willing to attend the gym on a daily basis.

[1] This modeling choice is guide by the semester-based structure of the university's gym contracts; students who purchased a membership in the last week of the semester would pay the same amount as students who purchased the membership on the first day of classes. The late purchasers, however, would only get a few days of access.

Now suppose users have a sunk-cost fallacy, and the membership fee enters into their daily net utility function. When users suffer from the sunk-cost fallacy, users have "non-standard preferences." Although the sunk-cost fallacy is normally treated as a behavioral bias, agents with these non-standard preferences need not be irrational. Under the sunk-cost fallacy agents derive value from using something they have paid for already. As part of the value of gym attendance is undoubtedly psychological, even under standard preferences, it need not be irrational to derive psychological benefits from the sunk-cost fallacy.

Suppose a user purchased membership on day t_0. Let the new daily utility be given by $\tilde{u_t} = x + \epsilon_t + \gamma^{t-t_0+1}c$, where $\gamma \in (0, 1)$. The higher γ the more the user suffers from the sunk-cost fallacy. Under non-standard preferences, the user will go to the gym if and only if $\tilde{u_t} \geq 0$.

Lemma 1. *Conditional on having purchased a membership by period t, the probability a member goes to the gym in period t is increasing in c.*

Unsurprisingly, when an agent is factoring in high sunk costs the agent is more likely to use the gym. As the membership fee falls the psychic cost of foregoing gym attendance also falls. Hence, it becomes less likely that on a given day an agent will be able to motivate themselves to go to the gym.

Conditioned on having paid for a gym membership, the impact of the sunk-cost fallacy is clear, especially when memberships are costly. Since users must also decide whether to purchase a membership, the interaction of high membership fees and aggregate gym usage is less clear. The high fees do increase the perceived benefits of going to the gym. High fees, however, may prevent a user from purchasing a membership in the first place.

To see how high membership fees impact the decision to purchase a membership, first assume that the agent is naïve and does not factor in the sunk-cost fallacy when deciding whether to purchase a membership. Here the agent's expected utility will be the same as in the rational case, (2.1). Because of the sunk-cost fallacy, however, the user will be more likely to go to the gym then they estimated when deciding whether to purchase a membership.

Now consider a sophisticated user who knows they have non-standard preferences. When the sophisticated user decides to purchase a membership, they will factor in the impact of the sunk-cost fallacy on their daily usage. Thus, the sophisticated user's expected utility will be given by

$$\tilde{U}_t = \sum_{s=t}^{T} \mathbb{E}[\max(\tilde{u_t}, 0)] - c \tag{2.2}$$

Whether high membership fees will increase or decrease $\tilde{U}$ will depend on γ. If γ were sufficiently high, then a user might actually be more likely to purchase membership. With a high γ, the user gets a lot of psychic benefit from taking advantage of the membership they purchased, even though it is a sunk cost. For small values of γ, however, high costs discourage the purchase of membership. Although the user gets some psychic benefits, the high initial cost still outweighs these psychological benefits.

Lemma 2. *Suppose that the membership fee decreases from c to c'. There exists a $\bar{\gamma}$ such that for all $\gamma \leq \bar{\gamma}$, the probability a user is willing to purchase a membership in a given period increases with the membership fee decrease.*

So long as the sunk-cost fallacy is not too large, users will be less likely to purchase a membership when the membership cost is high even if the potential member is aware that they have non-standard preferences.

Model Predictions

Guided by the model, I make three predictions about the behavior of gym users to test whether cost salience and the sunk-cost fallacy are motivators of agents' usage. To make explicit the model predictions, I will introduce notation to analyze usage probability as costs decrease from c to c'. Let $p(c,t)$ be the probability that a user with standard preferences goes to the gym on day t when the membership fee is c. $p(c,t)$ can be subdivided into two components: $p_m(c,t)$ the probability a user purchased a membership by day t, and $p_a(c,t)$, the probability of attending the gym on day t having already purchased a membership.

$$p(c,t) = p_m(c,t)p_a(c,t). \tag{2.3}$$

Further, define $\Delta(t) := p(c',t) - p(c,t)$ as the difference in use probability when cost decrease from c to c'. Similarly, let $\tilde{p}(c,t)$ and $\tilde{\Delta}(t)$ be respectively the probability that an agent with non-standard preferences goes to the gym in period t and the difference in usage probabilities for an agent with non-standard preferences when costs decrease.

First, consider the decision whether to purchase a membership. The cost of membership is not pro-rated if purchased late in the semester. This implies that as the semester wears on, users will have fewer days to take advantage of their membership even though the cost is unchanged. Hence, when costs are high users who have yet to purchase a membership by period t are less likely to purchase the membership in period t; there are fewer days to spread the membership cost over.

Prediction 1. *So long as the sunk-cost fallacy is sufficiently small, the probability of membership purchase increases when the membership fee decreases from c to c' for all t.*

Although the first prediction is not unique to non-standard preferences, it still is important for two reasons. First, it tests whether users behave with some level of forethought when determining whether to purchase a gym membership. Even if users are not perfectly rational, it is reasonable to test whether gym users act as though they can, to some degree, predict their future behavior. Second, this prediction confirms that raising gym membership fees does not strictly increase gym usage. Higher fees mean users are less likely to purchase a membership in the first place reducing the number of folks who have access to the gym.

The second prediction examines the behavior of users conditional on purchasing a membership. Under standard preferences, once an agent has purchased a membership, the decision to go to the gym should be based only on the net benefits of going to the gym that period. Hence, the probability a user goes to the gym on a given day should not vary based on the membership cost. With the sunk-cost fallacy, however, the probability a user goes to the gym will be influenced by the cost of their membership. Since, the salience of this cost degrades over time the impact it will have on usage will decrease over time. When a user just purchased an expensive membership, the sunk-cost fallacy will have a much greater impact on usage behavior than months after the membership had been purchased.

Prediction 2. *Suppose a user purchases a gym membership in period t_0. For all periods $t > t_0$, the conditional probability a user goes to the gym is not a function of cost under standard preferences; however, when a user has non-standard preferences the conditional probability that a user goes to the gym is increasing in cost: $p_a(c,t) = p_a(c',t)$, but $\tilde{p_a}(c,t) > \tilde{p_a}(c',t)$ for all $c > c'$.*

This prediction differentiates between the behaviors of users with standard preferences and those with non-standard preferences (i.e. suffer from the sunk-cost fallacy). Under standard preferences once a membership has been purchased, the membership fee becomes a sunk cost. A standard user will not factor it in to their decision to use the gym. In contrast, users with non-standard preferences will be encouraged to go to the gym more given that they had already purchased a membership. These users will go to the gym in order to feel like they are getting their monies worth.

The final prediction concerns the total probability a user goes to the gym over time. From (2.3), the total probability a user goes to the gym on a given day is the product of two components: the probability a membership has been purchased and the probability that a user wants to go to the gym that day. With standard preferences, the second component, p_a will not vary with cost. Hence, the only time varying component of daily usage will be the probability a membership has been purchased. In contrast, when users have non-standard preferences, the cost of membership will enter into both the decision to purchase a membership p_m and the decision to use the gym each day, p_a. When c is high, the probability a user purchased a membership by day t will decrease over time. Also when c is high, however, the probability a user goes to the gym on a given day (conditional on purchasing a membership), $\tilde{p_a}$ will increase in c. This creates the possibility that the relationship between usage probability and cost is not a monotonic function of time.

Prediction 3. *Let membership costs decrease from c to c'. Suppose the difference in the probability of membership purchase increases over time. Under standard preferences, the difference in total usage probability, $\Delta(t)$, must be monotonic. Under non-standard preferences, however, the difference in total usage probability, $\tilde{\Delta}(t)$ need not be a monotonic function of time.*

By examining the relationship of gym usage over time, this prediction suggests a way to test whether users are behaving as though they have standard preferences. Under standard preferences, increasing costs will cause gym usage to fall over time as fewer individuals will be willing to buy a new membership late in the semester. If users suffer from the sunk-cost fallacy, however, the relationship will be less clear. Because high costs encourage gym attendance conditional on purchasing a membership, the difference in gym attendance when costs are raised need not be a monotonic function over time. This difference will provide direct evidence of whether or not the sunk-cost fallacy factors in to users' decisions to go to the gym.

2.3 Data and Institutional Background

To study the impact of gym membership fees on gym usage, I use an administrative data set of entries at a university gym. During the sample period, a change was implemented in how students paid for the gym which significantly reduced the salience of the students' gym membership costs. This change provides an opportunity to isolate the impact that changing the salience of gym usage fees have on gym usage as only some users (i.e. students) were impacted by the change.

Institutional Details

My study is set at a large, public West Coast university with an on-campus fitness center. The primary purpose of the gym is to improve the wellness of students, faculty, staff, and the community with a special emphasis on the well-being of students. All university students and university staff/faculty employees[2] are eligible to join the gym, although the cost does vary depending on the class of membership purchased (i.e. student vs. employee). Non-affiliated adults are also eligible to purchase membership; these community memberships, however, are much more expensive than a student or employee membership.

Prior to Fall 2015, students were required to pay a \$10 fee each semester to purchase membership at the gym. This fee was optional and had to be paid separately from the student's required tuition and fees. To pay the fee, students had two options. Students could apply for membership through the gym's online membership where they were given the option of either have the fee assessed to their student account or immediately pay with a credit card. For almost all students who choose to have the fee assessed to their account, the gym membership fee would be on a different billing cycle than required tuition and fees. In lieu of the online application students cold also opt to apply for membership in person at the gym. If the student applied in person, they would have the additional options of paying by cash or check.

[2]Since the costs and privileges associated with gym membership are the same for both staff and faculty for the remainder of this paper I will use the term "employee" to refer to staff and faculty members.

While 55% of students paid the membership fee each semester, students were not required to purchase a student membership as a condition of their university enrollment. Hence, students faced a discrete decision as to whether to access the gym that was not related to their decision to enroll at the university. Anecdotally, many non-members students reported that the $10 membership fee did serve as a barrier to their using the gym. In addition to the university gym, students could also choose to forego membership in the university gym and purchase membership at various off-campus gyms and fitness centers. To the best of my knowledge, however, all full-service off-campus facilities were significantly more expensive than the university gym and offered only small, if any, student discounts.

Starting in Fall 2015, the university eliminated the optional student membership fee, and all enrolled students automatically became gym members. To help pay the costs associated with running the gym, a "membership buyout" was added to all students' required tuition and fees starting in Fall 2015. Because of this membership buyout, student membership in the gym was no longer optional but instead became incidental to university enrollment. From a student's prospective the membership buyout eliminated the cost to join the gym.

The membership buyout was instituted as part of a large 2015 student referendum focused on improving campus wellness services. The membership buyout represented approximately 5% of the total wellness-focused fee increase. Further, turnout was relatively low with only 25% of students voting on the wellness-focused fee referendum. As student referendum are only advisory to campus leadership, the final decision to implement the fee was left to the university's administrative leadership. Based on the advisory referendum and support from numerous campus units, campus administrative did agree to begin levying the wellness-related fee on students starting in Fall 2015.

Although students are the main users of the university gym, employees could also purchase a semester-by-semester membership at the gym. The employee membership fee at $275 per semester was considerably more expensive than the student membership. This membership fee could be paid by cash, check, credit card, or automatic payroll deduction. Other than the difference in membership fees, employee members had the same rights and privileges as student members.

The elimination of the student membership fee in Fall 2015 had no effect on the cost or privileges associated with employee memberships. Given that employee memberships were not impacted by the change in student membership fees, the elimination of student membership fees can function as a natural experiment to gauge the impact that membership fees have on gym usage.

Gym Usage Data

My main data is records of entry at a university gym at a large, public West Coast university between August, 2012 and November, 2017. Each time a user enters the gym a record is made of the date & time of entry, user ID, user type (i.e. student or employee), and entry location. In order to access the gym, users are required to swipe their university IDs at one of two entry turnstiles. The entry turnstiles are set so that someone can enter the gym only if they swipe-in with a valid ID. Hence, as long as the turnstiles are operating there are precise records of all entries into the facility.

Since student usage drops significantly over the summer and winter break periods, I only consider usage during the fall and spring semester periods. The timing of when students arrive on campus for the start of classes and leave at the end of the semester exhibits significant heterogeneity. To address this variability in the number of possible student users at the very beginning and very end of the semester, the main results are all restricted to the period between the first day of classes and the day before final exams begin. In total there are between, 120 and 122 valid days per semester.

During the sample period, there were 78 days where the turnstiles system suffered significant technical difficulties. During these 78 days, the turnstiles recorded, on average, 6 entries per day. As the average number of entries is over 3,000 per day, I drop all observation from these days.

	Days	Entries	Entries/Day
Total Observations	1,864	5,171,330	2,774.3
Summer & Winter Break	551	1,354,499	2,458.3
Pre-Class Period	76	148,608	1,955.4
Exams	45	90,383	2,008.5
Broken Turnstiles	78	469	6.0
Final Sample	1,114	3,577,371	3,211.3

Table 2.1: Sample Construction

The final sample includes 1,114 days during both the spring and fall semesters. Within the sample period, the average number of entries per day was 3,211. Overall, approximately 87% of all entries during the sample period were by student users.

As the administrative entry data only includes ID numbers for those who used the gym at least once in a semester, I do not directly observe eligible users who elect not to use the gym. To account for users who choose not to use the gym, I use the campus's official bi-annual census to calculate the number of non-users. Each semester the university conducts an official count of all students and employees. Subtracting the number of individuals in the census from the observed number of users each semester, I calculate the number of non-users each semester. The campus census is conducted at the same time and in the same manner each semester. Although there may be day-to-day changes in the number of eligible users versus the official census count, these differences should not be correlated with the elimination of the discretionary student membership fee.

Using the records of entry, I then create an indicator variable, $used_{i,t}$ for each eligible user-day pair to record whether user i accessed the gym on day t. $used_{i,t}$ and the average daily usage rate across user type will be the main variable of interest in the empirical analysis that follows. In total, there are 58,061,623 user-day pairs. For students the average daily usage rate is 7.7% with students comprising 71% of eligible users. For employees the average daily usage rate is 1.5%.

2.4 Estimating the Impact of Cost Salience on Gym Usage

In this section, I test my model's prediction that salient gym membership fees serve as a commitment device by taking advantage of the sunk-cost fallacy. My main identification approach is a difference-in-differences model comparing the impact of the elimination of the discretionary student membership fee on treated users (students) and non-treated users (employees). The results of the difference-in-differences regressions support the main predictions of the model. Gym usage increases in the treated groups at the beginning and end of each semester membership period, but show no differences in the middle of the semester. These results suggest that gym membership fees may serve, when users have non-standard preferences, as a valuable commitment device.

Identification Strategy: Difference-in-Differences Model

The obvious correlation between an individual's propensity to go to the gym and their willingness to pay for gym membership presents a challenge to identifying the causal impact that eliminating membership fees have on usage behavior.

To address this endogeneity concern, I take advantage of the natural experiment created by the elimination of the discretionary student membership fee using a difference-in-differences framework. Under the natural experiment, the elimination of discretionary student membership fees serves as a treatment on the student population post-Fall 2015. Since employees were not impacted by the change in membership fees, the employee group serves as the control group.

The main empirical specification will be in the form of:

$$y_{i,t} = \alpha + \beta_1 * Student_i + \beta_2 * Post_t + \beta_3 * (Student_i * Post_t) + \delta X_{i,t} + \epsilon_{i,t}$$

where $Student_i$ is a dummy equal to 1 if observation i is a student and $Post_t$ is if time t is after the elimination of the membership fee (i.e. the policy change). $X_{i,t}$ is a set of controls that includes whether day t was a holiday, the day of the week, and semester fixed effects. The main parameter of interest will be the β_3 (and interactions thereof) as this term will capture the impact of the elimination of the discretionary membership fee on gym usage.

The main threat to identification is that patterns of usage between student and employee users began to diverge prior to the Fall 2015 student membership fee elimination. In figure 2.1, I plot average daily usage by semester. Prior to the policy change in Fall 2015, variations in student and employee usage statistics closely mirrored each other closely. This suggests

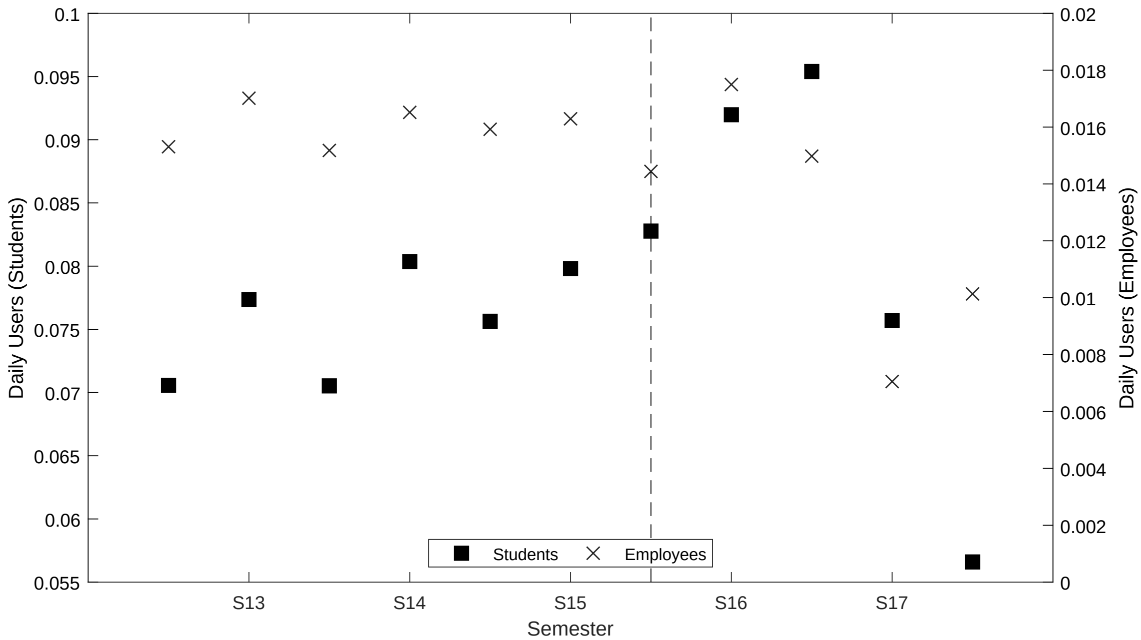

Figure 2.1: This figure shows the average % of elegible users accessing the gym each semester. Student usage is plotted against the left-axis, and employee usage is plotted against the right-axis. The dotted verticle line represents the elimination of the membership fee in Fall 2015.

that, in the data, the parallel trends assumption holds and the difference-in-differences approach is valid.

After eliminating the membership fee, however, student and employee usage began to diverge considerably. The graphical evidence is suggestive that eliminating the membership fee had a significant impact on student usage behaviors. Even though the membership fee was relatively small, it appears that its had an out-sized impact on usage patterns.

Another threat to identification is selection into the treatment (i.e. student) group. Although students and employees may switch between affiliation status, it is unlikely that there was any selection around the treatment effect. While there are many perks to being a student or university employee, it seems highly implausible that any individual would choose to enroll as a student versus accepting a job offer on the basis of the cost of gym access. Further, the natural progression of a student's studies will have a much greater impact on the timing of their graduation decision than any individual non-academic policy. Even if an individual wished to select into the treatment group such selection would be dependent on being admitted as a student or hired as an employee making it harder to select into the treatment or control group.

Changes in Student Gym Usage

Using the difference-in-differences strategy, I test the three key predictions of the model presented in section 2.2. All three tests suggest that the sunk cost fallacy plays a significant role in individuals' daily decision to use the gym.

Prediction 1: Membership Purchases

I start by considering the likelihood of students to purchase a gym membership both with and without the membership fee. In the data, I cannot see directly whether users purchase a membership. Instead, I observe the first day that a user chooses to go to the gym. Although there may be some students who purchased a membership but never used it, it seems unlikely that this is a large group since users could easily purchase a membership on the first day they wanted to attend the gym.

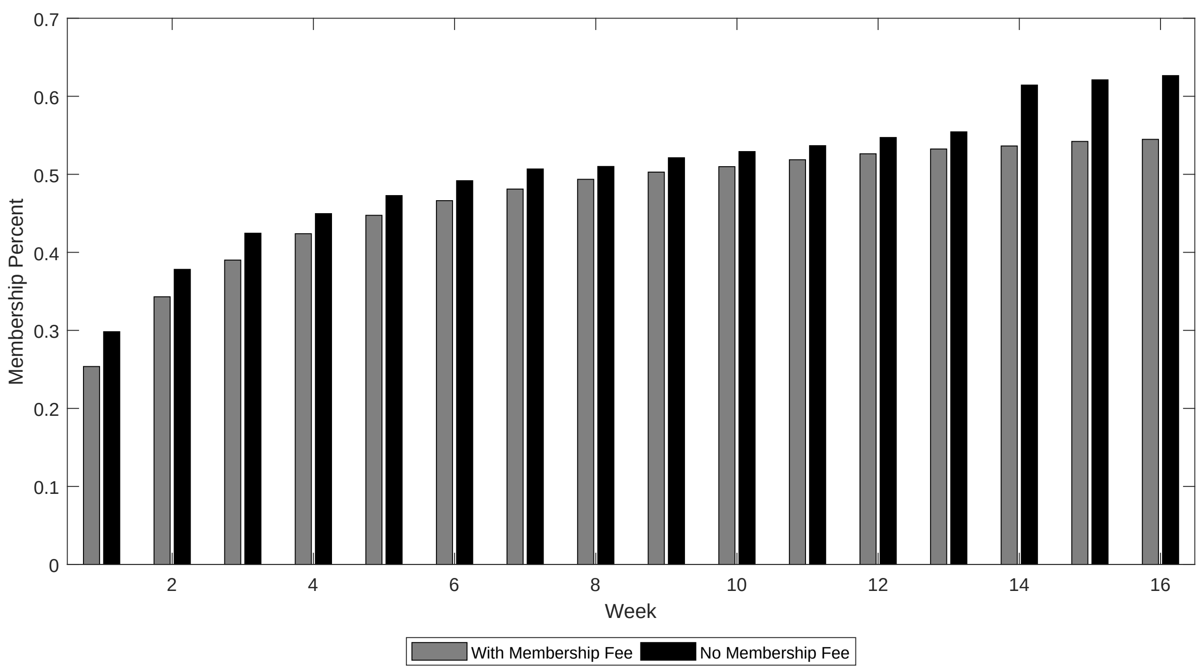

Figure 2.2: This chart plots the average percent of eligible students who have become members by the end of each week of the semester.

Figure 2.2 shows the average percent of students who are gym members at each week of the semester. Both with and without the membership fee, the percent of student members rises quickly over the first four weeks of the semester. With the additional membership fee, few students join the gym after the beginning of the semester. Once the fee was eliminated, however, another large spike in membership occurs in the last three week of the semester. Since the membership fee was not pro-rated joining at the end of the semester would have been especially costly on a per-day basis. Once the additional membership fee was eliminated, however, perspective student members no longer needed to worry that they wouldn't be able to utilize the gym enough to justify the membership fee. Hence, the spike in late semester memberships after the elimination of the membership fee.

As differences in membership sign-ups could be driven by semester specific factors, I next consider the difference-in-differences regression. In Table 2.2, I regress the percent of eligible users who have become members at each point in the semester and the interaction terms between student dummy and a post-membership buyout dummy. Each observation represents a day in a given semester. To construct the $Period_n$ dummies, I divide the semester into 6 equal length periods[3]; the $Period_n$ dummy is equal to 1 if and only if the i-th day of the semester is in $Period_n$. Columns (1)-(4) include no semester fixed effects; these fixed effects are added in columns (5)-(8)

The impact of eliminating the membership fee is strongly dependent on time. Without any measure of time, eliminating the membership fee had no statistically significant effect on the likelihood of membership. In columns (2) and (6), the impact that the policy change had on membership was positive and became much more likely to become members by the end of the semester. After a full semester, the elimination of the membership fee resulted in a 4.3 points increase in the number of students who became health center members; this corresponds to about 1,800 more unique student members each semester. Including the full set of $Period_n$ dummies (Columns (4) and (8)) produces similar results. These results are consistent with the model's prediction that eliminating the membership fee should increase the likelihood of students becoming gym members.

Prediction 2: Conditional Probability of Gym Use

Next, I test to see how the elimination of the membership fee impacted the conditional probability that a student accesses the gym given the users has a membership. For users with standard preferences, the elimination of the membership fee should have no impact on the conditional probability they access the gym. Under standard preferences once paid, the membership fee represents a sunk cost and should have no impact on the users daily decision making. If, however, users have non-standard preferences (i.e. they suffer from the sunk cost fallacy) then the membership fee will actually encourage usage especially right after the purchase of membership. Even under non-standard preferences, the impact of the sunk-cost fallacy should become smaller as time goes on.

In table 2.3, I consider the probability that a user goes to the gym on day t conditional on being a member on day t. In particular, I regress a dummy for whether member i accessed the gym on day t with measuers for how long the member has been a gym member. All regressions also include interactions for the student and post-membership buyout dummies.

[3] All of the results are robust to multiple numbers of quintiles.

	% Member							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Student	0.383***	0.268***	0.411***	0.232***	0.383***	0.268***	0.411***	0.232***
	(0.00410)	(0.00725)	(0.00338)	(0.00875)	(0.00249)	(0.00557)	(0.00209)	(0.00694)
Change	-0.0136	-0.00865	-0.0139	-0.00701	-0.00459	-0.00746	-0.00809	-0.00688
	(0.00895)	(0.00583)	(0.00977)	(0.00551)	(0.0196)	(0.0163)	(0.0182)	(0.0157)
Student*Change	0.0358	0.0255	0.0399	0.0475*	0.0358	0.0255	0.0399	0.0475**
	(0.0385)	(0.0355)	(0.0403)	(0.0250)	(0.0230)	(0.0222)	(0.0242)	(0.0179)
Day		0.000396***				0.000396***		
		(0.0000161)				(0.0000164)		
Student*Day		0.00212***				0.00212***		
		(0.0000713)				(0.0000715)		
Student*Change*Day		0.000399**				0.000399**		
		(0.000153)				(0.000145)		
$Period_1$			-0.0320***				-0.0320***	
			(0.00105)				(0.00106)	
Student*$Period_1$			-0.180***				-0.180***	
			(0.00595)				(0.00597)	
Student*Change*$Period_1$			0.00769				0.00769	
			(0.0208)				(0.0191)	
*Student*Change*								
*$Period_2$				-0.0106				-0.0106
				(0.0131)				(0.0118)
*$Period_3$				-0.0149				-0.0149
				(0.0181)				(0.0161)
*$Period_4$6				-0.0133				-0.0133
				(0.0267)				(0.0214)
*$Period_5$				-0.0106				-0.0106
				(0.0286)				(0.0233)
*$Period_6$				0.0423				0.0423**
				(0.0253)				(0.0187)
Semester FE?	N	N	N	N	Y	Y	Y	Y
N	2228	2228	2228	2228	2228	2228	2228	2228
adj. R^2	0.874	0.952	0.940	0.961	0.893	0.968	0.958	0.977

Table 2.2: This table reports the difference-in-differences regression of the percent of eligible users who are members on each day of the semester. The key interaction coefficients are the student*change terms. In all regressions, all independent variables were interacted with both the student, change, and student*change interactions; some of these student and change interaction coefficients were suppressed due to space constraints and are available upon request. Standard errors are reported in parentheses and are clustered at the membership class-by-semester level. *, **, and ***, indicate statistically different from zero at the 10%, 5%, and 1% levels of significance respectively.

Columns (3)-(6) also include semester fixed effects and day controls[4]. Columns (5)-(6) also include user fixed effects.

In Panel A, I consider the sample of all users who became members of the gym in each semester. As the elimination of the membership fee may have resulted in more low propensity users signing up, Panel B restricts the sample to only heavy users (defined as those who accessed the gym more than 30 times in a given semester). The results in the restricted sample are qualitatively similar to those in the full semester suggesting that these results are not driven by an influx of low propensity members.

The key coefficient of interest is the interaction term between the student dummy, policy change dummy, and the time variable. In all of the regressions, this variable is positive and significant. After students were shocked with the elimination of the membership fee, they became relatively more likely to use the gym after having been a member for a long-time. Because the policy change reduced the cost students paid to use the gym, the model predicts that the degradation in usage probabilities should be slower after the policy change.

The results in table 2.3 suggest that users and especially students do become less likely to use the gym the longer they've been members. Even under standard preferences, this result is not particularly surprising. For instance, users may become discouraged using the gym as time goes on due to a lack of results. Once the membership fee was eliminated, however, the degradation in student usage probability was approximately 15% slower. This is strongly suggestive that the sunk-cost fallacy plays a significant role in users decisions to access the gym on a daily basis.

[4]The set of day controls includes day of week fixed effects, a student holiday dummy, and a "dead week" dummy. "Dead week" is the university's one week period after the last day of instruction and the first day of exams.

Panel A: Full Sample						
	Daily Usage %					
	(1)	(2)	(3)	(4)	(5)	(6)
Student	-0.0303***	-0.0302***	-0.0277***	-0.0278***	-0.0124	-0.0124
	(0.00213)	(0.00210)	(0.00212)	(0.00209)	(0.0244)	(0.0244)
Change	-0.00116	-0.00183	-0.00710**	-0.00806**	-0.0375***	-0.0383***
	(0.00327)	(0.00322)	(0.00354)	(0.00349)	(0.00304)	(0.00298)
Student*Change	-0.00479	-0.00397	-0.00349	-0.00256	0.0274***	0.0280***
	(0.00335)	(0.00330)	(0.00334)	(0.00330)	(0.00293)	(0.00287)
Days(member)	-0.000612***		-0.000448***		-0.00103***	
	(0.0000248)		(0.0000280)		(0.0000237)	
Student*Days(member)	-0.000300***		-0.000318***		-0.000211***	
	(0.0000256)		(0.0000288)		(0.0000245)	
Change*Days(member)	-0.000203***		-0.000122***		-0.0000465	
	(0.0000469)		(0.0000466)		(0.0000387)	
Student*Change*Days(member)	0.000275***		0.000275***		0.000182***	
	(0.0000480)		(0.0000479)		(0.0000398)	
Weeks(member)		-0.00376***		-0.00250***		-0.00650***
		(0.000174)		(0.000196)		(0.000166)
Student*Weeks(member)		-0.00224***		-0.00237***		-0.00163***
		(0.000180)		(0.000202)		(0.000172)
Change*Weeks(member)		-0.00136***		-0.000777**		-0.000241
		(0.000330)		(0.000328)		(0.000272)
Student*Change*Weeks(member)		0.00191***		0.00189***		0.00124***
		(0.000338)		(0.000337)		(0.000280)
Semester FE?	N	N	Y	Y	Y	Y
Day Controls	N	N	Y	Y	Y	Y
User FE?	N	N	N	N	Y	Y
N	20,517,074	20,517,074	20,517,074	20,517,074	20,517,074	20,517,074
adj. R^2	0.006	0.005	0.017	0.017	0.134	0.133

Panel B: Heavy Users						
	Daily Usage %					
	(1)	(2)	(3)	(4)	(5)	(6)
Student	0.00793*	0.00780*	0.0138***	0.0135***	0.0731***	0.0727***
	(0.00411)	(0.00402)	(0.00417)	(0.00409)	(0.0241)	(0.0241)
Change	0.0139*	0.0126*	-0.000952	-0.00152	-0.0361***	-0.0367***
	(0.00731)	(0.00713)	(0.00765)	(0.00751)	(0.00693)	(0.00676)
Student*Change	-0.0123	-0.0109	-0.0176**	-0.0152**	0.000896	0.00323
	(0.00758)	(0.00740)	(0.00734)	(0.00717)	(0.00670)	(0.00650)
Days(member)	-0.000839***		-0.000659***		-0.000664***	
	(0.0000498)		(0.0000541)		(0.0000531)	
Student*Days(member)	-0.000530***		-0.000529***		-0.000537***	
	(0.0000530)		(0.0000574)		(0.0000564)	
Change*Days(member)	-0.0000906		0.0000406		0.0000558	
	(0.0000933)		(0.0000909)		(0.0000896)	
Student*Change*Days(member)	0.000292***		0.000383***		0.000375***	
	(0.0000978)		(0.0000954)		(0.0000941)	
Weeks(member)		-0.00537***		-0.00395***		-0.00398***
		(0.000350)		(0.000381)		(0.000373)
Student*Weeks(member)		-0.00391***		-0.00391***		-0.00397***
		(0.000372)		(0.000404)		(0.000396)
Change*Weeks(member)		-0.000472		0.000356		0.000466
		(0.000654)		(0.000638)		(0.000629)
Student*Change*Weeks(member)		0.00196***		0.00251***		0.00245***
		(0.000686)		(0.000670)		(0.000660)
Semester FE?	N	N	Y	Y	Y	Y
Day Controls	N	N	Y	Y	Y	Y
User FE?	N	N	N	N	Y	Y
N	3,712,768	3,712,768	3,712,768	3,712,768	3,712,768	3,712,768
adj. R^2	0.007	0.006	0.048	0.048	0.089	0.089

Table 2.3: This table presents the difference-in-difference regression of the probability to use the gym on how long a user has been a member. The day controls include a set of controls for the day of the week, an indicator for whether the day is a school holiday, and whether classes are in session. Some of student and change interaction coefficients were suppressed due to space constraints and are available upon request. Standard errors are reported in parentheses and are clustered at the user-by-semester level. *, **, and ***, indicate statistically different from zero at the 10%, 5%, and 1% levels of significance respectively.

Prediction 3: Aggregate Usage Probabilities

I next test how aggregate daily usage probabilities react to the elimination of the student membership fee. In table 2.4, I regress the percent of eligible users who access the gym on day t on time variables as well as student and policy change interactions. The $Period_n$ dummies are constructed identically as in table 2.2. Columns (5)-(8) also include day controls and semester fixed effects.

Recall that the probability a user accesses the gym on day t will be a product of the probability that a user has a membership times the probability that a user wants to go to the gym on day t. If users have standard preferences, the impact of eliminating the membership fee should be monotonic in time. Under non-standard preferences, however, a non-monotonic relationship may arise. While the probability of purchasing a membership increases when the fee is eliminated even under non-standard preferences, the conditional probability of wanting to go to the gym will decrease over time.

Table 2.4 shows that the change over time in aggregate usage probabilities after the membership buyout is non-monotonic. In columns (1) and (5), the only time variable is the linear *dayCount* term. In these regressions there is no statistically significant effect of eliminating fee, both overall and over time. In the remaining regressions I introduce additional measures of time that allow for a non-linear relationship between the change in aggregate usage probabilities and time. In columns (2) and (6), the coefficient on both the *dayCount* and *dayCount˙sq* interacted with the student and policy change dummies are statistically significant. These coefficients suggest a U-shaped relationship between the change in aggregate usage probabilities and time. A similar U-shape is produced, when I measure time by the 6 period quintiles that were also used in 2.2. This U-shaped relationship is only possible under non-standard preferences where users suffer from the sunk-cost fallacy.

Figure 2.3 plots the coefficients on the interaction terms between $Period_n$ with the student and policy change dummies. At the start of the semester 1.5% more students use the gym then before the elimination of the membership fee. In the middle period of the semester, the change in usage is statistically insignificant. At the very end of the semester, usage again peaks due to an increase in new membership sign-ups. Prior to the elimination of the membership fees, these new members likely would have never signed up.

When membership fees are eliminated under standard preferences, usage should increase throughout the semester. In this case, however, eliminating a barrier to the gym only has an effect on student usage at the beginning and end of the semester. In the middle of the semester, there is no evidence that aggregate usage of the gym changed. These results are all in line with a model where users suffer from a sunk-cost fallacy and factor their membership fee into preferences.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Usage %	Usage %	Usage %	Usage %	used	Usage %	Usage %	Usage %
Student	0.0731***	0.0732***	0.0577***	0.0709***	0.0732***	0.0751***	0.0607***	0.0718***
	(0.00140)	(0.00275)	(0.00146)	(0.00213)	(0.00149)	(0.00250)	(0.00194)	(0.00190)
Change	-0.000682	-0.00174	-0.00297	-0.00168	0.000117	-0.000884	-0.00192	-0.000867
	(0.00322)	(0.00184)	(0.00265)	(0.00265)	(0.00340)	(0.00224)	(0.00280)	(0.00296)
Student*Change	0.00678	0.0148*	0.00615	0.0129	0.00671	0.0144*	0.00573	0.0131*
	(0.00778)	(0.00726)	(0.00495)	(0.00722)	(0.00784)	(0.00666)	(0.00553)	(0.00691)
Student*Day	-0.000246***	-0.000251**			-0.000214***	-0.000345***		
	(0.0000196)	(0.0000938)			(0.0000262)	(0.0000751)		
Student*Change*Day	0.000000481	-0.000474**			0.00000201	-0.000454***		
	(0.0000597)	(0.000156)			(0.0000584)	(0.000120)		
Student*Day^2		4.37e-08				0.00000146		
		(0.000000927)				(0.000000819)		
Student*Change*Day^2		0.00000451**				0.00000434**		
		(0.00000177)				(0.00000142)		
Student*$Period_1$			0.0133***				0.0112***	
			(0.00150)				(0.00157)	
Student*Change*								
$Period_1$			0.00679**				0.00742***	
			(0.00286)				(0.00229)	
$Period_2$				-0.0107***				-0.0109***
				(0.00313)				(0.00257)
$Period_3$				-0.00959***				-0.00979***
				(0.00197)				(0.00228)
$Period_4$				-0.00677				-0.00825
				(0.00900)				(0.00611)
$Period_5$				-0.00946***				-0.00843***
				(0.00169)				(0.00184)
$Period_6$				0.000351				0.0000508
				(0.00861)				(0.00806)
Semester FE?	N	N	N	N	Y	Y	Y	Y
Day Controls	N	N	N	N	Y	Y	Y	Y
N	2216	2216	2216	2216	2216	2216	2216	2216
adj. R^2	0.887	0.889	0.876	0.893	0.917	0.919	0.913	0.921

Table 2.4: This table presents the difference-in-differences regression of the daily total usage probability (present of elegible users who access the gym each day). The day controls include a set of controls for the day of the week, an indicator for whether the day is a school holiday, and whether classes are in session. Some of these student and change interaction coefficients were suppressed due to space constraints and are available upon request. Standard errors are reported in parentheses and are clustered at the membership class-by-semester level. *, **, and ***, indicate statistically different from zero at the 10%, 5%, and 1% levels of significance respectively.

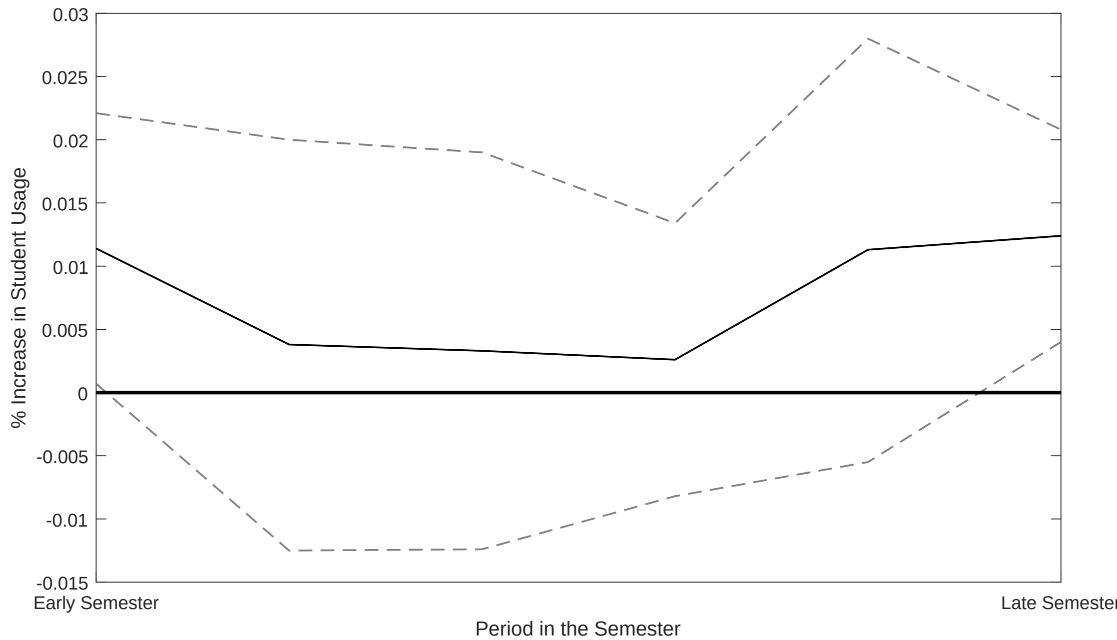

Figure 2.3: Plots the coefficent on the $Period_n$*change*student interaction term for the OLS regression for % usage. The regression also includes semester fixed effects and day controls. The dotted lines are the 95% confidence intervals.

2.5 Conclusion

Using a unique natural experiment at a large university health fitness center, I use a difference-in-differences approach to examine how the elimination of optional student gym fees impacted usage. Overall, I find that eliminating the usage fee did increase the number of users who accessed the gym at least once during the membership period. The impact on overall gym usage, however, was much more ambiguous. The results suggest that membership fees encouraged users to use the gym more conditional on having purchased a membership. Under standard preferences, membership fees are simply a sunk cost and should not influence the conditional usage probability. Under a model of usage with the sunk-cost fallacy, however, costly membership fees may actually encourage users to go to the gym more. Hence, the elimination of the membership fee can actually discourage users from going to the gym regularly as they are no longer concerned about getting their monies worth.

Since gym membership fees can encourage users to go to the gym more regularly, they function similarly to a commitment device. A self-aware gym user may be willing to choose a costly membership option in order to take advantage of the sunk-cost fallacy. For instance, while a monthly gym membership may be more costly than a pay-per visit option, the membership cost may serve as a commitment device; even though the membership fee is a sunk cost, the user becomes more likely to go to the gym in order to minimize their regret for spending money on a costly membership. Understanding the role the sunk-cost fallacy plays in consumer decision making can help rationalize how consumers choose contracts.

These results have significant implications for both behavioral economics research and public policy. Gym usage has been a classic setting to test behavioral economic theories. This paper shows the importance that the sunk-cost fallacy may can play in this environment. In fact, the seemingly irrational choices that consumers often make with gym membership purchases may be rationalized by incorporating the sunk-cost fallacy into a non-standard preference function. From a public policy standpoint, this paper stress the importance of understanding the interaction of behavioral biases when attempting to “nudge” consumers to make choices. While the policy change in this study was small (eliminating a $ 10 membership fee), the impact on behavior was substantial with approximately 7% more students accessing the gym each semester. The elimination of the fee, however, discouraged regular gym usage. Hence, when engaging in nudge policies it is vital to understand the complex interactions of behavioral biases in agents’ decision making processes.

Chapter 3

Looking Good: Charitable Giving as a Signaling Mechanism

3.1 Introduction

In 2015, US corporations gave over 18 billion dollars to charity with the median corporation giving nearly 58.2 million dollars to charity. For the median firm, this represented 1.31% of their pre-tax profits. Further, these direct charitable contributions represent only a small fraction of corporate social responsibility (CSR) spending. Even though CSR programs have become a more significant aspect of corporate culture and spending, conclusive evidence to explain the reason for these programs remain elusive. Bénabou and Triole (2010) suggest 3 possible explanations for CSR programs:

1. Value-Maximization: CSR programs increase the firm's long-term value (e.g. improved consumer perception, increased employee morale, better leverage with local leaders)

2. Agency Costs: Managers have private preferences to do "good" and so divert firm resources into CSR programs that achieve their private social objectives (e.g. CEOs like to get invited charitable balls or publicly participate in events honoring their firms' donations)

3. Pro-Social Motives: Investors have preferences to avoid causing excess social harm in their pursuit of profits providing firms incentives to conduct business in a socially responsible manner (e.g. even if it is the profit maximizing investment, investors don't want to invest in a firm that will dump oil into the ocean)

Evidence has been found to support all three of these hypothesis; however, the results thus far have been weak and inconclusive suggesting that no one explanation can account for all CSR spending (Margolis, Elfenbein & Walsh, 2009). I add to the discussion on the merits of corporate charitable giving by proposing an alternative hypothesis that has only received limited attention in the literature. We will argue that corporate charitable giving can and does serve as a signaling device.

Under my signaling hypothesis, charitable giving is never the firm's best available investment meaning that this giving is not a value maximizing investment. The fact, however, that corporate philanthropy is not the best investment means that only the strongest firms are able to give. Thus, we would expect that firms that give to charity should perform better in the future, not because corporate donations enhance firm value but rather because only the strongest firms are in a position to engage in such altruism.

The prediction that firms perform better after giving to charity, however, is not unique to my signaling hypothesis; a positive correlation between giving and future performance would also support the value-maximization or pro-social motives stories. To differentiate the signaling hypothesis from other possible explanations, I can look at managers who have different incentives to engage in signaling. When managers are focused on the short-term, signaling today is more important than for manager more concerned with long-term value creation. Hence, the marginal information carried in a dollar spent signaling will be lower for short-term managers. As the marginal information signaled varies with the managers focus, the relationship between corporate philanthropy and firm performance should vary between short-term and long-term focused managers. This prediction is unique to my signaling hypothesis. Under other explanations for corporate giving there should be no difference in the giving behavior of short-term and long-term focused managers.

To test my signing hypothesis, I will examine the relationship between corporate giving, managerial short-termism, and firm performance. In order to identify short-term CEOs, Iuse a combination of age and tenure in a manner similar to Anita, Pantzalis, and Park (2010). They found that, after adjusting for industry averages, older CEOs and CEOs with longer tenures exhibited behaviors consistent with a greater focus on short-term results. One explanation for this behavior is that older and longer tenured CEOs are more likely to retire in the near-future; as such these CEOs have fewer incentives to think about their companies' long-term health.

I find no evidence to suggest that corporate giving today predicts better performance next year nor is there any difference between short-term and long-term CEOs. When I consider the relationship at a 2-year lag, however, my results change dramatically. Increasing a firm's giving ratio (defined as charitable giving over total assets) by 1 standard deviation results in an increase in expected ROA of 76 bps at a 2-year's time horizon. I also find evidence that charitable giving is a much weaker predictor of firm performance in the group of firms with short-term focused CEOs. Amongst short-term CEOs increasing their giving ratio by 1 standard deviation results in an increase in expected ROA of only 24 bps. These results are strongly suggestive of my signaling hypothesis.

In addition to accounting returns, the signaling hypothesis requires that markets react to charitable giving. In contrast to my analysis of real returns, Ifind statistically and economically significant evidence that giving predicts excess returns at *both* a 1- and 2-year time horizon. Further, at the 2-year time horizon, the relationship between giving and excess market returns is much smaller for firms managed by a short-term CEO.

Although I suggest that intentional signaling may be driving corporate philanthropy, I cannot rule out an indirect signaling channel. Under this indirect signaling channel, stronger firms are able to "burn" more money via corporate giving as they expect the negative consequences of such actions to be smaller than it would be in weaker firms; the burning, however, may be taking place for other exogenous reasons, including for the manager's private benefit. Under either channel, investors appear to interpret corporate giving as a signal of firm strength. Thus, corporate giving would still serve as a useful tool for investors in analyzing different companies' future prospects.

The remainder of this chatper is organized as follows. In section 3.2, we review the relevant literature on corporate philanthropy and signaling. In section 3.3, I construct a simple model to identify predictions that I can use to test my signaling hypothesis and differentiate form other explanations for corporate giving. In section 3.4 and 3.5, I discuss my data and present my main results. Section 3.6 concludes the chapter.

3.2 Related Literature

Since Friedman (1970) famously argued that "the social responsibility of business is to increase its profits," researchers have tried to identify whether CSR programs actually increased profits or are, as Friedman would view it, a failure of the firm in its principal responsibility. Over time, the absolutest view of Friedman has given way, in many circles, to a more holistic understanding of business recognizing that profit maximization at the expense of *anything else* is impractical and unsustainable. With the growth of socially responsible investment funds, investors have demonstrated a clear willingness to accept moderately lower returns in exchange for socially just outcomes (Benson and Humphrey, 2008; Renneboog, Ter Horst, & Zhang, 2011). Similarly, higher risk-adjusted returns have been documented on "sin stocks" such as tobacco, alcohol, or casino companies (Hong & Kacperczyk, 2009) and firms with questionable environmental records (Chava, 2014). The basic debate regarding CSR programs, however, has tended to ask whether CSR programs, including charitable giving, is a value maximizing activity for the firm.

Current work on CSR programs tend to fall into three broad categories identified in Bénabou and Triole (2010): value-maximization, agency costs, and pro-social preferences. Under the value maximization hypothesis, CSR programs are the first-best investment for the firm and even in a world with no frictions, I would see the same level of corporate giving prevail. Much of the research in this area argues that corporate giving serves a purpose similar to advertising (Navarro, 1988). A more commonly cited channel for the value-maximization hypothesis is through the alignment of the firm's and its employees' values. When potential employees have a desire to engage in socially responsible work aligning the firm with its potential employees has the potential to help the firm attract workers (Akerlof and Kranton, 2000, 2005). In this case CSR programs help a company attract a better workforce (Greening and Turban, 2000; Maignan and Ferrell, 2001). CSR programs have also been shown to improve the loyalty of a firm's consumer base even in light of negative information (Sen and Bhattacharya, 2001; Bhattacharya and Sen, 2003).

When discussing employee and consumer retention and recruitment, CSR has occasionally been referred to as a signaling device (Fisman, Heal, and Nair, 2008). These papers, however, are conflating what I will call signaling with value maximization. In such cases, the firm is engaging in an activity more akin to advertising; the firm is signaling potential consumers that their product is worth purchasing in an attempt to increase the firm's profits. Under my definition of signaling, the firm is spending money that does not improve the firm's profits in order to signal to investors that the firm's future prospects are good.

In contrast to the value maximization hypothesis, the agency hypothesis suggests that the only reason for charitable giving is the misalignment of incentives between the firm's shareholders and its manager. A common test of this hypothesis has been to look at the 2003 Dividend Tax Cut as an exogenous increase in the cost of CSR programs arguing that this tax cut made the relative cost of wasting money on CSR programs higher. After the 2003 tax cut, the level of insider ownership predicted CSR spending cuts (Cheng, Hong, Shue, 2013) and corporate philanthropy (Masulis and Reza, 2016). Firms tend to engage in major CSR programs only when they have financial slack suggesting that CSR programs may not be the best investment a firm can make with its limited resources (Hong, Kubik, Scheinkman 2012). Di Giuli and Kostovetsky (2014) found that Democratic managers spent more on CSR than their Republican counterparts; however firms with Democratic managers did not exhibit better performance. Assuming that Democratic managers place a higher private value on CSR programs, then this finding would be suggestive of an agency hypothesis.

Bénabou and Triole (2010) have recently advanced a pro-social hypothesis where investors like when socially responsible outcomes occur. Even if donations do not maximize the firm's value in the purely financial sense, corporate philanthropy may still be utility maximizing for shareholders. Under their hypothesis firms are able to monitor the charities to which their firms donate. This monitoring functioning is valuable to investors who want to be sure that non-profits are acting in a manner that is consistent with the general welfare of society.

Shapira (2012) argues that even if charitable giving does not directly increase firm value, the signaling value of these contributions makes philanthropy a valuable investment opportunity. When insiders have positive but private information about the firm's future prospective, managers may have incentives to find costly mechanisms to signal this information. For example under the Pecking Order Theory, of financing firms prefer debt as the issuance of equity can be seen as a negative signal (e.g. Heinkel, 1982; Myers & Majluf, 1984). Similarly, high dividend levels can signal to the market that managers have private information that the firm's future is bright (Watts, 1973; Miller & Rock, 1985).

Spence (1973) shows that so long as a signal is costly, separating equilibrium can emerge whereby only strong agents are able to bear the cost necessary to signal their strength to the market. If charitable contributions are not the best available investment for a firm, then corporate philanthropy can be used as a signaling device. Firms that expect to do well in the future will give more money away. Since resources are more valuable to firms with weaker growth prospects, weak firms will not be able to contribute as much to charity making it too costly to imitate stronger firms.

Both the best investment and information asymmetry hypothesis predict that there is a positive relationship between corporate giving and future performance. Hence, a simple regression between the two variables would be unable to disentangle the two hypotheses. To explore these two explanations, I examine differences in the horizon of CEOs between firms. Since managers usually have shorter tenures then the lifetime of the firm, rational managerial myopia can cause managers to invest in less-valuable short-term investments (Jensen & Smith 2000). When managers have short horizons, the value of signaling becomes greater; the need to let the market know today that the firm will do well tomorrow is paramount when the CEO only cares about today's stock price. If, however, charitable giving is the best long-term investment, CEOs with long horizons should give at least as much as their short horizon counterparts.

Early research attempting to differentiate between investment and information explanations for CSR spending has provided preliminary evidence suggesting that signaling may provide a better explanation for observed patters of CSR spending. In at least some cases, firms that deviate with higher than optimal levels of CSR spending do experience better stock performance. Such deviations may signal to the market that the firm is expected to have high future cash flows (Lys, Naughton, & Wang, 2015). Cash-giving has also been associated with higher future cash flows; no relationship has been found between in-kind contributions and future performance. Such a result would hold if cash-giving conveys information that the donations of unsold inventory or other assets does not (Chang, Jo, & Li, 2016).

3.3 Philanthropy as a Signal

In this section I propose a stylized two-period model that demonstrates how charitable giving can serve as a signal of firm strength. I then use the model to construct predictions that can be used to differentiate signaling from other explanations of corporate philanthropy.

Model

I construct a simple two-period, one decision model to examine how firms can use charitable giving as a signaling device. The model is adapted form the classical dividend signaling model of Miller and Rock (1985). In contrast to their model, the firm uses charitable giving instead of dividends to signal their strength to the market.

I normalize each firm's available, investable assets to 1 at time 0. To make stark the role of charitable signaling, firms are not allowed to raise outside capital. At time 0, the manager must choose how much to invest in the firm's core activites versus give to charity. The base return on an investment of I in core activities is given by I^α, where $\alpha \in (0, 1)$ is a publicly known and constant parameter. While α is constant across firms, each company is also subject to a firm-specific multiplicative shock $\gamma \geq 1$. Although α is common knowledge at time 0, γ is the firm's time 0 private information.

Firms may also "burn" assets by contributing to charity some fraction of their assets C. Any philanthropic spending returns 0 at time 1. Although charitable giving adds no direct value to the firm, investors are still able to observe C. Given the return to investments in core activities and charitable giving, the value of firm i at time 1 is:

$$V^1(C, \gamma_i) = \gamma_i(1 - C)^\alpha \tag{3.1}$$

In a friction-less world, the assumption that charitable giving provides no time 1 benefit to the firm should rule out corporate philanthropy. Thus, either charitable giving is a valuable corporate investment or some friction must exist in the market explaining the empirical observation that firms do in fact give to charity. In particular, I will consider the role that asymmetric information can play in driving charitable giving.

At time 0, the firm-specific shock is observed by the firm's manager, but not the market. The market, however, is able to observe the firm's time 0 charitable giving. As markets are competitive, I assume that the value of the firm at time 0 equals the expected value of the firm:

$$V^0(C) = \mathbb{E}[\gamma(1 - C)^\alpha | C] \tag{3.2}$$

I will assume and verify later that there exists a one-to-one matching from the multiplicative shock to corporate giving, $C(\gamma)$. With this one-to-one mapping, the amount a firm gives to charity will be a sufficient statistic to determine the size of the multiplicative shock. After observing C, investors will be able to deduce the exact value of a given firm's γ. Since I assume there exists a one-to-one mapping from the firm-specific shock to giving, I can invoke the revelation principal and assume the firm truthfully reports their shock and then gives $C(\gamma)$ to charity. This simplifies my analysis by allowing me to look at the type $\hat{\gamma}$ reported at time 0. Under the revelation principal, I can rewrite (3.1):

$$V^1(\gamma, \hat{\gamma}) = \gamma(1 - C(\hat{\gamma}))^\alpha$$

Similarly I can rewrite (3.2) as:

$$V^0(\hat{\gamma}) = \hat{\gamma}(1 - C(\hat{\gamma}))^\alpha$$

In line with Miller and Rock (1985), I assume that the objective of the firm's manager is to maximize some linear combination of the time-0 price and time-1 firm value:

$$W_i(\gamma_i, \hat{\gamma}) = k_i V^0(\hat{\gamma}) + (1 - k_i)V^1(\gamma, \hat{\gamma})$$

, where $k_i \in (0, 1)$ represents a measure of how responsive the manager is to short-term versus long-term objectives. I further assume that k_i is public knowledge, but does vary across firms.

One way to think about k is that it represents how much of the manager's incentives are aligned to short-term stock price based goals versus long-term value maximization. Higher values of k imply that the manager is more sensitive to fluctuations in the firm's current stock price in relation to the firm's long-term value.

In order to ensure the manager truthfully reports the firm's type, the function $C(\gamma)$ must satisfy the incentive compatibility constraint:

$$W_i(\gamma, \gamma) \geq W_i(\gamma, \hat{\gamma}) \ \forall \gamma, \hat{\gamma} \tag{IC}$$

In order for my assumption that there exists a one-to-one matching from the shock to giving to hold it must be the case that the function $C(\gamma)$ is strictly monotonic. (IC) provides me with a first-order condition that charitable giving must satisfy:

$$\frac{\partial C}{\partial \gamma} = \frac{k_i}{\alpha\gamma}(1 - C(\gamma)) \tag{3.3}$$

The first order condition given by (3.3) is a basic ODE which I can solve explicitly for $C(\gamma)$. I will impose the boundary condition where the weakest firms give nothing to charity. Since charitable donations only provide a benefit through the signaling channel, there is no reason in a seperating equilibrium for the weakest firm to give anything to charity. Hence, I must have that $C(1) = 0$[1] as my boundary condition. Combining my boundary condition with (3.3), I have:

$$C(\gamma, k) = 1 - \gamma^{-\frac{k}{\alpha}} \tag{3.4}$$

Figure 3.1 presents the charitable giving function for various values of k. Notice that different values of k (i.e. short-term focus) produce differently sloped giving functions. I will exploit differences in the slope of the giving functions in order to test my signaling hypothesis. As a starting point for my analysis I will consider the relationship between firm giving and future returns holding k fixed. Proposition 1 confirms are maintained hypothesis that there is a monotonic relationship between firm giving and the firm-specific shock, γ.

Proposition 1. *Stronger firms give more to charity,* $\frac{\partial C}{\partial \gamma} > 0$

Proof. From (3.3), the first derivative of charitable giving is given by,

$$\frac{\partial C}{\partial \gamma} = \frac{k_i}{\alpha\gamma}(1 - C(\gamma))$$

Since the firm is unable to raise any outside funds $C < 1$. Therefore, $\frac{\partial C}{\partial \gamma} > 0$ implying that charitable giving is a strictly increasing in firm strength. □

[1] Recall that $\gamma \geq 1$

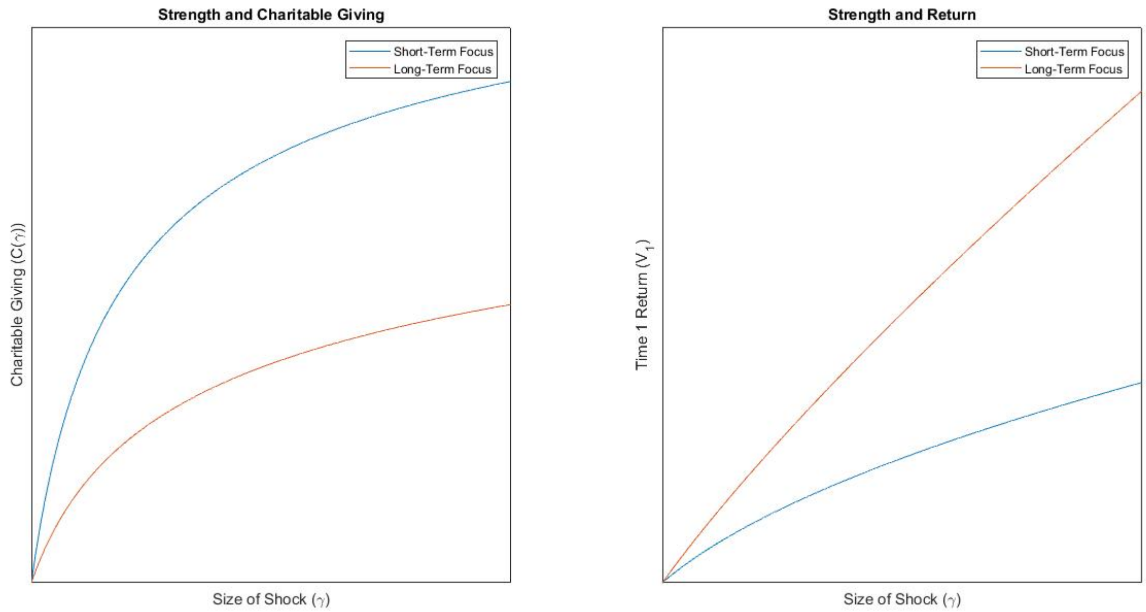

Figure 3.1: **Charitable Giving and Firm Strength:**Panel 1 presents the relationship between the firm-specific shock and charitable giving for short- and long-term focused firms. Panel 2 presents the relationship between future value and the firm-specific shock, accounting for differences in giving behavior.($\alpha = 0.9,\ k_{Short} = 0.5,\ k_{Long} = 0.2$)

Proposition 1 also allows me to verify my assumption that there is a one-to-one correspondence between firm strength and charitable giving. Holding k_i fixed, for every level of charitable giving C there will be exactly one γ that induces that level of giving. Hence, after observing C, investors can infer γ.

Since $C(\gamma)$ is a strictly increasing function, I would expect stronger firms to give more to charity. As an econometrician, however, I cannot observe γ directly; thus, there is no way to verify whether or not stronger firms actually do give more to charity. In order to test my model and whether firms use charitable giving as a signal, I will have to rely on what I can observe, the firm's performance.

Proposition 2. *Stronger firms have higher values at time 1,* $\frac{\partial V^1(\gamma)}{\partial \gamma} > 0$

Proof. See Appendix. □

As I would expect, stronger firms generate more value at time 1 even though these stronger firms engage in more corporate giving which is not, at least in my basic model, a value-add activity. If this had not been the case, the equilibrium I generated would not hold as CEOs of strong companies would have an incentive to appear marginally weaker as this would result in a greater time 1 value. I can use this to identify the correlation between firm giving and future firm value,

Proposition 3. *There is a positive relationship between firm giving as measured by $C(\gamma)$ and firm value at time 1: $\frac{dV^1}{dC} > 0$.*

Proof. By the chain rule, $\frac{dV^1}{dC} = \frac{\frac{\partial V^1}{\partial \gamma}}{\frac{\partial C}{\partial \gamma}} > 0$. The inequality follow because the derivatives of both V^1 and C with respect to γ are strictly positive. $\square$

Under my proposed model, positive firm-specific shocks drive both higher charitable giving and better future performance. Hence, I would expect firms that give more to charity to experience better future performance.

Prediction 1. *Firms that give more to charity experience better future performance.*

In addition under a signaling hypothesis, the markets should also react to charitable giving. Higher giving implies that the firm will do better in the future. Since the value of the firm at time 0 equals the expected value of the firm at time 1, the positive correlation between future firm value and giving should also imply a positive correlation between current firm value and giving.

Prediction 2. *Firms that give more to charity experience higher short-run stock returns.*

Short-Termism and Corporate Giving

If CEOs use charitable giving to signal their firms strength to the market, I would expect future firm value to be positively correlated with charitable giving; the stronger the firm the more money the CEO has to "burn." This prediction, however, is not unique to a signaling explanation. If charitable giving represents a positive NPV investment, even in a frictionless world, high levels of charitable giving should also correspond to a higher future firm value. In order to differentiate these two possible explanations for giving, I can use differences in short-term focus levels across firms. If charitable giving were the first-best investment, I would expect no difference between the giving of short-term focused and long-term focused firms. In contrast, however, signaling is more important to firms with a short-term focus. Thus, I should see that firms with a short-term focus give more to charity, holding fixed the hidden, firm-specific shock, γ.

Lemma 1. *Firms with a short-term focus give more to charity: $\frac{\partial C}{\partial k} > 0 \; \forall \gamma > 1$*

Proof. Using (3.4) I can take the partial of C with respect to k.

$$\frac{\partial C}{\partial k} = \frac{1}{\alpha} \ln(\gamma) \gamma^{-\frac{k}{\alpha}} \geq 0$$

The inequality follows from my assumption that $\gamma \geq 1$. Also note that $\frac{\partial C}{\partial k}$ is strictly positive whenever $\gamma > 1$. □

Holding firm strength constant, companies with a short-term focus will give more to charity. Although philanthropy isn't providing a direct benefit to the firm, the signaling value of giving incentivizes firms to give. The incentives to signal are greatest in firms that prioritize short-term stock returns over long-term value creation.

Signaling, however, comes at a cost. When firms gives to charity, they cannot invest those funds in their core activities. The loss of investable dollars limits the firms future value. Firms that are more focused on the short-term "burn" more via philanthropy, all else being equal. Thus, firms with a long-term focus should realize better future performance.

Proposition 4. *Holding C fixed, the more long-term focused a firm is, the greater its value at time 1: $\frac{\partial V_1}{\partial k} < 0 \; \forall \gamma > 1$.*

Proof.

$$\frac{\partial V_1}{\partial k} = -\gamma \left(1 - C\right)^{\alpha - 1} \frac{\partial C}{\partial k} < 0$$

, where the inequality follows from lemma 1. □

Signaling via charitable giving is costly as fewer assets can be allocated to productive uses. If firms donate too much, then the benefits from signaling are overwhelmed by the losses in productivity. When a firm has a high focus on the short-run, the marginal benefit of signaling is high. Thus, short-term focused firms, *cetris peribis*, should donate more to charity.

Proposition 5. *Suppose two firms donate the same amount to charity, the firm with a greater focus on the long-run is a stronger firm: Let $C(\gamma_i, k_i) = C(\gamma_j, k_j)$ and $k_i > k_j$ then $\gamma_i < \gamma_j$.*

Proof. Using (3.4)

$$C(\gamma_i, k_i) = C(\gamma_j, k_j) \iff \gamma_i^{-\frac{k_i}{\alpha}} = \gamma_j^{-\frac{k_j}{\alpha}} \iff \gamma_i < \gamma_j$$

The final statement follows from the assumption that $k_i > k_j$. □

When two firms give the same amount to charity, the firm with a longer-term focus should be stronger. In order to induce the same level of philanthropy, the long-term focused firm must have better news to signal. Hence, the firm with a long-term focus should perform better in the future.

Prediction 3. *Controlling for the level of charitable giving, firms with a long-term focus should perform better in the future.*

This prediction is a marked contrast from what I would expect in a world where charitable giving was the firm's best available investment in terms of *generating* profits. In such an environment, firms which differ based on their degree of short-term focus should not exhibit differing degrees of charitable giving. With signaling, however, firms with a short-term focus give more.

Proposition 6. $\frac{\partial V_1}{\partial C \partial k} < 0$

Proof. See Appendix. □

Since signaling has a a larger marginal benefit to firms with a short-term focus, these firms will exhibit less spread in their philanthropy. When a CEO cares about tomorrow's stock price, the signaling benefit from an extra dollar of charitable giving is greater. In these firms, small difference in charitable giving will not predict a large difference in future performance and by extension stock returns. In contrast in firms where signaling is unimportant (i.e. long-term focused firms), small difference in charitable giving should predict large differences in future performance.

Prediction 4. *The relationship between future performance in charitable giving is larger in firms with a long-term focus than those with a short-term focus.*

Again, this is a prediction that a best available investment explanation of charitable giving would not predict. If managers do not use charitable giving as a signaling mechanism there is no reason to expect that long-term focused firms will see a greater relationship between philanthropy and future performance.

In the following sections, I test whether corporate philanthropy is being used as a signaling device. To test my hypothesis, I rely on the key predictions of my model. First, I examine the extent to which firm's performance, both in real and market terms, is correlated with charitable giving. Predictions 1 and 2 suggest there should be a positive correlation. I then examine if there is a difference in the correlation between short-term focused and long-term focused firms. Predictions 3 and 4 both predict that, under a signaling hypothesis, the relationship between giving and performance should be weaker in short-horizoned firms.

3.4 Sample

Data

I focus on U.S. public companies in the Thomson Reuters *Asset4* database over the sample period from 2002-2013. The *Asset4* database provides data on over 1,000 key environment, social, and governance (ESG) variables from auditable sources. Much of this data is hand-collected by the database provider so coverage on individual variables can vary considerably. My key variable of interest will be the firm's total donations in a given year. Only corporate

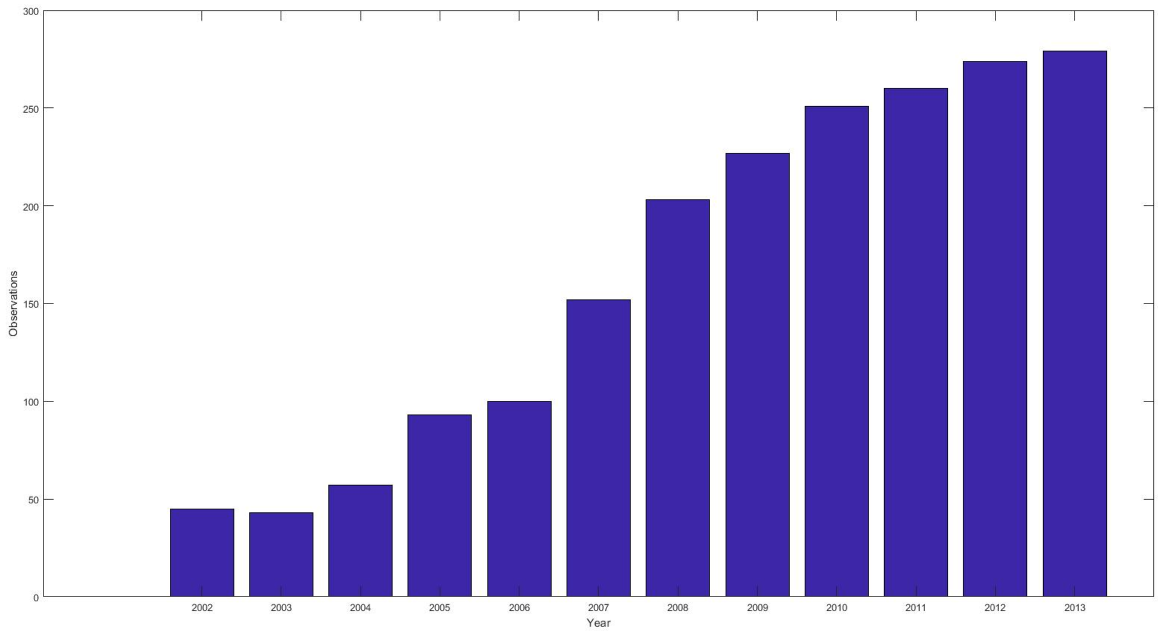

Figure 3.2: **Observations Per Year:** Total Number of Firms with Donations Data in the *Asset4* database for a given year

giving, both direct and indirect (i.e. through a company controlled and financed foundation) is included in this number; employee donated or raised funds are excluded from this total. Thus, the corporate giving number only captures philanthropy that is approved by the firm's management.

In total, there were 1,670 firm-year observations over the sample period representing 351 unique firms. As the corporate giving information was hand-collected by the database provider, most of these firms tend to be larger, often S&P 500, firms. Further, there is a clear pattern of increased coverage (see figure 3.2) over time partially as a result of firms increasingly publicizing their charitable contributions.

Most of my regressions will use scaled charitable giving, defined as the ratio of corporate giving to total assets. As the charitable giving data exhibits a heavy right-tail, I winsorize the giving ratio at the 1% and 99% level by year to ensure that such outliers do not contaminate my results.

In addition to information on coprporate philanthropy from the *Asset4* database, I will use data from Compustat to identify and measure relevant firm characteristics as well as firm performance. ExecuComp will be used to measure CEO characteristics and incentives that will help me identify whether a firm has a short-term or a long-term focus.

I will use CRSP to measure stock returns. As my model predicts that corporate giving serves as a signal of firm strength, I predict that the market will react to the firm's annual giving. I will primarily use excess returns that have been adjusted using the classical Fama-French 3 factors model.

Short-Termism

As I predict that firms where the CEO has a short-decision horizon to behave differently, I will use a measure of short-termism suggested by Antia, Pantzalis, and Park (2010) that measures CEOs' relative age and tenure at their firm. Their intution is that older CEOs and CEOs who have been in their role for a long-time are likely to be closer to retirement. By accounting for the average age and tenure in their industry, I can account for industry specific differences in how long it takes for a CEO to reach his/her position and industry norms regarding CEO tenure. Let $H_{i,j,t}$ be the decision horizion of the CEO of firm i in industry j in year t,

$$H_{i,j,t} = \left(Tenure_{i,j,t} - \overline{Tenure_{j,t}}\right) + \left(Age_{i,j,t} - \overline{Age_{j,t}}\right).$$

CEOs with high H-scores are likely to exhibit short-term biases as they are nearer retirement. As a CEO approaches retirement, the long-term performance of his/her firm becomes less relevant. The CEO is less likely to be held personally responsible for future performance, good or bad, incentivizing the CEO to put less emphasis on long-term projects. Also, these CEOs may have greater financial incentives to focus on the firm's short-term stock price in order to improve the value of their soon-to-expire options.

Data to calculate firms' H-score are from Execucomp. As the coverage of the *Asset4* database is centered on larger firms, using Execucomp does not result in a significant loss of firm-year observations. Industry level averages are calculated using the Fama-French 12 industry classification. All firm-year pairs in a given industry-year are dropped if there exists 5 or fewer observation for that industry-year.

For the purpose of my analysis, I will say that CEOs with an H-socre in the upper tercile in a given year are "short-term." Looking at CEOs with high H-scores, only those in the highest tercile are likely to exit the firm in the near-future. No difference exists in the exit behavior of CEOs in either the lowest or middle tercile. Although the H-score measure is likely to be noisy, figure 3.3 demonstrates that it is a predictor of whether or not a CEO is likely to exit in the short-run. When a CEO leaves the firm, his or her investment in the firm's long-term performance is almost surely lower. Being in the highest H-score tercile appears to be a reasonable proxy for whether a manager has a short-term focus.

Descriptive Statistics

In table 3.1, I show firm-year summary statistics for my key variables of interest. The average amount of corporate contributions is $ 86.5 million per year The average firms in my

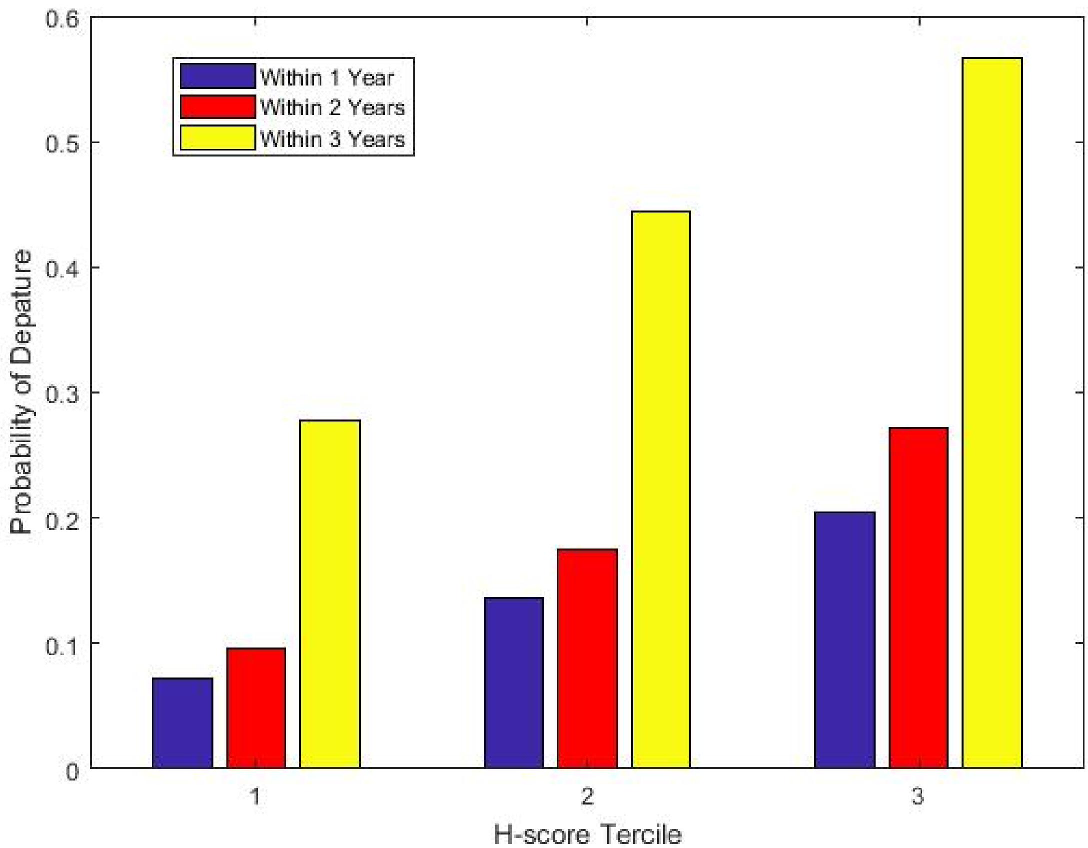

Figure 3.3: **CEO exit as predicted by H-score:** CEOs in the highest tercile (i.e. the most short-term focused) are much more likely to exit in the following years. There, however, is no difference between CEOs in the lowest and middle tercile.

sample do exhibit considerably more giving than Masulis and Reza's (2016) sample. This, however, is not surprising as I only consider firms where there is data available for charitable giving, whereas they set charitable giving to zero for any firm-year for which giving data is not available. Summary statistics for other variables are similar in magnitude and range to other studies involving corporate giving and CSR data.

Table 3.2 presents the univariate comparisons between long-term and short-term focused CEOs. As relatively older and longer tenured CEOs were, by construction, placed in the short-term group, CEOs in the short-term group are both older (61.5 years vs. 54.1 years) and have had a longer tenure (10.25 years vs. 3.74 years). Based on other observables, however, there appears to be only minor differences in the firm characteristics between

Table 3.1: Descriptive Statistics

Variable	Obs.	Mean	SD	10th	25th	Median	75th	90th
Corporate Giving ($M)	1,670	70.876	271.303	1.600	4.331	12.082	36.304	133.213
Corporate Giving Ratio (%)	1,670	0.189	0.368	0.009	0.026	0.062	0.163	0.443
log(Assets)	1,670	9.962	8.251	8.952	9.891	10.726	11.691	
Leverage	1,670	0.647	0.198	0.402	0.514	0.642	0.787	0.906
ROA	1,670	0.066	0.071	0.006	0.023	0.058	0.104	0.150
R&D	1,670	0.023	0.046	0	0	0	0.026	0.082
Adv.	1,670	0.013	0.031	0	0	0	0.012	0.042
Dividend Payer	1,670	0.851	0.356	0	1	1	1	1
Excess Stock Return	1,082	-0.115	0.609	-1.016	-0.384	-0.056	0.278	0.561
Age	1,670	56.67	5.46	50	53	57	60	63
Tenure	1,670	5.96	5.88	1	2	5	8	11

Table 3.2: Univariate Comparisons of Short-Term vs. Long-Term Firms

	Long-Term Focus		Short-Term Focus		Difference	p-Value
Variable	Mean	SD	Mean	SD		
Corporate Giving ($M)	61.895	239.466	88.254	323.679	-26.359*	0.087
Corporate Giving Ratio (%)	0.183	0.348	0.200	0.404	-0.018	0.377
log(Assets)	9.987	1.477	9.915	1.341	0.071	0.320
Leverage	0.647	0.194	0.646	0.204	0.001	0.904
ROA	0.066	0.069	0.067	0.074	-0.001	0.850
R&D	0.022	0.047	0.026	0.045	-0.004	0.130
Adv.	0.014	0.034	0.011	0.025	0.003**	0.024
Dividend Payer	0.844	0.363	0.865	0.342	-0.021	0.247
Excess Stock Return	-0.101	0.558	-0.111	0.568	0.010	0.739
Age	54.19	4.25	61.49	4.18	-7.30***	0.000
Tenure	3.74	2.76	10.25	7.67	-6.51***	0.000
Number of Observations	1,101		569			
% of Observations	65.9%		34.1%			

This table compares firms controlled by firms which I defined as having long-term focused CEOs (those with an H-score in the middle or lower tercile) and those with a short-term focused CEO (those with an H-score in the highest tercile). ***,**, and * denote statistical significance based on a two-sided t-test at the 1%, 5%, and 10% level respectively.

long-term and short-term focused CEOs. In particular, there is no statistically significant difference between *ROA*, which will be my primary measure of firm performance, suggesting that firms with a short-term CEO do not perform systemically worse than their longer-term counterparts.

Although short-term firms appear to give more than long-term firms in absolute dollars (88.3 M$ vs. 61.9 M$), once I control for firm size by scaling by total assets (0.20% vs.

0.18%), there is no statistical difference between the two groups of firms. Although not conclusive, the lack of significant differences in the univariate giving behavior, once I control for firm size, of the two groups suggests that agency problems arising from a short-term focused CEO may not be the major driver of corporate philanthropy. I conduct a more complete tests to rule out the possibility that short-term focused CEOs give more solely because of their short-term focus in section 3.5.

3.5 Results

Charitable Giving and Firm Performance

I will now turn my attention to examining the relationship of corporate giving with future firm performance. In particular, my model predicts that firms with high levels of giving will perform better than their less charitable counterparts. Further, I predict that this relationship will be weaker for the group of firms where the CEO is focused primarily on the short-term. My full specification is given by:

$$Y_{i,t+1} = \beta_0 + \beta_1(Giving_t) + \beta_2(Giving_t) * (Short - Termism_t) + \\ + \beta_3(Short - Termism_t) + \gamma X_t + \nu_t + \nu_i + \epsilon_{i,t}$$

, where X_t is a vector of control variables that are known to impact future firm performance, including ROA_t, $\log(Assets_t)$, and $Tobin's\ Q_t$.

Based on my predictions, firms with high giving should perform better in future periods. Table 3.3 presents the baseline regression of charitable giving on ROA at time $t+1$. Surprisingly, for no combination of fixed effects was the coefficient on either $Giving$ or $(Giving) * (Short - Termism)$ significant. When adding firm and year fixed effects, the coefficients on $Giving$ and the $(Giving) * (Short - Termism)$ variables were actually the opposite of my model's predictions. In almost all of the specifications, however, most of the control variables were statistically significant suggesting that the included variables do convey information about future firm performance.

As my control variables will be available to investors at the same time as the information on charitable giving, table 3.3 seems to suggest that charitable giving conveys little information to investors beyond other more readily accessible performance predictors. If charitable giving were to serve as a signal, it is clear that giving is not informative to short-lived information (i.e. next year's performance). Should the manager's private information, however, be long-lived, then it is possible that charitable giving could in fact provide investors with useful information.

Table 3.3: Short-Run Firm Performance and Charitable Giving

	Baseline Regression			Short-Termism		
	No FE (1)	Year & Industry FE (2)	Year & Firm FE (3)	No FE (4)	Year & Industry FE (5)	Year & Firm FE (6)
Giving	0.582	0.253	-0.285	0.670	0.363	-0.384
	(0.496)	(0.588)	(1.168)	(0.736)	(0.823)	(1.450)
(Giving)*(Short-Termism)				-0.236	-0.284	0.313
				(1.090)	(1.031)	(1.333)
Short-Termism				0.001	0.001	0.003
				(0.003)	(0.003)	(0.005)
ROA_t	0.215***	0.198**	-0.099	0.215***	0.198**	-0.099
	(0.081)	(0.080)	(0.077)	(0.081)	(0.080)	(0.077)
log(Size)	-0.003***	0.000	-0.068***	-0.002***	0.000	-0.068***
	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)	(0.010)
Tobin's Q	0.039***	0.041***	0.034***	0.039***	0.041***	0.034***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Dividend Payer	0.018***	0.017***	-0.000	0.018***	0.017***	-0.000
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)
R&D	-0.017	-0.059	-0.067	-0.014	-0.060	-0.59
	(0.075)	(0.089)	(0.100)	(0.075)	(0.089)	(0.101)
Adv.	-0.041	-0.089	0.142	-0.040	-0.089	0.136
	(0.062)	(0.062)	(0.207)	(0.063)	(0.063)	(0.213)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Clustered At	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,669	1,669	1,669	1,669	1,669	1,669
Adjusted R^2	0.51	0.54	0.65	0.51	0.54	0.65

Results from an OLS estimation with the dependent variable being the firm's performance at a 1-year time horizon. The independent variables are various firm-level variables that have been shown to predict CSR spending and firm performance. ***, ***, and * indicate statistical significance at the 1%,5%, and 10% level, respectively using two-tailed tests.

In Table 3.4, I show the relationship between giving and the firm's performance at a two-year time horizon. Using a longer time horizion significantly changes my results and confirms the predictions of my original model. Columns (1)-(3) show the relationship between giving and ROA_{t+2} without including the impact of short-termism. The relationship, however, is only significant when I do not include industry or firm fixed effects. In columns (4)-(6), I add the interaction of giving with short-termism. In all of my specifications, I find that the coefficients of interest are fairly stable even when I add year and firm or industry fixed effects. Further, in all of the specifications including the interaction of giving with short-termism, both the giving and interaction terms were significant. This strongly contrasts with the results at the one-year time horizon.

Here, I find that giving is generally associated with higher firm performance. An increase of 1 standard deviation in a firm's giving ratio is associated with a 76bp increase in its ROA at a two-year time horizion. In the case of short-term firms, however, the relationship is much lower as indicated by the negative coefficient on the term interacting giving with short-termism. For firm's managed by a CEO with a short-term focus an increase of 1 standard deviation in its giving ratio is only associated with a 24bp increase in its two-year ROA.

Both these findings are consistent with the predictions of my signaling model. As charitable giving involves burning firm resources, only the strongest firms will be in a position to engage in large philanthropy programs. For firms with a short-term CEO, however, the marginal value of signaling is larger. In these firms, each dollar of charity is conveying marginally less good news. Hence, I would expect the elasticity of charitable giving to future performance to be lower. This is the exact relationship that I find.

Table 3.4: Long-Run Firm Performance and Charitable Giving

	Baseline Regression			Short-Termism		
	No FE	Year & Industry FE	Year & Firm FE	No FE	Year & Industry FE	Year & Firm FE
	(1)	(2)	(3)	(4)	(5)	(6)
Giving	1.144**	0.996	1.383	1.716***	1.654**	2.061*
	(0.545)	(0.648)	(1.135)	(0.653)	(0.737)	(1.204)
(Giving)*(Short-Termism)				-1.516*	-1.711**	-1.405**
				(0.792)	(0.747)	(0.709)
Short-Termism				0.004	0.004	0.005
				(0.003)	(0.003)	(0.004)
ROA_t	0.216***	0.207***	-0.051	0.215***	0.206***	-0.053
	(0.039)	(0.035)	(0.052)	(0.039)	(0.036)	(0.051)
log(Size)	-0.002**	-0.000	-0.048***	-0.002**	-0.000	-0.047***
	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.011)
Tobin's Q	0.031***	0.033***	0.014***	0.031***	0.034***	0.014***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Dividend Payer	0.021***	0.022***	0.003	0.021***	0.022***	0.004
	(0.006)	(0.064)	(0.006)	(0.006)	(0.006)	(0.007)
R&D	0.001	-0.063	0.019	-0.002	-0.068	0.012
	(0.074)	(0.087)	(0.097)	(0.074)	(0.086)	(0.093)
Adv.	0.124**	0.029	0.353*	0.122**	0.027	0.299
	(0.052)	(0.045)	(0.181)	(0.053)	(0.046)	(0.182)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Clustered At	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,670	1,670	1,670	1,670	1,670	1,670
Adjusted R^2	0.43	0.48	0.58	0.43	0.48	0.58

Results from an OLS estimation with the dependent variable being the firm's performance at a 2-year time horizon. The independent variables are various firm-level variables that have been shown to predict CSR spending and firm performance. ***, ***, and * indicate statistical significance at the 1%,5%, and 10% level, respectively using two-tailed tests.

Market Reaction

Under my proposed signaling hypothesis, charitable giving serves as a signal to investors that the firm's future prospects are strong. My previous results demonstrated that patterns of charitable giving seems to be consistent with a signaling hypothesis in terms of future firm performance. For signaling to hold in equilibrium, it must be the case that short-term returns adjust for the signal. I will now turn my attention to the relationship between corporate philanthropy and the firm's stock performance.

In Table 3.5 I show the OLS regression of excess stock returns on my corporate giving measure and the short-term interaction. In the first 3 columns, I consider the reaction of the firm's stock price at a 1-year horizon to charitable giving. Overall, firms that give to charity generally have higher excess returns than firms that exhibit lower giving. Although not significant at conventional significance levels I also observe similar and negative coefficients across specifications on the interaction term between giving and short-termism. These results contrast strongly with the firm's one-year accounting return, where I found that charitable giving today is not predictive of next year's accounting returns. It appears that the market is reacting to charitable giving much quicker than the firm's accounting performance is changing.

When I look at the two-time horizon the prediction of my model holds. The coefficient on my giving term is positive, whereas the coefficient on the (Giving)*(Short-Termsim) term is negative. These results are suggestive of my signaling hypothesis where giving signals firm strength; however, for short-term focused firms the marginal information in each dollar of giving is lower.

Also of note, is the strength of the relationship between giving and the 2-year excess market return. Most of my control variables become weaker predictors of excess market return when I switch from a 1 to a 2 year time horizon; the giving term and the (Giving)*(Shor-Termism) interaction term both become much stronger predictors of the excess market return.

Overall, my finding are largely consistent with my signaling hypothesis. Both accounting returns and market returns are positively correlated with corporate philanthropy. This relationship, however, is much weaker for firms where the manager appears to have a short-term focus. In these firms, managers have a greater incentive to signal to the market that they are strong. Hence, a marginal increase in how much these firms give conveys less information to the market. Overall, I find that the relationship between giving and performance in these short-term focused firms does in fact appear to be smaller.

Alternative Explanation

my initial evidence suggests that charitable giving serves as a signal of future firm strength. To provide further evidence that signaling provides a plausible explanation for this behavior, I consider an alternative hypothesis combining elements of both the investment hypothesis

Table 3.5: Stock Performance and Corporate Giving

	$ExcessStockReturn_{t+1}$			$ExcessStockReturn_{t+2}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Giving	7.840***	5.504***	6.153**	7.679	8.691***	9.330***
	(2.777)	(2.516)	(2.600)	(5.359)	(2.619)	(2.776)
(Giving)*(Short-Termism)	-3.606	-4.141	-4.828	-7.996	-10.932***	-11.253***
	(3.671)	(3.137)	(3.371)	(6.854)	(4.025)	(3.769)
Short-Termism	-0.001	0.001	0.002	-0.002	0.004	0.005
	(0.029)	(0.016)	(0.017)	(0.028)	(0.016)	(0.016)
$ExcessStockReturn_t$			-0.145***			-0.146***
			(0.031)			(0.040)
ROA_t	-1.177**	-0.650**	-0.595**	-0.267	-0.071	-0.016
	(0.532)	(0.299)	(0.284)	(0.315)	(0.188)	(0.198)
log($Size$)	-0.050***	-0.027***	-0.029***	-0.014*	-0.022***	-0.024***
	(0.008)	(0.006)	(0.007)	(0.07)	(0.005)	(0.006)
Tobin's Q	-0.043	-0.005	-0.001	-0.014	-0.031**	-0.026*
	(0.033)	(0.018)	(0.017)	(0.024)	(0.014)	(0.015)
Dividend Payer	0.064	0.019	0.009	-0.037	-0.033	-0.045
	(0.040)	(0.028)	(0.030)	(0.041)	(0.033)	(0.032)
R&D	0.340	-0.262	-0.343	-0.607	-0.380	-0.468
	(0.413)	(0.382)	(0.383)	(0.310)	(0.293)	(0.303)
Adv.	0.824**	0.366	0.293	0.212*	0.107	0.038
	(0.378)	(0.226)	(0.235)	(0.319)	(0.203)	(0.220)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Clustered At	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,043	1,043	1,043	1,082	1,082	1,082
Adjusted R^2	0.03	0.78	0.79	0.00	0.73	0.74

Results from an OLS estimation with the dependent variable being the firm's excess stock return at the 1-year or 2-years time horizons. Stock returns are adjusted using the Fama-French 3-factor model. The independent variables are various firm-level variables that have been shown to predict CSR spending and firm performance. ***, ***, and * indicate statistical significance at the 1%,5%, and 10% level, respectively using two-tailed tests.

(charitable giving is a positive NPV investment) and the agency problem (CEOs recieve a private benefit from giving).

Under this alternative hypothesis, suppose that their is an optimal level of giving that maximizes firms NPVs. In addition to the benefits that accrue to the firm, CEOs also receive a private benefit from their firms' donations. As the firm benefit occurs in the long-term, but the private benefit occurs immediately under this alternative explanation short-term CEOs should give more.

My univariate comparison showed that the giving ratio of short-term versus long-term firms was not statistically different; however, I did find that firms with a short-term CEO did tend to give more in absolute dollars. In table 3.6 I perform a regression of various measures of short-termism (including my short-term indicator) on charitable giving, both as a ratio and in absolute dollars. Once I control for various factors of current firm performance, I find no evidence that firms with a short-term CEO give more. In fact, the direction and relative magnitude of the coefficients on my measures of short-termism vary considerably from one specification to the next.

Table 3.7 implements a nearest-neighbor matching between firms with short-term and long-term CEOs to compare their giving behavior. Even using nearest-neighbor matching, I find no evidence to suggest that firms with a short-term CEO are giving more than comparable firms with a CEO who has a longer decision horizon.

If CEOs with a shorter decision horizon donate more to charity in order to capture some private benefit, I would expect firms with short-term CEOs to give more than similar firms with a long-term CEO. My results, however, strongly suggest that this is not the case. It seems doubtful that short-term CEOs are giving more to capture private benefits that hurts their firm's future performance. Hence, differences in agency costs between short-term and long-term CEOs do not appear to account for the differences in the relationship between firm performance and giving seen in my earlier results.

3.6 Conclusion

Traditionally, three hypotheses have been advanced to explain corporate philanthropy: the investment hypothesis, agency costs, or pro-social investors. I propose that costly signaling could plausibly explain giving behavior. Under my signaling hypothesis CEOs possess private information about their firm's prospects. By engaging in corporate philanthropy CEOs are able to send a costly signal to investors of the firm's future strength.

My signaling model makes two key predictions that enable me to differentiate signaling from alternative hypotheses. First, corporate donations should be positively associated with future firm performance, both in terms of accounting performance and stock performance. This differs from the agency explanation, advanced most recently by Masulis & Reza (2016),

Table 3.6: The Effect of Short-Termism on Charitable Giving

Panel A: Giving Ratio (bps)						
	Year & Industry FEs			Year & Firm FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
Short-Termism	-0.003			-0.019		
	(0.025)			(0.014)		
H-Score		-0.002			0.000	
		(0.001)			(0.001)	
Age			0.001			-0.001
			(0.002)			(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Clustered At	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,670	1,670	1,670	1,670	1,670	1,670
Adjusted R^2	0.31	0.31	0.31	0.85	0.85	0.85

Panel B: Corporate Giving ($M)						
	Year & Industry FEs			Year & Firm FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
Short-Termism	8.676			0.581		
	(7.557)			(6.186)		
H-Score		-0.822			-0.270	
		(0.620)			(0.465)	
Age			0.621			0.648
			(0.918)			(0.742)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Clustered At	Firm	Firm	Firm	Firm	Firm	Firm
Observations	1,670	1,670	1,670	1,670	1,670	1,670
Adjusted R^2	0.29	0.29	0.29	0.76	0.76	0.76

In Panel A, I regress my indicator variable for short-termism on the giving ratio. I also regress the H-Score and age variables on the giving ratio. In Panel B, I perform the same regressions using absolute charitable giving as my dependent variable. In all regressions I include controls for current ROA, log(size), Tobin's Q, R&D spending, advertising spending, and whether the firm is a dividend payer. ***, ***, and * indicate statistical significance at the 1%,5%, and 10% level, respectively using two-tailed tests.

Table 3.7: Difference in Charitable Giving Using Nearest-Neighbor Matching

	Giving-Ratio (%)	Charitable Giving ($M)
Difference	25.712	8.672
	(22.430)	(8.672)
p-Value	0.252	0.335

This table reports the difference in giving behavior of firms that are managed by a short-term vs. long-term CEO. Differences are computed as average treatment effects using nearest-neighbor matching. Robust starandard errors are reported in parentheses.

where CEOs divert corporate funds to charities in order to receive some private benefit at the cost of future firm performance.

Second, under my model CEOs with shorter decision horizons (i.e. CEOs whose expected tenure is shorter) have a greater incentive to signal the market their firm's strength. Because the marginal value of signaling is highest in firms with a short-term CEO, the marginal information carried in a dollar of charitable giving is lower. Hence, the relationship between giving and future performance should be weaker in firms with a short-term CEO.

The evidence provides support for both of my predictions. At a 1-year time horizon charitable giving provides no information about a firm's accounting performance. In contrast, I get very different results when I consider the relationship between giving and the firm's results 2 years into the future. Here, I find confirmation of my signaling hypothesis; both in the relationship between giving and future performance and in the difference in giving behavior between long-term focused and short-term focused CEOs. An increase of the firms giving ratio (defined by total corporate giving over assets) by 1 standard deviation predicts a nearly 76 bp increase in the firm's expected ROA at a 2-year's time horizon. This relationship, however, drops by over 2/3's for firms with a short-term CEO. In these short-term firms, a 1 standard deviation increase in giving predicts only a 24 bp increase in the firm's expected ROA in 2 years.

Although charitable giving predicts the real performance of firms at longer time horizons, the relationship between giving and stock returns is much quicker. This suggests that investors do in fact interpret charitable giving as a costly signal of future firm strength. Such investor responses are a necessary condition for signaling to be a plausible explanation for observed corporate philanthropy.

The debate on corporate social responsibility has largely focused on whether or not CSR programs, of which philanthropy plays a major role, is or is not in shareholders' best interest. In a world with no information asymmetries, charitable giving can only be a worthwhile investment, from the shareholders' prospective, if it raises their expected utility from holding the firm's stock. We, however demonstrate that corporate giving can serve as a valuable signal of firm strength. Even if the NPV of the donation's expected cash flows is negative, the information value can still make the donation valuable from the shareholders' prospective.

Better understanding how CSR programs influence investors' expectations presents an exciting area for further research. The traditional view in the finance literature has been that CEOs begin and encourage these programs as a result of their private preferences. As thinking the thinking of investors, managers, and other stakeholders continues to evolve on the importance of social considerations, the relationship between firm performance and CSR is likely to evolve as well. In order to fully understand how these changes in thinking will impact firm performance, it is important that I gain a better understanding of what drives these programs today. My results contribute to the debate on today's CSR programs by opening up a new line of thinking in the finance literature; I show that corporate philanthropy can be explained using a novel signaling framework.

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Appendix A

Definition of Variables Used

A.1 Variables Used in Chapter 2

Variable	Definition of Variable
Student	Indicator variable equal to 1 when observation i is a student user (or group of students)
Change	Indicator variable equal to 1 for observations after the Fall 2015 when students no longer were required to purchase an optional gym membership to use the university fitness center
Day	Day since the first day of classes in the semester
Day^2	Day variable squared
$Period_i$	an indicator variable for whether a day is in the i-th sextile of the semester
Days(member)	Count of the number of days since the user first accessed the gym in the semester
Weeks(member)	Count of the number of weeks since the user first accessed the gym

A.2 Variables Used in Chapter 3

Variable	Definition	Source
Giving Behavior		
Corporate Giving	Total corporate donations via direct giving and through company control foundations	Asset4
Giving Ratio	Corporate Giving/Total Assets	Calculated
Firm Characteristics		
Total Assets	Total Assets as listed on balance sheet at the start of the year	Compustat
Size	Log(Total Assets)	Calculated
Leverage	Total Debt/Total Assets	Compustat
R&D	R&D expenses/Total Assets; treated as zero if R&D expense is missing	Compustat
Adv	Advertising expenses/Total Assets; treated as zero if advertising expense is missing	Compustat
Dividend	Indicator equal to 1 if the firm paid a dividend that year; 0 otherwise	CRSP
Tobin's Q	(Liabilities+Market Value of Equity)/Total Assets	Compustat
Performance Measures		
ROA	Income before extraordinary items/Total Assets	Compustat
Excess Market Return	Excess holding stock return adjusted for the Fama-French 3 factor returns	CRSP
Measures of Short-Termism		
Tenure	Current Year-Start Year	Execucomp
Age	CEOs Age as reported in proxy statement	Execucomp

Appendix B

Proofs

B.1 Proofs for Chapter 1

Proof of Lemma 1: The lenders' IR condition requires that, in equilibrium, $\forall\theta\ V_L(R;\theta) \geq 0$.

Now let $R_i(\theta)$ be the interest rate charged by the i-th lender in equilibrium and let $p_i(\theta)$ be the probability that the i-th lender's loan is accepted in equilibrium.

Suppose towards contradiction $\exists\theta$ such that, in equilibrium, some lender j makes a positive profit: $V_L(R_j(\theta);\theta) * p_j(\theta) > 0$ Observe that this implies that $p_j(\theta) > 0$ and $V_L(R_j(\theta);\theta) > 0$. Since the borrower's utility is strictly decreasing in R, $p_j(\theta) > 0$ implies that R_j is the lowest interest rate offered in the market.

Now select some lender i such that $p_i(\theta) < 1$. Note that the profit of lender i conditional on being choosen will have to be $V_L(R_j(\theta);\theta)$ as lender i would never be choosen if $R_i(\theta) > R_j(\theta)$ and j would never be choosen if $R_i(\theta) < R_j(\theta)$. Without loss I can then assume that lender i's profit will be $V_L(R_j(\theta);\theta) * p_i(\theta)$ (either $V_L(R_i(\theta);\theta) = V_L(R_j(\theta);\theta)$ or $p_i(\theta) = 0$). I will shows that this lender will have a profitable deviation.

Let V' be some value such that $p_i(\theta) * V_L(R_j(\theta);\theta) < V' < V_L(R_j(\theta);\theta)$. By the completness of the reals I know that V' must exist. Now define R' as the solution to the equation $V_L(R';\theta) = V'$. Note that since V_L is continuous in R and $V_L(0;\theta) = -1$ and $V_L(R_j(\theta);\theta) > V'$, I can apply the intermediate value theorem to conlude that $\exists R' \in (0, R_j(\theta))$.

If lender i offered R' then the borrower would strictly perfer the offer from lender i as $V_B(R;\theta)$ is a strictly decreasing in R. Hence, the borrower will either accept loan offer R' with probability 1 or all loan offers will be rejected. Finally, I can show that R' will be accepted as:

$$\mathbb{E}[V_B(R';\theta)|(R';R_{-i}(\theta))] > \mathbb{E}[V_B(R_j(\theta);\theta)|(R';R_{-i}(\theta))] \geq \mathbb{E}[V_B(R_j(\theta);\theta)|(R_i(\theta);R_{-i}(\theta))] \geq 0 \tag{B.1}$$

The second-to-last inequality follows from our imposition of monotonic beliefs, and the last inequalty follows from the fact that $p_j(\theta) > 0$. (B.1) implies that the borrower would accept offer R' with probability 1 if it were offered. Hence, by offering R' instead of $R_i(\theta)$, lender

i's profit would be $V' > p_i(\theta) * V_L(R_j(\theta);\theta)$. This implies that there can exist no equilibrium where some lender earns a striclty positive profit on some type θ. Therfore, in equilibrium for each type θ, the lenders must break-even. □

Since $V_L(R;\theta)$ is a continuous and increasing function in R, $V_L(R_j(\theta);\theta) > 0$ implies $\exists R' < R_j(\theta)$ such that $V_L(R';\theta) > 0$. . As $R' < R_j(\theta)$, the borrower will strictly perfer loan offer R' to $R_j(\theta)$ no matter the borrower's expectations □

Lemma B.1.1. $\forall\theta \in (0,1)$, $\frac{\partial V_L(R,s;\theta)}{\partial\theta} > 0$.

Proof. Let $\pi(w,s,R)$ be the lender's profit when payout w is realized,and the interest rate is R:

$$\pi(w,s,R) = \begin{cases} s + (1-s)w & \text{if } w < 1 \\ w & \text{if } 1 \leq w < R \\ R & \text{if } R \leq w \end{cases}.$$

As $s < 1$, $\pi(w,R)$ must be an increasing, and continuous finite function of w. This definition implies that $V_L(R,s\theta) = \mathbb{E}_w[\pi(w,s,R)|\theta]$. Given our assumption of strict FOSD, $\mathbb{E}_w[\pi(w,s,R)|\theta]$ must be a strictly increasing function of θ. Now by definition,

$$\frac{\partial V_L(R,s;\theta)}{\partial\theta} = \int_0^{\bar{w}} (\pi(w,s,R) - 1) f_\theta(w|\theta) dw.$$

Given assumption 2 that f_θ exists and is continuous, it must be the case that $\frac{\partial V_L(R,s;\theta)}{\partial\theta}$ must exist. Since V_L is a strictly increasing function of θ the fact that the derivative exist implies that $\frac{\partial V_L(R,s;\theta)}{\partial\theta} > 0$. □

□

Proof of Lemma 2: The lender will be willing to offer a loan if and only if $\exists R$ such that $V_L(R,s;\theta) \geq 0$. Since, the lender can at most demand $\bar{w}$ (any interest rate higher than $\bar{w}$ would result in the same payments as interest rate $\bar{w}$), a loan will be offered if and only if $V_L(\bar{w},s;\theta) \geq 0$. Note that when $R = \bar{w}$, the lender captures the entire output generated by the project.

Per lemma B.1.1, $V_L(\bar{w},s;\theta)$ must be continuous in θ. Now, assumption 5 gives us that $V_L(\bar{w},s;\theta) < 0$. From assumption 4, it follows that $V_L(\bar{w},s;\theta) > 1 + c$. Therefore, I can apply the intermediate value theorem to conclude $\exists\underline{\theta}$ such that $V_L(\bar{w},s;\underline{\theta}) = 0$.

Finally, lemma B.1.1 guarantees that $\forall\theta > \underline{\theta}$, $V_L(\bar{w},s;\theta) > 0$. Therefore, a borrower will be offered a loan if and only if $\theta \geq \underline{\theta}$. □

Proof of Lemma 3: From Lemma B.1.1, I know that $\frac{\partial V_L}{\partial\theta} > 0$. As the lender's zero profit condition implies that $V_L(R(\theta,s),s;\theta) = 0$, I can use the implicit function theorem to find $\frac{dR}{d\theta}$:

$$\frac{dR}{d\theta} = -\frac{\frac{\partial V_L}{\partial\theta}}{1 - F(R|\theta)} < 0.$$

Therefore, it must be the case that $R(\theta, s)$ is a strictly decreasing function of θ. □

Proof of Proposition 1: First note that as R is a strictly monotonic function of θ, R is invertible; after observing R, the borrower knows θ. Hence, the borrower faces no uncertainty as to her true type when interest rates vary.

Since the lender's always break-even in expectation, (1.1) can be rewritten as as:

$$V_B(R(\theta, s); \theta) = \mathbb{E}[w|\theta] + \int_0^1 s(1-w)dF(w|\theta) - 1 - c = \mathbb{E}[y(w)|\theta] - 1 - c$$

, where

$$y(w) = \begin{cases} s + (1-s)w & \text{if } w < 1 \\ w & \text{otherwise} \end{cases}.$$

For any $s < 1$, $y(w)$ must be a continuous, non-decreasing function. Then using the same logic as in lemma B.1.1, it is trivial to show that $\mathbb{E}[y(w)|\theta]$ is a strictly increasing and continuous function in θ. Given that $\mathbb{E}[y(w)|\theta]$ is a strictly increasing and continuous function, it must also be the case that V_B is as well.

Now consider the threshold offer type $\underline{\theta_s}$, the lender offers $R(\underline{\theta_s}) = \bar{w}$. It is obvious that $V_B = 0 - c < 0$. Now when $\theta = 1$,

$$V_B(R(1, s), 1) = \int_{1+c}^{\bar{w}} (w-1)dF(w|\theta) - c = \mathbb{E}[w|\theta = 1] - (1+c) > 0$$

, where the inequality follows from assumption 4. I can then apply the intermediate value theorem to conclude $\exists \hat{\theta}_s \in (\underline{\theta_s}, 1)$ such that $V_B(R(\hat{\theta}_s); \hat{\theta}_s) = 0$.

Then as V_B is a strictly increasing function in θ, I know that $\forall \theta \geq \hat{\theta}_s$ the loan will be accepted and any borrower with $\theta < \hat{\theta}_s$ will reject the loan (or not be offered a loan). Therefore, a loan will be accepted if and only if $\theta > \hat{\theta}_s$. □

Proof of Lemma 4: From lemma B.1.1, I know that V_L is a continuous function of θ. Now choose an arbitrary $R^U > 1$. Since $s < 1$, assumption 5 implies that $V_L(R^U, s; 0) < 0$. Similarly assumption 6 implies that $V_L(R^U, s; 1) = \max\{\int_{1+c}^{R^U} w dF(w|1), 0\} + R^U[1 - F(R^U|1)] - 1 > 0$. Therefore, by the intermediate value theorem, $\exists \tilde{\theta} \in (0, 1)$ such that $V_L(R^U, s; \theta') = 0$.

Then as V_L is a strictly increasing function of θ $V_L \geq 0$ if and only if $\theta \geq \theta'$. Therefore, as indvidual rationality dictates that the lender will offer a loan at rate R^U if and only if $V_L \geq 0$, a loan will be offered if and only if $\theta \geq \theta'$. □

Lemma B.1.2. Suppose θ' is an implementable threshold with risk-based interest rates. Then $(\theta', 0)$ is an implementable threshold with uniform rates.

Proof. Since θ' is a threshold type under risk-based rates and subsidy level s', there must exist some $R(\theta', s') < \bar{w}$. Now let $(R(\theta', s'), s')$ be the mandated interest rate and subsidy under a uniform rate scheme. By construction $V_L(R(\theta', s'), s'; \theta') = 0$ and as V_L is strictly increasing in θ for all $\theta \geq \theta'$ $V_L \geq 0$. Therefore, the lender will lend so long as the borrower is at least as strong as θ'.

From the borrower's perspective, the fact that θ' is the threshold type in the risk-based scheme implies that $V_B(R(\theta', s'); \theta') = 0$. With a uniform rate scheme the borrower's expected value is given by:

$$\int_{\theta'}^{1} \frac{V_B(R(\theta', s'); \theta)}{1 - G(\theta'|\sigma)} dG(\theta|\sigma) \tag{B.2}$$

As V_B is a strictly increasing function of θ and $V_B(R(\theta', s'); \theta') = 0$, (B.2) must be non-negative for any σ. In particular, this must hold for $\sigma = 0$. Hence with threshold type θ' and interest rate $R(\theta', s')$ all borrowers will accept the loan regardless of their signal. Therefore, $(\theta', 0)$ can be implemented using a uniform rate scheme. □

Lemma B.1.3. Suppose that the social planner wants to implement thresholds $(\theta', 0)$ with a uniform rate scheme. If $\alpha > 0$, it will always be socially optimal to ensure that the $\sigma = 0$ borrower's IR constraint holds with equality.

Proof. Let $R' = R(\theta', s'_{RB})$ be the interest rate that is charged to the θ' borrower, when θ' is the threshold type under a risk-based rate scheme.

Now, to ensure that the $\sigma = 0$ borrower is willing to accept the loan, her IR constraint cannot be violated (i.e. $\mathbb{E}[V_B(R; \theta)|\theta \geq \theta', \sigma = 0] \geq 0$). Observe that V_B is a continuous function in θ, $\mathbb{E}[V_B(R'; \theta)|\theta \geq \theta', \sigma = 0]$ and from (B.2), it is easy to show that $\mathbb{E}[V_B(R', s'_{RB}); \theta)|\theta \geq \theta', \sigma = 0] > 0$. Hence, there exists some $R^* \in (R', \bar{w})$ such that $\mathbb{E}[V_B(R^*; \theta)|\theta \geq \theta', \sigma = 0] = 0$.

Since V_B is a strictly decreasing function in R, the $\sigma = 0$ borrower would never accept a loan if θ' is the threshold type and $R^U > R^*$. Hence, any uniform interest rate must satisfy $R^U \leq R^*$.

Now suppose $R^U < R^*$. Let s^* be the subsidy rate that solves $R^* = R(\theta', s^*)$. By construction $V_L(R^*, s^*; \theta') = 0$. Since V_L is a strictly increasing function in R, $V_L(R^U, s^*; \theta') < 0$. However as V_L is also continuous and strictly increasing in s with $V_L(\cdot, \infty; \theta') = \infty$, it must be the case that $\exists s^{**} > s^*$ such that $V_L(R^U, s^{**}; \theta') = 0$.

Finally, when the type threshold is θ' the difference in the social planner's value function when using scheme (R^*, s^*) and (R^U, s^{**}) is given by:

$$\int_0^1 \int_{\theta'}^1 [V_{SP}(R^*, s^*; \theta) - V_{SP}(R^U, s^{**}; \theta) dG(\theta|\sigma) d\sigma =$$
$$= -(\alpha - 1) \int_0^1 \int_{\theta'}^1 \int_0^1 (s^* - s^{**})(1 - w) dF(w|\theta) dG(\theta|\sigma) d\sigma > 0,$$

with the inequality following from the fact that $s^* < s^{**}$. Therefore, when $\alpha > 1$, the social planner will always want to ensure the borrower's IR constraint holds with equality. □

Proof of Proposition 2: Let (θ', σ') be thresholds such that a borrower accepts a loan if their type is at least θ' and their signal is at least σ'. If a social planner allows for risk-based interest rates, $\sigma' = 0$ as the borrower is able to infer her type perfectly from interest rates.

Suppose the social planner wants to have a type threshold θ' and this threshold type could be implemented using a risk-based interest rate scheme with a subsidy s'_{RB}. From lemma B.1.2, thresholds $(\theta', 0)$ can be implemented under a uniform rate scheme. I will now show that for any θ' that is implementable under a risk-based interest rate scheme, when $\alpha > 1$ the social planner is better off using a uniform interest rate scheme at thresholds $(\theta', 0)$.

Step 1: The subsidy rate is lower under a uniform rate scheme:

From lemma B.1.3, when $\alpha > 1$ the $\sigma = 0$ borrower's IR constraint should hold with equality. Thus to implement the uniform rate scheme (R^U, s_U) must solve the following equations:

$$\begin{cases} \mathbb{E}_\theta[V_B(R^U;\theta)|\theta \geq \theta'; \sigma = 0] = 0 \\ V_L(R^U, s_U; \theta') = 0 \end{cases}$$

Then under the risk-based rate scheme, the subsidy amount must satisfy:

$$\begin{cases} V_B(R(\theta'; s_{RB}); \theta') = 0 \\ V_L(R(\theta'; s_{RB}), s_{RB}; \theta') = 0 \end{cases}$$

Since V_B is a strictly decreasing function in the second argument and $G(\cdot|\sigma = 0)$ has full support, it must be the case that $V_B(R;\theta') < \mathbb{E}_\theta[V_B(R;\theta)|\theta \geq \theta'; \sigma = 0]\forall R$. Thus, $R(\theta'; s_{RB}) < R^U$. Since the lender breaks even at the threshold type regardless of the scheme $R(\theta'; s_{RB}) < R^U$ implies that $s_{RB} > s_U$.

Step 2: The total social value is higher when using a uniform rate scheme

Comparing the social planner's value when using the two schemes:

$$\int_{\sigma'=0}^{1} \int_{\theta'}^{1} [V_{SP}(R^U, s_U; \theta) - V_{SP}(R(\theta; s_{RB}), s_{RB}; \theta)] dG(\theta|a) d\sigma =$$

$$= \int_{\sigma'=0}^{1} \int_{\theta'}^{1} \int_{0}^{1} -(\alpha - 1)(1 - w)(s_U - s_{RB}) dF(w|\theta) dG(\theta|a) da \tag{B.5}$$

As $s_U < s_{RB}$, (B.5) will be positive if and only if $\alpha > 1$. Since, this will hold for any θ', there will always be a uniform rate scheme that can increase total social value when compared to a risk-based rate scheme. □

Proof of Proposition 3: From proposition 2, the socially optimal lending program will result in all borrower's being pooled at the same interest rate. Further under any pooling program either $\sigma' = 0$ or $\sigma' > 0$. When $\sigma' = 0$, lemma B.1.3 implies that $\mathbb{E}[V_B(R;\theta)|\theta \geq \theta', \sigma = 0] = 0$. When $\sigma' > 0$, IR requires that at the threshold σ', $\mathbb{E}[V_B(R;\theta)|\theta \geq \theta', \sigma = \sigma'] = 0$. Since V_B is a strictly decreasing function in θ, $\mathbb{E}[V_B(R;\theta)|\theta \geq \theta', \sigma = \sigma'] = 0$ implies that $V(R;\theta') < 0 < V(R;1)$.

Since $G(\cdot|\sigma')$ has full support, θ' is in the support of $G(\cdot|\sigma')$. Since $V_B(R;\theta') < 0 < V_B(R;1)$ and $V_B(R;\theta)$ is strictly increasing in θ', with non-zero probability there must exist some borrowers who accept a loan even though $V_B(R;\theta) < 0$. These borrowers will accept a predatory admissions offer. □

Proof of Proposition 4: The lender will be willing offer a loan at rate R so long as $V_L(R, s; \theta) \geq 0$. Hence, the threshold offer type θ' will be given by solving $V_L(R, s; \theta') = 0$. As V_L is a strictly increasing function of θ, then $\forall \theta > \theta'$ $V_L(R, s; \theta') > 0$. Therefore, the lender makes a strictly positive profit on all borrowers other than the threshold type. □

Proof of Lemma 5:

Step 1: That for any lender strategy, there exists a threshold $\tilde{\tilde{\theta}}_B \in (0, 1)$ such that the borrower accepts the loan if and only if $\theta_B \geq \tilde{\tilde{\theta}}_B$.

Consider an arbitrary lender strategy Θ_L where Θ_L is a set with a non-zero measure such that the lender offers a loan if and only if $\theta_L \in \Theta_L$. Define $V_B^2(\theta_B)$ as a borrower's expected value with private information θ_B:

$$V_B^2(\theta_B) = \int_{\Theta_L} V_B(R, s; \theta, \theta_B) d\theta * \mathbb{P}(\theta_L \in \Theta_L)$$

Clearly a borrower will accept a loan if and only if $V_B^2(\theta_B) \geq 0$. By our assumption on the differentiability of $F(\cdot|\theta_L, \theta_B)$, I know that V_B must be a continuous function of θ_B implying that $V_B^2(\theta_B)$ must be continuous as well. Further our assumption that $V_B(\cdot, 0) < 0 < V_B(\cdot, 1)$ implies that $V_B^2(0) < 0 < V_B^2(1)$. Thus, I can apply the intermediate value thereom to conclude that there exists some $\tilde{\tilde{\theta}}_B \in (0, 1)$ such that $V_B^2(\tilde{\tilde{\theta}}_B) = 0$.

By our assumption that $F(\cdot|\theta_L, \theta_B)$ displays strict FOSD in θ_B, I can show that $V_B(R, s; \theta, \theta_B)$ is a strictly increasing function in θ_B. Hence, $V_B^2(\theta_B)$ must be a strictly increasing function in θ_B as well. Therefore, the borrower will accept a loan if and only if $\theta_B \geq \tilde{\tilde{\theta}}_B$ where $\tilde{\tilde{\theta}}_B$ is a function of Θ_L.

Step 2: The lender's optimal response must be a threshold strategy

In step 1, I showed that the borrower's optimal strategy for any arbitrary lender strategy will be a threshold strategy. I will know take the borrower's strategy $\tilde{\tilde{\theta}}_B(\Theta_L)$ as given. Let $V_L^2(\theta_L)$ as the lender's expected value with private information θ_L:

$$V_L^2(\theta_L) = \int_{\tilde{\tilde{\theta}}_B}^{1} \frac{V_L(R, s; \theta_L, \theta)}{1 - \tilde{\tilde{\theta}}_B} d\theta$$

A lender will want to offer a loan if and only if $V_L^2(\theta_L) \geq 0$. By the continuity of $F(\cdot|\theta_L, \theta_B)$ in θ_L I can show that V_L^2 is continuous. Further I also know that $V_L(R, s; 0, \theta_B) < 0 < V_L(R, s; 1, \theta_B)$. Thus, I can apply the intermediate value thereom to conclude that there exists $\tilde{\tilde{\theta}}_L \in (0, 1)$ such that $V_L^2(\tilde{\tilde{\theta}}_L) = 0$ for any borrower strategy.

Given our assumption on the strict FOSD of $F(\cdot|\theta_L, \theta_B)$ with respect to θ_L, it is trivial to show that $V_L^2(\theta_L)$ is a strictly increasing function in θ_L. Therefore, $V_L^2(\theta_L) \geq 0$ if and only if $\theta_L \geq \tilde{\tilde{\theta}}_L$ implying that the lender will always play a threshold strategy.

Step 3: There exists a $\tilde{\tilde{\theta}}_L$ such that $\tilde{\tilde{\theta}}_L$ is the optimal response to the borrower's strategy $\tilde{\tilde{\theta}}_B(\tilde{\tilde{\theta}}_L)$.

Let $V_B^2(\theta_L, \tilde{\tilde{\theta}}_B)$ be the lender's expected value at θ_L the when the borrower plays threshold $\tilde{\tilde{\theta}}_B$. In equilibrium it must be the case that $V_B^2(\tilde{\tilde{\theta}}_L, \tilde{\tilde{\theta}}_B(\tilde{\tilde{\theta}}_B)) = 0$. If not, the lender could improve its payoff by choosing a different threshold.

We'll start by showing that $\frac{d\tilde{\tilde{\theta}}_B(\theta_L)}{d\theta_L}$ exists and is well-defined. Given lender threshold θ_L, the borrower's threshold rule will satisfy:

$$\int_{\theta_L}^{1} \frac{V_B(R, s; \theta, \tilde{\tilde{\theta}}_B)}{1-\theta_L} d\theta = 0 \tag{B.6}$$

Applying the implicit function thereon to (B.6), I get:

$$\frac{d\tilde{\tilde{\theta}}_B(\theta_L)}{d\theta_L} = \frac{V_B(R, s; \theta_L, \tilde{\tilde{\theta}}_B) + \int_{\theta_L}^{1} V_B(R, s; \theta, \tilde{\tilde{\theta}}_B) d\theta * \log(1-\theta_L)}{\int_{\theta_L}^{1} \frac{\partial V_B}{\partial \theta_B} d\theta} \tag{B.7}$$

Our assumption, on the strict FOSD combined with the assumption that the derivative of F with respect to θ_B exists implies that $\frac{\partial V_B}{\partial \theta_L}$ is well-defined almost everywhere. Hence, $\frac{d\tilde{\tilde{\theta}}_B(\theta_L)}{d\theta_L}$ must be well-defined $\forall \theta_L \in (0,1)$ implying that $\frac{d\tilde{\tilde{\theta}}_B(\theta_L)}{d\theta_L}$ is continuous in the interval $(0,1)$.

I can then use this fact to show that $V_B^2(\theta_L, \tilde{\tilde{\theta}}_B(\theta_L))$ is a continuous function in θ_L. To see this consider the first derivative:

$$\frac{dV_B^2(\theta_L, \tilde{\tilde{\theta}}_B(\theta_L))}{d\theta_L} = \int_{\tilde{\tilde{\theta}}_B(\theta_L)}^{1} \frac{\partial V_L(R, s; \theta_L, \theta)}{\partial \theta_L} d\theta - \frac{d\tilde{\tilde{\theta}}_B(\theta_L)}{d\theta_L} V_L(R, s; \theta_L, \tilde{\tilde{\theta}}_B(\theta_L))$$

Our assumption on the differntiability of F with respect to θ_L guarantees that the first-term is well-defined. The fact that the derivative defined by (B.7) exists and is well-defined guarantees that the second-term is well-defined as well. Hence, I now that V_B^2 must be continuous in θ_L. Then by our assumption that $\forall \theta_B \; V_L(R, s; 0, \theta_B) < 0 < V_L(R, s; 1, \theta_B)$ I can apply the intermediate value theorem to conclude $\exists \tilde{\tilde{\theta}}_L \in (0,1)$ such that $V_L^2(R, s; \tilde{\tilde{\theta}}_L, \tilde{\tilde{\theta}}_B(\tilde{\tilde{\theta}}_L)) = 0$. Therefore $(\tilde{\tilde{\theta}}_L, \tilde{\tilde{\theta}}_B(\tilde{\tilde{\theta}}_L))$ will be an equilibrium threshold strategy. □

Proof of Proposition 5: In our construction of the two-sided equilibrium (see proof of lemma 5), I showed that when the borrower is at her threshold, $\tilde{\tilde{\theta}}_B$, the borrower is indifferent between accepting and the rejecting the loan (see (B.6)). Given our assumption on strict FOSD, $V_B(R, s; \tilde{\tilde{\theta}}_L, \tilde{\tilde{\theta}}_B) < V_B(R, s; 1, \tilde{\tilde{\theta}}_B)$. Hence, the only way that the borrower's expected value conditional on being offered a loan can be zero is if $V_B(R, s; \tilde{\tilde{\theta}}_L, \tilde{\tilde{\theta}}_B) < 0$. Therefore, predatory admissions must occur. □

Proof of Lemma 6: Let Θ be the set of borrowers accepted by the screener. The screener's objective is to maximize the mass of accepted borrowers subject to the government imposed average earnings requirement ($\int_\Theta E[w|\theta]d\theta \geq \underline{w}$).

Suppose towards contradiction the screener's optimal Θ cannot be written in the form $[\theta', 1]$ (i.e. either the highest acceptable type is not $\theta = 1$ or there are some types between θ' and 1 who are rejected). There must exist some θ' such that $\mathbb{P}(\theta \in \Theta) = \mathbb{P}(\theta \geq \theta')$. However, since $\Theta \neq [\theta', 1]$, it must be the case that $\int_{\theta'}^1 \mathbb{E}[w|\theta]d\theta > \int_\Theta \mathbb{E}[w|\theta] \geq \underline{w}$. This inequality implies that there must exist some $\theta'' < \theta'$ such that $\int_{\theta''}^1 \mathbb{E}[w|\theta]d\theta \geq \underline{w}$ with $\mathbb{P}(\theta \geq \theta'') > \mathbb{P}(\theta \in \Theta)$. Contradiction! Therefore, the optimal screening policy must be a threshold strategy. □

Proof of Lemma 7: From lemma 6 I know that the optimal screening policy is a threshold strategy. The screening cutoff θ' will solve:

$$\int_{\theta'}^1 \mathbb{E}[w|\theta]d\theta - \underline{w} = 0$$

Applying the implicit function theorem, I get:

$$\frac{d\theta'}{d\underline{w}} = \frac{1}{\mathbb{E}[w|\theta']} > 0$$

□

Proof of Proposition 6: Under our direct lending program, the social planner's value from extending credit to borrower θ at interest rate R is given by:

$$\begin{aligned} V_{SP}(R;\theta) &= V_B(R;\theta) + \alpha V_L(R;\theta) + e - \zeta \\ &= \mathbb{E}[W|\theta] + (\alpha - 1)\left[\int_0^R w dF(w|\theta) + R(1 - F(R|\theta))\right] + e - (\alpha + c + \zeta) \end{aligned}$$

Step 1: If a direct lending program is used, the borrower's IR constraint will be binding.

Taking the first derivative of V_{SP} with respect to R I get:

$$\frac{\partial V_{SP}}{\partial R} = (\alpha - 1)(1 - F(R|\theta)) > 0$$

Hence for any desired threshold level, the social planner will want to ensure that R is as small as possible while still ensuring lending occurs. The borrower will accept the loan if and only if $\mathbb{E}[V_B(R;\theta)|\theta \geq \theta'] \geq 0$. Since the borrower's expected utility is strictly decreasing in R, the maximum interest rate that can be set while still allowing for lending occurs when R is set such that $\mathbb{E}[V_B(R;\theta)|\theta \geq \theta'] = 0$.

Step 2: A direct lending program is preferable to independent lenders when ζ is sufficiently small.

Suppose the social planner wants to induce threshold θ'. I know that whenever $\alpha > 1$, the social planner will want to set interest rates so that the borrower's IR constraint holds with equality regardless of the type of program used. Hence, for a given threshold regardless of which program is used the offered interest rate, R, will be the same.

Now the difference in the planner's total value will be given by:

$$\int_{\theta'}^{1}(V_{SP}^{Direct} - V_{SP}^{Private})d\theta = \int_{\theta'}^{1}\Bigg((\alpha-1)\Bigg[\int_{0}^{R} wdF(w|\theta) + R[1-F(R|\theta)] + \\ + \int_{0}^{1} s(1-w)dF(w|\theta) - 1\Bigg] - (\alpha-1)\zeta\Bigg)d\theta$$

$$\int_{\theta'}^{1}(V_{SP}^{Direct} - V_{SP}^{Private})d\theta = \int_{\theta'}^{1}[(\alpha-1)V_L(R,s;\theta) - (\alpha-1)\zeta]d\theta$$

Since private lenders are willing to lend to a type, θ, if and only if $V_L(R,s;\theta) \geq 0$, $\int_{\theta'}^{1}(\alpha-1)V_L(R,s;\theta)d\theta > 0$. Therefore, for any threshold θ' there exists a $\zeta > 0$ such that $\int_{\theta'}^{1}(V_{SP}^{Direct} - V_{SP}^{Private}) > 0$ implying that for any desired threshold there exists a ζ sufficiently smaller that a direct lending program is optimal. □

B.2 Proofs for Chapter 2

Proof of Lemma 1: Conditional on being a member, a user will go to the gym if and only if $\epsilon_t \geq -(x + \gamma^{t-t_0+1}c)$. This probability will be given by $1 - F(-(x+\gamma^{t-t_0+1}c))$. Taking the first derivative with respect to c, $f(\cdot)\gamma^{t-t_0+1} > 0$. Therefore, under non-standard preferences, the conditional probability of going to the gym will be increasing in c. □

Lemma B.2.1. *The probability of joining on day t is given by* $1 - F\left((1-\gamma)c - x - \sum_{s=t+1}^{T}\mathbb{E}[\max(\tilde{u_s},0)]\right)$.

Proof. A user will sign-up for the gym on day t if and only if $\tilde{U_t} \geq 0$. Since ϵ_t is known on day t, (2.2) can be rewritten as:

$$\tilde{U_t} = x + \epsilon_t + \sum_{s=t+1}^{T}\mathbb{E}[\max(\tilde{u_s},0)] + (\gamma-1)c. \tag{B.10}$$

The probability that (B.10) will be greater than or equal to zero will be given by

$$\mathbb{P}\left(\epsilon_t \geq (1-\gamma)c - x - \sum_{s=t+1}^{T}\mathbb{E}[\max(\tilde{u_s},0)]\right)$$

This is equivalent to $1 - F\left((1-\gamma)c - x - \sum_{s=t+1}^{T}\mathbb{E}[\max(\tilde{u_s},0)]\right)$. □

Proof of Lemma 2: Define $p_j(c,t;\gamma)$ as the probability that a user with sunk-cost fallacy γ is willing to pay membership fee c on day t. From lemma B.2.1, p_j will be given by

$$p_j(c,t;\gamma) = 1 - F\left((1-\gamma)c - x - \sum_{s=t+1}^{T} \mathbb{E}[\max(\tilde{u_s},0)]\right).$$

Note that $\mathbb{E}[\max(\tilde{u_s},0)]$ can be rewritten as

$$\mathbb{E}[\max(\tilde{u_s},0)] = \int_{-(x_s+\gamma^{s-t+1}c)}^{\infty} \epsilon f(\epsilon) d\epsilon.$$

Now let $\Delta_j(t;\gamma) = p(c',t;\gamma) - p(c,t;\gamma)$ be the change in the probability that a user is willing to join on day t when the cost changes from c to c'. If $\Delta_j(t;\gamma) \geq 0$ for all t and γ then by construction $\bar{\gamma} = 1$. Now suppose there exists some t and γ such that $\Delta_j(t;\gamma) < 0$. Let $\hat{T} = \{t \leq T : \exists \gamma < 1 \text{ where } \Delta_j(t;\gamma) < 0\}$.

I will now show that for each $t \in \hat{T}$ there exists a $\bar{\gamma}_t$ such that $\forall \gamma \leq \bar{\gamma}_t$ $\Delta_j(t;\gamma) \geq 0$. Choose an arbitrary $t \in \hat{T}$.

$$\Delta_j(t;\gamma) = F\left((1-\gamma)c - x - \sum_{s=t+1}^{T} \int_{-(x_s+\gamma^{s-t+1}c)}^{\infty} \epsilon f(\epsilon) d\epsilon\right) - \\ - F\left((1-\gamma)c' - x - \sum_{s=t+1} \int_{-(x_s+\gamma^{s-t+1}c)}^{\infty} \epsilon f(\epsilon) d\epsilon\right) \quad \text{(B.11)}$$

When $\gamma = 0$, (B.11) reduces to $F(c - x - \sum_{s=t+1}^{T} \int_{-x^s}^{\infty} \epsilon f(\epsilon) d\epsilon) - F(c' - x - \sum_{s=t+1}^{T} \int_{-x^s}^{\infty} \epsilon f(\epsilon) d\epsilon)$. Since $c > c'$ and $F(\cdot)$ is a CDF of a probability distribution with full support on $\mathbb{R}$, it follows that $\Delta_j(t;0) > 0$. Second, since $t \in \hat{T}$, there exists some $\gamma < 1$ such that $\Delta_j(t;\gamma) < 0$.

Finally, observe that taking the first derivative of Δ_j with respect to γ,

$$\frac{\partial \Delta_j}{\partial \gamma} = f(\cdot)\left(-c + \sum_{s=t+1}^{T} (x_s + \gamma^{s-t+1}c) f((x_s + \gamma^{s-t+1}c))\gamma^{s-t}(s-t+1)\right) - \\ - f(\cdot)\left(-c' + \sum_{s=t+1}^{T} (x_s + \gamma^{s-t+1}c') f((x_s + \gamma^{s-t+1}c'))\gamma^{s-t}(s-t+1)\right) \quad \text{(B.12)}$$

Since (B.12) is the sum and product of various continuous functions in γ (recall that $f(\cdot)$ is a continuous function), $\frac{\partial \Delta_j}{\partial \gamma}$ must be continuous in γ implying that Δ_j is also continuous in γ. Then by the intermediate value theorem, there must exist some $\gamma \in (0,1)$ such that $\Delta(t;\gamma) = 0$. Let $\bar{\gamma}_t$ be the smallest such γ that satisfies $\Delta(t;\gamma) = 0$. Then for all $\gamma \geq \bar{\gamma}_t$ $\Delta(t;\gamma) \leq 0$

Let $\bar{\gamma} = \min\{\bar{\gamma}_t : t \in \hat{T}\}$. As $\Delta(t;\gamma) \geq 0$ at each t for all $\gamma \leq \bar{\gamma}_t$, $\Delta(t;\gamma) \geq 0$ for all $\gamma \leq \bar{\gamma} \leq \bar{\gamma}_t$. Therefore, for all $\gamma \leq \bar{\gamma}$, the probability a member is willing to join on day t is increasing when costs decrease from c to c'. □

Proof of Prediction 1: To show that prediction 1 holds, I will use induction. Suppose $\gamma \leq \bar{\gamma}$. First, I will show that $p_m(c,1) \leq p_m(c',1)$. $p_m(\cdot,1)$ is equivalent to $p_j(\cdot,1)$. From lemma 2 when $\gamma \leq \bar{\gamma}$, $p_j(c,t;\gamma) \leq p_j(c',t;\gamma)$, $\forall t$. In particular, this implies that $p_m(c,1) \leq p_m(c',1)$.

Now, I'll make the induction hypothesis that for $t \in \{1,2,...,T-1\}$, $p_m(c,t) \leq p_m(c',t)$. Observe that $p_m(c,t)$ can be rewritten as

$$p_m(c,t) = 1 - \prod_{s=1}^{t} \left(1 - p_j(c,t;\gamma)\right).$$

Thus, to prove that $p_m(c,t+1) \leq p_m(c',t+1)$ it is sufficient to show that,

$$\prod_{s=1}^{t+1} \left(1 - p_j(c,t;\gamma)\right) \geq \prod_{s=1}^{t+1} \left(1 - p_j(c,t;\gamma)\right).$$

$$\begin{aligned}
\prod_{s=1}^{t+1}(1 - p_j(c,t;\gamma)) =& (1 - p_j(c,t+1;\gamma)) \prod_{s=1}^{t}(1 - p_j(c,t+1;\gamma)) \\
\geq& (1 - p_j(c,t+1;\gamma)) \prod_{s=1}^{t}(1 - p_j(c',t;\gamma)) \\
\geq& (1 - p_j(c',t+1;\gamma)) \prod_{s=1}^{t}(1 - p_j(c',t;\gamma)) \\
=& \prod_{s=1}^{t+1}(1 - p_j(c',t;\gamma)),
\end{aligned}$$

,where the first inequality follows from the induction hypothesis that $p_m(c,t) \leq p_m(c',t)$ which implied that $\prod_{s=1}^{t} \left(1 - p_j(c,t;\gamma)\right) \geq \prod_{s=1}^{t} \left(1 - p_j(c,t;\gamma)\right)$, and the second inequality follows from lemma 2. Hence $p_m(c,t+1) \leq p_m(c',t+1)$. Therefore by induction whenever c decreases to c' the probability of membership purchases increases. □

Proof of Prediction 2: Under standard preferences the conditional probability that a user goes to the gym is given by $p_a(c,t) = F(-x)$. Clearly, this function is not a function of c. Hence $p_a(c',t) = p_a(c,t)$.

Under non-standard preferences the probability that a user goes to the gym is given by $\tilde{p_a}(c,t) = F(-x - \gamma^{t-t_0+1}c)$. Taking the first order condition of $\tilde{p_a}$, $\frac{\partial \tilde{p_a}}{\partial c} = -\gamma^{t-t_0+1} f(-x - \gamma^{t-t_0+1}c) < 0$. □

Proof of Prediction 3: Under standard preferences, the difference in total usage probability on day t is

$$\Delta(t) = p_m(c,t)p_a(c,t) - p_m(c',t)p_a(c,t)$$

Hence, the change in *Delta* from t to $t+1$ is given by

$$\Delta(t+1) - \Delta(t) = p_m(c,t+1)p_a(c,t+1) - p_m(c',t+1)p_a(c',t+1) - \\ - [p_m(c,t)p_a(c,t) - p_m(c',t)p_a(c',t)]$$

Since p_a is not a function of time and $\mathbb{P}(\epsilon_t \geq -x)$ is not a function of time, (B.13) reduces to

$$\Delta(t+1) - \Delta(t) = [p_m(c,t+1) - p_m(c',t+1)] - [p_m(c,t) - p_m(c',t)] \geq 0.$$

The inequality follows from the assumption that the difference in the probability of membership purchase increases over time. Hence, over time the difference in the total probability of gym usage is monotonic under standard preferences.

Now, under non-standard preferences the change in probability is given by:

$$\tilde{\Delta}(t+1) - \tilde{\Delta}(t) = [p_m(c,t+1)\tilde{p_a}(c,t+1) - p_m(c',t+1)\tilde{p_a}(c',t+1)] - \\ - [p_m(c,t)\tilde{p_a}(c,t) - p_m(c',t)\tilde{p_a}(c',t)] .$$

By inspection, it is clear that (B.15) need not be monotonic. Since $p_m(c,\cdot) \leq p_m(c',\cdot)$, but $\tilde{p_a}(c,\cdot) \geq \tilde{p_a}(c',\cdot)$. Hence, it is possible that $\tilde{\Delta}(t)$ could be positive or negative for any t. Thus, without creating a functional form for the model it is impossible to say anything about the sign $\tilde{\Delta}(t+1) - \tilde{\Delta}(t)$. Therefore the function $\tilde{\Delta}$ need not be monotonic in t. □

B.3 Proofs for Chapter 3

Proof of Proposition 2:

$$\frac{\partial V^1(\gamma)}{\partial \gamma} = \frac{\partial}{\partial \gamma}\gamma(1-C(\gamma))^\alpha$$

$$= (1-C(\gamma))^\alpha - \gamma\alpha(1-C(\gamma))^{\alpha-1}\frac{\partial C}{\partial \gamma}$$

Plugging in from (3.3),

$$= (1-C(\gamma))^\alpha - \gamma\alpha(1-C(\gamma))^{\alpha-1}\frac{k_i}{\alpha\gamma}(1-C(\gamma))$$

$$\frac{\partial V^1(\gamma)}{\partial \gamma} = (1-k_i)(1-C(\gamma))^\alpha > 0$$

□

Proof of Proposition 6: Using (3.4) we can rewrite γ in terms of C,

$$\gamma = (1-c)^{-\frac{\alpha}{k}} \tag{B.17}$$

Plugging (B.17) into (3.1),

$$V_1 = (1-C)^{-\frac{\alpha}{k}(k-1)}$$

Taking the partial with respect to C,

$$\frac{\partial V_1}{\partial C} = -\frac{\alpha(k-1)}{k}(1-C)^{\frac{\alpha(k-1)}{k}-1}$$

Taking the second partial with respect to k,

$$\frac{\partial^2 V_1}{\partial C \partial k} = \frac{\alpha(1-C)^{\frac{\alpha(k-1)}{k}}\left[\alpha \ln(1-C)(k-1)+k\right]}{(c-1)k^3} < 0$$

The inequality follows from the fact that $0 < C < 1$ and $0 < k < 1$. □