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Beliefs, Preferences and Traits: Essays on Charitable and Innovative Behavior

by

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Contents

List of Tables iii

List of Figures v

Acknowledgements vi

Dedication vii

Abstract viii

1 Waiting to Give 1

1.1 Introduction 1
1.2 Design 5
1.2.1 Institutional Details 5
1.2.2 Data 6
1.2.3 Identification 8
1.2.4 Econometric Specification, Conceptual Framework and Hypotheses 10
1.3 Results 15
1.3.1 Main Findings 15
1.3.2 Instrumenting Wait Time 16
1.3.3 Competing Risks 17
1.3.4 Heterogeneity in Wait Time Effects 21
1.4 Conclusion 23
1.5 Tables and Figures 25
1.6 Appendix A 39
1.6.1 Conceptual Model 41

2 We Should *Totally* Open a Restaurant: How Optimism and Overconfidence Affects Beliefs 44

2.1 Introduction 44
2.2 Optimism and Overconfidence 47
2.2.1 Conceptual Framework 49
2.3 Experimental Design 52
2.3.1 Overview 52
2.3.2 Treatments 53
2.4 Data Construction and Preliminary Data Analysis 57
2.4.1 Raw Data 57
2.4.2 Measuring Optimism and Overconfidence 58

2.4.3 Measuring Within-Subject Correlation . . . 59
2.4.4 Average Treatment Effects . . . 60
2.5 Main Results . . . 61
2.5.1 How Optimism Relates to Overconfidence . . . 62
2.5.2 How Optimism and Overconfidence Affect Beliefs . . . 63
2.5.3 Explaining Variation in Over-estimation . . . 63
2.6 Robustness of Main Results . . . 64
2.6.1 Alternative Specification . . . 64
2.6.2 Measuring Overconfidence as Miscalibration . . . 67
2.7 Discussion of Results . . . 68
2.8 Tables and Figures . . . 70

3 The Innovative Personality 78
3.1 Introduction . . . 78
3.2 Design and Data . . . 87
3.2.1 The Industry Game . . . 87
3.2.2 Risk preferences, cognitive and non-cognitive skills . . . 89
3.2.3 Data . . . 93
3.3 Main Findings . . . 95
3.3.1 Effects of Information . . . 95
3.3.2 Information Choice . . . 101
3.3.3 Additional Findings . . . 104
3.4 Conclusion . . . 105
3.5 Tables and Figures . . . 106
3.6 Appendix C . . . 118
3.6.1 Profit Functions . . . 118
3.6.2 Signals . . . 118

References 131

List of Tables

1.1 DONORS IN OUR SAMPLE . . . 25
1.2 SUMMARY STATISTICS . . . 26
1.3 INSTRUMENT RELEVANCE, OLS ESTIMATES . . . 27
1.4 AVERAGE EFFECT OF WAIT TIME ON ALL DONORS . . . 28
1.5 DISCRETE TIME HAZARD AND IV ESTIMATORS: LIKELIHOOD TO RETURN . . . 29
1.6 PROPORTIONAL HAZARDS WITH COMPETING RISKS . . . 30

1.7 EFFECT OF WAIT TIME ON THE WHOLE BLOOD SUPPLY 31
1.8 SOCIAL COST OF WAITING, WHOLE BLOOD DONORS ONLY 31
1.9 PROPORTIONAL HAZARDS COEFFICIENT, GENDER EFFECTS 32
1.10 DONATION FREQUENCY AND WAIT TIME EFFECTS 33
A.1 EFFECT OF WAIT TIMES, ROBUSTNESS TO SPECIFICATION 40
2.1 TREATMENT, BELIEFS AND TREATMENT EFFECTS 70
2.2 EXPERIMENTAL DESIGN AND DISTRIBUTIONS 70
2.3 DATA GENERATION 71
2.4 OBSERVATIONS 71
2.5 SUMMARY STATISTICS: SAMPLE SIZE OF WITHIN SUBJECT SHIFTS 72
2.6 AVERAGE TREATMENT EFFECTS: REGRESSIONS 72
2.7 CORRELATION BETWEEN OPTIMISM AND OVERCONFIDENCE 73
2.8 THE ROLE OF OPTIMISM AND OVERCONFIDENCE 73
2.9 DECOMPOSING VARIATION IN BELIEFS IN THE COMBINED TREATMENT 74
2.10 CORRELATION BETWEEN OPTIMISM AND OVERCONFIDENCE 74
2.11 THE ROLE OF OPTIMISM AND OVERCONFIDENCE 75
2.12 CORRELATION BETWEEN OPTIMISM AND OVERCONFIDENCE 75
2.13 THE ROLE OF OPTIMISM AND OVERCONFIDENCE 76
2.14 ROBUSTNESS TO MISCALIBRATION 76
3.1 SUMMARY STATISTICS 106
3.2 EXPLORATION, TREATMENT EFFECTS 106
3.3 SUCCESSFUL INNOVATION, TREATMENT EFFECTS 107
3.4 TREATMENT EFFECT OF SUCCESSFUL INNOVATION (FINDING COMPLEMENTARITIES) 107
3.5 PREFERENCE FOR ENTREPRENEURSHIP, PROPENSITY TO EXPLORE AND SUCCESSFUL INNOVATION 108
3.6 INFORMATION AND PERSONALITY INTERACTIONS: PROPENSITY TO INNOVATE AND SUCCESSFUL INNOVATION 109
3.7 TESTING FOR SIGNIFICANCE, F-STATISTICS FOR COLUMN (3) TABLE 3.6 . . . 110
3.8 DETERMINANTS OF INFORMATION CHOICE 110
3.9 EXPLORATION, TREATMENT EFFECTS 111
3.10 SUCCESSFUL INNOVATION, TREATMENT EFFECTS 111
3.11 PREFERENCE FOR ENTREPRENEURSHIP, PROPENSITY TO EXPLORE AND SUCCESSFUL INNOVATION, INFORMATION CHOICE TREATMENT ONLY 112
3.12 INFORMATION AND PERSONALITY INTERACTIONS: PROPENSITY TO EXPLORE AND SUCCESSFUL INNOVATION 113
3.13 NON-PECUNIARY UTILITY OF ENTREPRENEURSHIP 114
C.1 INVESTMENT PRODUCT BLISS POINTS 118

List of Figures

1.1 Satisfaction and Intention, survey responses . . . 34
1.2 Distribution of wait time . . . 34
1.3 Donation Frequency and Wait Times . . . 35
1.4 Donation Frequency and Strategic Arrivals . . . 35
1.5 Figure A.1 Percent of Female Donors, pooled across centers. Figure A.2 Average Age, pooled across centers. . . . 36
1.6 Figure 6(a) Duration until next donation. Figure 6(b) Estimated Non-Parametric Hazard Function of All Donors. Figure 6(c) Estimated Non-Parametric Hazard Function of All Donors, stratified by type of return donation. . . . 37
1.7 Estimated Survival Curve . . . 38
A.1 Figure 1(a) Percent of Female Donors, Center A. Figure 1(b) Percent of Female Donors, Center D. . . . 39
A.2 Figure 2(a) Average Age, Center A. Figure 2(b) Average Age, Center D. 39
2.1 Experimental Treatments . . . 77
2.2 Distribution of Proxy IQ . . . 77
2.3 Average Treatment Effects . . . 78
2.4 Optimism and Overconfidence . . . 79
2.5 This figure relates shifts in beliefs in the payment and performance treatments. This plot shows evidence that optimistic individuals also tend to be overconfident. . 79
2.6 Optimism and Beliefs in the Combined Setting . . . 80
2.7 Overconfidence and Beliefs in the Combined Setting . . . 81
2.8 Imputed Beliefs . . . 82
2.9 Average Calibration . . . 83
3.1 Investment Exploration, all treatments pooled Figure 1(a) Distribution of Average Standard Deviation in Investment Strategies. Figure 1(b) Distribution of Average Exploration Index. . . . 115
3.2 Industry Exploration, all treatments pooled Figure 2(a) Percentage of Rounds with an Industry Switch. Figure 2(b) Total Industries explored, excluding Industry D. Figure 2(c) Total Industries explored. . . . 116
3.3 Successful Innovation, all treatments pooled Figure 3(a) Average Distance from Optimal Investment Strategy. Figure 3(b) Frequency of Operating in Minimum Cost Industry. Figure 3(c) Frequency of Operating in Minimum Cost Industry, rounds 1-10. . . . 117

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Abstract

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In the first essay, we estimate the effect of an increase in time cost on behavior and ask what happens when pro-social behavior becomes more costly in terms of time. We use the length of time a blood donor spends waiting to make his donation as our measure of cost and instrument for a donor's wait time to address the possibility that wait times are endogenously determined. Consistent with theory we develop, our results indicate that waiting has a significant longer-term social cost: we estimate that a 38% increase in the average wait results in a 14% decrease in donations per year.

In the second essay, we distinguish between two biases in beliefs, both of which could explain why individuals over-estimate the probability of high-payoff outcomes. The first is optimism or wishful thinking, where individuals, independent of their own performance, over-estimate the probability of outcomes they prefer. The second is overconfidence, where agents believe they perform better than they actually do. We design and implement an experiment to assess (i) how optimism and overconfidence relate at the individual level and (ii) how optimism and overconfi-

dence jointly affect how individuals form beliefs about uncertain outcomes. A key strength of our experimental design is that it establishes a subject-level control against which all experimentally induced shifts are measured. We report two main findings. First, optimism and overconfidence are positively correlated at the individual level. Second, both optimism and overconfidence help to explain why individuals over-estimate high-payoff outcomes. Previous work tends to focus solely on overconfidence to explain puzzling economic behavior. A leading example is over-entry into self employment. Our findings suggest that, since the role of optimism is omitted, the estimated impact of overconfidence on behavior is upwardly biased.

In the third essay, we study how individual traits shape information demand and acquisition to drive exploratory and innovative behavior. Using a laboratory experiment, we are able to examine how traits directly drive innovation versus how they indirectly drive innovation through information acquisition. We first study the impact of exogenously-assigned information on innovative behavior and we show that the exogenously-assigned information treatments generate two types of entrepreneurs: "Jacks of All Trades" accumulate a wider range of knowledge by exploring more ideas and "Specialists" are more exploitative and fine tune their ideas. Further, we find that individual traits play a predictive role in determining exploratory behavior and successful innovation, but that the same traits play a differential role depending on the type of information assigned. In particular, we find that Extroversion and Openness are assets for "Jacks of All Trades" while Risk-Aversion is an asset for "Specialists". In an Information Choice Treatment, we allow another group of subjects to choose the type of information that prefer to receive and find that more Extroverted prefer information consistent with becoming a "Jack of All Trades", while the more risk-averse choose information consistent with becoming a "Specialist". Further, once the choice of information is endogenous, individual traits fail to predict innovative behavior.

1 Waiting to Give

1.1 Introduction

When deciding whether to engage in pro-social behavior, individuals weigh both the benefits and costs. Benefits ranging from increased social status and personal feelings of warm glow are weighed against the opportunity cost of time. Economists have almost exclusively examined this decision from the benefits' side (i.e., demand-side) and specifically focused on the effectiveness of incentives to encourage pro-social behavior (Fehr and Gächter, 2000; Fehr and Falk, 2002; Gneezy and Rustichini, 2000; Lacetera et al., 2013, 2014). One of the reasons for the almost exclusive attention to the benefits side is that in pro-social settings, individuals do not always respond to incentives as standard economic theory predicts (Gneezy et al., 2011). In particular, individuals are less responsive to extrinsic benefits when pro-social behavior is highly intrinsically motivated (Deci et al., 1999) or when there are social status concerns (Ariely et al., 2009; Bénabou and Tirole, 2006). However, there is much less research focusing on whether (and how) individuals respond to changes in costs for pro-social behavior,[1] and no research has examined how the costs of volunteering time affect pro-social behavior.

This paper asks what happens when pro-social behavior becomes more costly in terms of time. We do so in the context of blood donations, where an individual obtains new information about the donation process when he donates (e.g., how he felt after the donation, the degree of discomfort and the length of time he waited) and this new information can then affect future donation decisions. Wait time, in particular, is a cost incurred by all donors, is observable and exogenously varies, providing a good test of whether longer waits (i.e., higher costs) affect future behavior.

We hypothesize that, ceteris paribus, longer waits will have a negative effect on: (1) donors' reported satisfaction with their experience; and (2) donors' future donation behavior. The second

[1] There is also a smaller supply-side literature that examines charitable contributions at various matching rates (Eckel and Grossman, 2008; Karlan and List, 2007; Meier, 2007). This literature exclusively examines the price of giving in terms of monetary value (i.e., where the price to donate each dollar falls as the match increases), whereas the "price" of giving in our study is determined by variations in the time to make a blood donation.

hypothesis is theoretically motivated in Section 1.2.4 by (1) assuming donors update future wait time expectations based on current experience (i.e., a longer current wait indicates a longer future wait) and (2) that volunteer donors respond to costs and benefits in standard ways, i.e., donate more (less) when the benefits (costs) increase. Field studies have found a positive significant relationship between economic reward offers and blood donations (Lacetera et al., 2013), but none have examined the effects of donor costs.

The first hypothesis is motivated by past research that finds that longer waits incite customer frustration and annoyance and lead to lower service evaluations in non-pro-social contexts (Dube-Rioux et al., 1989; Hui and Tse, 1996; Taylor, 1994). However, previous wait time research has had to rely on service evaluation and future intentions as proximal outcome measures since return behavior at the individual level has been unavailable. Hence, our results offer the first test that longer waits not only negatively affect attitudes but also future behavior such as delayed returns or not returning at all.

Access to actual behavioral data means that we are not forced to rely on satisfaction and intentions data to draw inferences on actual behavior (Card et al., 2012). This is particularly advantageous as stated preferences may not support, and at worst may contradict, revealed preferences. Extensive research in psychology finds that stated preferences align with aspirations and goals while revealed preferences may reflect more pragmatic concerns and greater responsiveness to costs (Glasman and Albarracín, 2006; Sheeran, 2002). The difference between stated intentions and actions may be further exacerbated by social desirability biases in an altruistic context. For instance, Levitt and List (2007) report a gap between subjects' stated preferences for pro-social behavior in the laboratory and their actual behavior in the field. In the context of blood donations, Glynn et al. (2003) report that survey respondents indicate that offering health-related services would be an effective incentive to donate blood and lottery tickets would not. Subsequently, Goette and Stutzer (2008) offer incentives for blood donations and find that cholesterol tests are ineffective, while lottery tickets are effective.

We use data from the Australian Red Cross Blood Service (the Blood Service), supplemented by survey data, collected across four centers in July 2009 to test the effect of wait time on three outcomes: satisfaction, intention to donate and actual return donation behavior. Our wait time measure is provided by the Blood Service administrative records that records arrival time and needle-in time.[2] Our sample consists of whole blood donors in July 2009 who donate whole blood or plasma on their subsequent return donation or do not return within the following 44 months (see Section 3.2 for a discussion). The return data is the key component of our contribution and highlights the institutional features of the Blood Service that make it particularly suitable for our question. Namely, in Australia, the Blood Service has a monopoly on all blood product collection and thus, unlike most countries including the United States, we need not be concerned that individuals switch to alternative donation services in response to experiences with the Blood Service (Lacetera et al., 2012). Additionally, unlike other studies, we follow donors for nearly four years after the survey and thus our results are not driven by an arbitrary stopping time or truncated observation.

We report two main sets of findings. First, longer waits negatively affect future donation behavior. As hypothesized, we find that donors who experienced longer waits delay their next donation, regardless of the blood product being donated upon return. In Australia, whole blood donors can donate plasma 3 weeks after a successful whole blood donation and can donate whole blood 12 weeks after a successful whole blood donation. Thus, a delayed return translates into substantial losses in the expected number of yearly donations. Based on our estimates, we calculate that if whole blood donors waited one standard deviation longer than average (20 minutes) this would result in a loss of approximately 14% (or 88,000) of whole blood donations in Australia.

We further observe that longer waits negatively affect additional pro-social activities; similar to many contexts in which donors have a range of volunteer options, whole blood donors have several alternatives for volunteering. We find that longer waits to donate whole blood not only cause whole

[2] The variation in wait times is mainly driven by staffing constraints, but additional variation may also come from differences in the time to complete paperwork and time for the donor's eligibility interview (discussed in Section 1.2.1). The key identifying assumption is that the length of time a donor waits is not correlated with unobservable factors that may also affect his propensity to donate. We address this concern by instrumenting for the donor's wait time using the wait time of the donor who arrived at the center immediately before and immediately after the focal donor.

blood donors to delay their return to donate whole blood, but to also be less likely to convert to a plasma donation at their next donation.[3]

Second, while we draw similar overall conclusions from the survey responses to satisfaction and future intentions as with the actual return behavior, we also show that there are two major shortcomings of relying on the satisfaction and intention data. First, without the actual return data, we would not be able to calibrate the magnitude or costs of the effects of longer waits on the whole blood supply. The second shortcoming is that the survey responses do not reflect the heterogeneity we capture in the actual return behavior. In particular, men and women respond to increased time costs in different ways. Male whole blood have an elastic response: longer waits cause male whole blood donors, but not female, to delay their return to give whole blood. This finding corroborates existing laboratory and field evidence that demand for altruism is more elastic for males than females (Andreoni and Vesterlund, 2001; Andreoni et al., 2003; Conlin et al., 2003).

However, we also find that female donors respond to longer wait times by a decreased propensity to donate through alternative channels. Namely, longer waits cause women, and not men, to be less likely to convert to plasma in their subsequent donation. Our results suggest that both males and females are responsive to cost changes, but respond along different dimensions. These results contribute to the literature that seeks to understand gender differences in response to variations in costs and benefits of altruism (Cox and Deck, 2006; Croson and Gneezy, 2009; Dellavigna et al., 2013).

Overall, our results suggest that cost management, in addition to incentives, can be an effective tool for policy-makers and organizations to encourage pro-social behavior. The most direct way of managing the cost of waiting is by reducing wait times by restructuring personnel. In fact, in 2013 the Blood Service began moving administrative tasks away from the center operations, effectively

[3]This is important because most countries experience much greater plasma than whole blood shortages and thus converting donors from whole blood to plasma is a goal of many blood collection agencies (Slonim et al., 2014). In fact, worldwide plasma shortages are so severe that many countries, including Australia, rely on importing plasma from the United States. Slonim et al. (2014) give a comprehensive review of the benefits of plasma donation over whole blood donation. For instance, plasma donors can give more plasma and make donations more frequently than whole blood donors. Further, recipients can receive plasma donations from a donor of any blood type.

lowering average wait times by over 20%.

1.2 Design

1.2.1 Institutional Details

Australia provides an ideal setting in which to study blood donor behavior at the individual level because the Blood Service has a monopoly on donation services. We are thus able to precisely measure the effects of wait time on future donations no matter what blood product a donor supplies or where the donor supplies the blood product within Australia.[4]

To give whole blood in Australia, a donor must not have made a whole blood donation within the preceding 12 weeks or a plasma donation in the preceding 3 weeks.[5] Thus, a donor who donates only whole blood can make 4 or 5 whole blood donations per year. The eligibility requirements for other blood products are often individual-specific and depend on the health needs of the donor. Table 1.1 classifies the type of donation in July 2009 by blood product–whole blood and other. For our purposes, we will focus only on donors who gave whole blood in July 2009 and returned to give whole blood or plasma, or did not return.[6]

When a donor arrives at the donation center, he registers at the front desk, completes a short personal history survey and then waits in the lobby until he is escorted to the processing interview where his eligibility is assessed via an interview with the Blood Service staff. If deemed eligible, he is directed to a second waiting room and waits until a staff member calls him into the donation

[4] From the researcher's perspective, the lack of alternative donation organizations means that we do not have to be concerned with past donors choosing to make their future donation with another organization (Cairns and Slonim, 2011; Gross, 2005). This is a particularly important feature when studying the effect of costs and benefits on subsequent donation behavior. As shown in Lacetera et al. (2012), donors will substitute across donation locations in search of the best donation experience.

[5] In Australia, there are several requirements to be an eligible whole blood or plasma donor, however only the requirements relevant to our study will be discussed here. See http://www.donateblood.com.au/ for a full description of the eligibility requirements in Australia.

[6] We do not study the behavior of donors who give anything other than whole blood mainly because the number of these donors that we observe is too small. We also do not study donors who give for therapeutic reasons since their donations are the result of health conditions that require they give blood. We also do not study less common blood product donations since they do not have the same standard window of eligibility as whole blood that is key for our identification of delayed return behavior.

room where he begins his donation. The centers record the time the donor registers with the front desk upon arrival and the time the needle is inserted to begin the draw of blood. We consider the total wait time to be the number of minutes that elapse from the time the donor registers at the front desk to the time the needle is inserted.

During a whole blood donation, 470 milliliters of whole blood are extracted in a procedure that lasts approximately 8-12 minutes. When his donation is complete, he exits the donation room and enters the recovery room where drinks and food are provided. The donor is encouraged to remain in the recovery room for at least 15 minutes for precautionary health reasons, but is free to leave at will.

1.2.2 Data

We administered a field survey from July 8 to July 31, 2009 in four donation centers in the greater Sydney region.[7] Trained surveyors administered the survey in the recovery room after the donation process. The survey took approximately 5-10 minutes to complete and 98% of donors completed the survey, resulting in 1,370 completed surveys.[8]

We then matched the respondents with administrative data provided by the Blood Service. The administrative data include donation histories after July 2009 so that it is possible to identify when, if ever, survey respondents returned and the blood product donated upon return. Table 1.1 shows that of the 1,370 survey respondents 1,251 donors were successfully matched to an administrative record.[9] Of those 1,251, 73% donated whole blood, 20% donated plasma and 7% gave another blood product.

Since blood products require varying time lags between donations, it is necessary to know the type of blood product the donor gave when (if ever) he returned to analyze return behavior. Of

[7] See Appendix A for a copy of the survey instrument. There are a number of variables from the survey that we chose not use, in particular data on expectations. While this could be a valuable variable, the survey was given after the donation (and importantly after the donor experienced his wait time) and thus we cannot be sure to what extent the current wait time influenced the self-reported expectations about the wait time.

[8] The 98% response rate is not surprising in this context; the blood service encourages donors to remain up to 15 minutes before leaving the center, thus the survey offers them something to do before leaving.

[9] Unsuccessful matches occurred due to invalid donor numbers.

the 916 whole blood donors in July 2009, 66 observations were dropped due to missing outcome data and implausible wait times (see below for a further discussion), 649 returned to donate whole blood, 72 returned to donate plasma, and 127 had not returned within 44 months after the survey date, our last collection of data (henceforth referred to as never returned).[10]

For the majority of our analyses, we will focus on the 848 individuals we could match to administrative records, have a complete record on all outcomes, donated whole blood during our survey time and subsequently returned to donate whole blood, plasma or did not return. Table 3.1 describes these 848 donors in our survey sample together and by their actual return behavior. The average time spent waiting before the donation begins was 43 minutes (median of 39 minutes) and donors arrived throughout the day (morning, lunch, and afternoon) in relatively similar proportions. Survey respondents made an average of 1.4 donations per year. Slightly less than half of our survey respondents are female and the average donor was 44 years old. Nearly all of the survey respondents made their donation at two of the four donation centers. Roughly 4% and 10% percent of our sample have AB Positive and O Negative blood types, reflecting the national average; controlling for blood type is important because the Blood Service encourages (discourages) AB positive (O Negative) donors to convert to donating plasma because of the relatively limited (universal) usage of their blood type.[11]

Our results focus on three outcomes: satisfaction, intention and return behavior. Satisfaction is measured by the donor's response to the question "How satisfied were you with the overall experience today?" where 1 indicated "Not at all satisfied" and 7 indicated "Completely satisfied". Intention to donate is measured by the donor's response to the question "What is the likelihood that you will donate again in the next 6 months?" where 0 indicated "No Chance" and 10 indicated "Completely certain". Figure 1.1 shows the heavy left skew of the responses to these two survey

[10]There may be an additional group of individuals we do not observe who arrive at the donation centers to make a donation, but then leave prior to checking in. These individuals may leave for a variety of reasons, including reasons that are orthogonal to the wait time. However, they may also leave because they are discouraged by observing long lines or crowded waiting rooms that could signify a long wait. To the extent that these individuals leave because they are more sensitive to longer wait times, while the donors in our analysis chose to wait, we will under-estimate the true population effect of wait time on the outcomes.

[11]We focused our collection efforts at the busiest of the four centers.

questions, which is a common feature in satisfaction and intention survey responses (Peterson and Wilson, 1992).

We analyze return behavior from three perspectives. First, we examine the return behavior of all whole blood donors irrespective of the product they donated upon return. Second, we analyze the return behavior of the same whole blood donors, but distinguish whether the return donation was whole blood or plasma. Third, we exclude the whole blood donors from July 2009 who returned to donate plasma in their subsequent donation in order to quantify the effect of longer waits on the whole blood supply.

Our measure of wait time is taken from the administrative data and is recorded as the difference, in minutes, between the registration time (i.e, arrival time) and the start of donation (i.e., “needle in” time). This includes the time the donor spends completing paper work and waiting for the eligibility interview, the interview time, and then the time after the interview before the needle is inserted to begin the blood draw.[12] Figure 1.2 shows the distribution of wait time in minutes. Interpretation of the estimates is facilitated by subtracting the average wait time, $\overline{\text{Wait}}$. Thus our measure of wait is

$$\widetilde{\text{Wait}}_i = Wait_i - \overline{Wait}$$

1.2.3 Identification

Figure 1.2 shows the variation in wait time across donors. Variation in wait time is mainly driven by variation in staffing and variation in the length of the processing interviews that determine eligibility. Figure 1.3 plots the wait time by average yearly donation rate and shows a slight downward trend. To address this potential endogeneity, we will explore two channels through which more frequent donors may obtain shorter wait times. First, donors who donate more frequently may know when the donation center is likely to have shorter wait times and thus plan their arrival accordingly.

[12] We dropped 10 observations whose wait times appeared to be data entry errors: four donors with recorded wait times less than 8 minutes and 6 donors with recorded wait times beyond 2 hours. A wait time of less than 8 minutes seems technically impossible given the time for an eligibility interview, and the wait times over two hours are more than four standard deviations above the average wait time. The results that follow are not sensitive to the exclusion of these 10 observations.

Second, more frequent donors may have shorter processing time at the center due to unobservable characteristics that may also influence their propensity to donate in the future, such as health issues or frequent travel that complicate the eligibility assessment.[13] Section 1.2.3 discusses and rules out the former and Section 1.2.3 instruments for wait time to address endogeneity due to the latter.

Strategic Arrival First, we examine the possibility that wait time is endogenously determined by more frequent donors that strategically plan their arrival in order to obtain a shorter wait time. For this to be possible, there must be certain days of the week or times of day that have significantly shorter waits at each center. Using historical data (all data before July 2009), we estimate the average wait time each day of the week and at three times during the day (morning, lunch hour, and afternoon) at each center (resulting in 15 time blocks per center). Figure 1.4 plots the 15 times blocks in order from the shortest historical wait times to the longest historical wait times at centers A and D.[14] The height of each of the 15 bars represents the average yearly donation rate of the donors from our sample who arrived during the time block. Strategic arrivals would suggest that the height of the bars would decrease from left to right (i.e., more frequent donors arrive during the historically shortest wait times and less frequent donors arrive at during the longest wait times). Instead, we find no evidence of strategic arrivals; the average donation frequency of donors across the 15 times blocks are not different at center A or center D.

Instrumenting for Wait Time Second, we address whether the variation in wait times that may be generated by unobservable differences in completing the paperwork and the length of the eligibility interview, as opposed to exogenous variation in wait times, drive our results. We instrument the donor's wait time with the wait time of the donor who arrived just before and just after the focal donor. The first stage results are presented in Table 1.3 and show that the set of instruments

[13]These unobservable factors might result in different wait times due to differences completing the required paperwork or answering questions during the eligibility interview.

[14]At center A, the list of the 15 time blocks from shortest to longest historical wait times is as follows: Monday PM, Monday AM, Wednesday AM, Friday PM, Tuesday PM, Thursday AM, Firday AM, Monday Lunch, Thursday Lunch, Tuesday AM, Wednesday PM, Wednesday Lunch, Tuesday Lunch, Friday Lunch. At center D, the equivalent list is: Monday AM, Monday PM, Tuesday AM, Wednesday AM, Friday AM, Friday PM, Wednesday PM, Monday Lunch, Tuesday Lunch, Thursday AM, Thursday PM, Thursday Lunch, Wednesday Lunch, Tuesday PM, Friday Lunch.

are strong. Table 1.3 shows that donors' wait times are highly correlated with the wait time of the donor who arrives just before and just after them (p-value$<$.001). We present the IV estimation results in Section 3.3.

A potential concern with our instrument would occur if donors who are similar along the dimensions that may jointly affect the propensity to donate and the length of eligibility interview (in particular, age- and gender-specific health concerns) are more likely to arrive at the center at similar times. For example, if female donors are less likely to donate due to gender-related health concerns (e.g., pregnancy or low iron levels) and these health concerns also prolong the eligibility interview and lengthen wait times, then our instrument is only valid if the donors who arrive before and after the female donor are equally likely to be female and male. This is indeed the case; Figures A.1 and A.2 show that the average age and proportion of females does not significantly vary by arrival time throughout the week at each center.[15] Thus, the wait time of the donor who arrived just before and just after a donor provides a strong instrument for donor's wait time.

1.2.4 Econometric Specification, Conceptual Framework and Hypotheses

We estimate a hazard model to study return behavior of whole blood donors for two main reasons. First, nearly 88% of whole blood donors eventually return to donate. Thus, in understanding the effect of wait times on subsequent donation behavior the question is not whether donors return, but by how long their return is delayed. A delayed return has long-lasting repercussions; a donor who had planned to donate every 6 months may delay a return after a long wait, and thus all other planned donations are now delayed by at least 6 months. Second, unlike a discrete choice model (i.e., return or not return), the hazard model does not require us to choose a "return date", which will be arbitrary. Additionally, the hazard model accounts for the non-normality of the duration distribution (see Figure 6(a)) and the right censoring of the data.

We parameterize the baseline hazard in order to estimate the expected number of days a donor delays his return donation. Our choice of parametrization varies depending on the shape of the

[15]Figures A.1 and A.2 in Appendix show the arrival by gender and by age for the two main centers separately.

non-parametric baseline hazard of the relevant sample and model diagnostics. We will consider three main hazard models.

First, we will consider the return behavior of all 848 whole blood donors, irrespective of their return donation choice (i.e., plasma or whole blood). Figure 6(b) shows the non-parametric baseline hazard. Although the baseline hazard is non-monotonic and thus suggests the use of a Log-logistic parametrization, the Gompertz distribution performs better in terms of likelihood. For this reason, we will present the Gompertz proportional hazard specification in Section 3.3 and the Log-Logistic specification in Appendix A, which provides qualitatively equivalent results.

Second, we will consider the return behavior of all 848 whole blood donors, but we will allow the baseline hazard to vary depending on the type of product donated upon return. When the baseline hazard is stratified by product type donated upon return, as shown in Figure 6(c), then the hazards are monotonic and the Gompertz distribution provides the best fit in terms of likelihood.

Third, we consider only the return behavior of the 776 whole blood donors who returned to give whole blood and those who did not return. Again, the baseline hazard is monotonic and the Gompertz distribution provides the best fit.

Conceptual Framework We model the decision of when to return to donate after a successful donation. Let t denote time, where a donation event occurs at $t = 0$ and a second donation event occurs at $\hat{t} > 0$. At $t = 0$, donor i receives a benefit, b^i, and pays a cost of $c^i_{t=0}$ at the time of donation. A donor's preferences for blood donation can be represented by a utility function $u(b^i, c^i_t)$ which maps $(b^i, c^i_t) \rightarrow \mathcal{R}^+$, where $\frac{\partial u(b^i,c^i_t)}{\partial b} \geq 0$, $\frac{\partial u(b^i,c^i_t)}{\partial c} \leq 0$, $\frac{\partial^2 u(b^i,c^i_t)}{[\partial b]^2} < 0$. For each $t \in [0, \hat{t} - 1]$, the donor receives utility of $\delta^t u(b^i, 0)$ with $\delta \in (0, 1)$, which captures the idea that donors continue to receive benefits over time from having made a donation t periods earlier, but we assume that this utility diminishes over time reflecting the pure, impure and warm glow benefits of the donation depreciating over time. At time t, the donor has an expectation of the cost given by $E_t[c^i_t|c^i_0] = f(c^i_0)$, where $\frac{\partial f(c^i_0)}{\partial c^i_0} > 0$. Additionally, donor i discounts future utility by a factor of β^t, where $\beta \in (0, 1)$. The donor's problem is to choose $\hat{t} = t^*$ where t^* maximizes his lifetime utility.

$$u(b^i, c_t^i) = \Sigma_{n=1}^{\infty} \left[\Sigma_{t=0}^{\hat{t}-1} (\delta\beta)^{nt} u(b^i) - \beta^{n\hat{t}} E \left[c_{nt}^i \right] \right] \quad (1)$$

Equation 1 can be written recursively:[16]

$$V(c_0^i) = max_{\hat{t}} \left[u(b^i) \frac{1 - (\beta\delta)^{\hat{t}}}{1 - \beta\delta} - \beta^{\hat{t}} E \left[c_{\hat{t}}^i \right] + \beta^{\hat{t}} V(c_{\hat{t}}^i) \right], \;\; E_t \left[c_{\hat{t}}^i \right] = f(c_0^i) \quad (2)$$

From the perspective of time t, the problem for $t' > t$ is exactly the same and so $V(c_0^i) = V(c_{\hat{t}}^i)$. Hence we substitute $V(c_0^i) = V(c_{\hat{t}}^i) = V$ into equation 2 and obtain

$$V = max_{\hat{t}} \frac{1}{1 - \beta^{\hat{t}}} \left[u(b^i) \frac{1 - (\beta\delta)^{\hat{t}}}{1 - \beta\delta} - \beta^{\hat{t}} f(c_0^i)] \right] \quad (3)$$

Maximizing equation 3 to determine the optimal time until the next donation, t^*, the first order condition simplifies to:

$$ln(\beta) \left[1 - (\beta\delta)^{t^*} \right] - \delta^{t^*} ln(\beta\delta) \left[1 - \beta^{t^*} \right] = \frac{f(c_0^i)(1 - \beta\delta) ln(\beta)}{u(b^i)} \quad (4)$$

Implicitly differentiating 10, it is straightforward to show that t^* increases as the cost of the last donation c_0^i increases and the benefits of donating decrease:

$$\frac{\partial t^*}{\partial c_0^i} = -\frac{f'(c_0^i)(1 - \beta\delta) ln(\beta)}{u(b^i) \delta^t ln(\beta\delta) ln(\delta)(1 - \beta^{t^*})} > 0 \quad (5)$$

$$\frac{\partial t^*}{\partial b^i} = \frac{f(c_0^i) u'(b^i)(1 - \beta\delta) ln(\beta)}{u(b^i)^2 \delta^t ln(\beta\delta) ln(\delta)(1 - \beta^{t^*})} < 0 \quad (6)$$

Equation 13 indicates that as the experienced cost increases, the optimal time until the next donation will be longer; intuitively, the higher expected future costs will be pushed further into the future as the anticipated marginal cost of donating $(f'(c_0^i))$ increases. Equation 14 shows that

[16]The Principle of Optimality indicates that the solution to the maximization problem of the sequential problem written in equation 1 is equivalent to the solution of the recursive problem in equation 2.

as the benefits of donating increase, the optimal time until the next donation will become shorter; intuitively, donors will return sooner to receive the higher benefits.[17]

Empirical Model To analyze the effect of wait time on the delay until the next donation, we estimate the following log-likelihood equation via maximum likelihood[18]

$$lnL(p,\theta) = \Sigma_{i=1}^{n} d_i ln\lambda(t_i, \mathbf{x_i}|p,\theta)S(t_i,\mathbf{x_i}|p,\theta) + \Sigma_{i=1}^{n}(1-d_i)lnS(t_i,\mathbf{x_i}|p,\theta) \quad (7)$$

where the Gompertz distribution specifies $\lambda(t_i, \mathbf{x_i}|p,\theta) = \exp(pt)\exp(\mathbf{x_i'B} + \gamma\widetilde{Wait_i})$ is the hazard function, $S(t_i, \mathbf{x_i}|p,\theta) = \exp(-p^{-1}\exp(\mathbf{x_i'B} + \gamma\widetilde{Wait_i})\exp(\gamma t) - 1)$ is the survival function, p is the shape parameter of the Gompertz distribution. The parameters on the covariates, γ_i and $\mathbf{B}$, govern the relationship between wait time and likelihood to return at time t and a vector of control variables (dummy for age 65, female, donation history, blood type, center fixed effects, time of day fixed effects and day of week fixed effects), respectively.

Equation 13 predicts that longer wait times decrease the hazard; that is, the longer a donor waits the less likely he will return at time t conditional on having not yet returned. In particular, we predict that $\frac{\partial t^*}{\partial c_0} > 0$.

Hypothesis 1. *Longer wait times have a negative effect on the hazard rate,* $exp(\hat{\gamma_i}) < 1$ *or* $\hat{\gamma_i} < 0$.

To study the effect of wait time on satisfaction and intention we estimate an ordered probit model, which takes into account the ordinal nature of the discrete survey responses (Aitchison and Silvey, 1957; McKelvey and Zavoina, 1975).

We estimate the probability that a donor states each level of satisfaction by maximum likelihood. We model the probability of donor i choosing response m as

[17] Appendix A also shows that the relationship between t^* and δ and β depends on the relative magnitudes of β and δ.

[18] We have also estimated a random effects estimator in which we allow for unobserved heterogeneity. The results are qualitatively similar and available upon request.

$$P[\text{satisfaction} = m] = \Phi(\mu_m - \alpha_i \widetilde{Wait_i}) - \Phi(\mu_{m-1} - \alpha_i \widetilde{Wait_i}) \tag{8}$$

We hypothesize that the reaction to wait time in the pro-social context will be similar to the reaction observed in the non-pro-social contexts (Dube-Rioux et al., 1989; Hui and Tse, 1996; Taylor, 1994). Specifically, we hypothesize that a longer wait will decrease the donor's satisfaction with his experience.

Hypothesis 2. *Longer wait times have a negative effect on satisfaction,* $\hat{\alpha}_i < 0$.

Similarly, we estimate the probability that a donor states each level of intention to donate by maximum likelihood and model the probability of a donor i choosing response m as

$$P[\text{intention} = m] = \Phi(\mu_m - \beta_i \widetilde{Wait_i}) - \Phi(\mu_{m-1} - \beta_i \widetilde{Wait_i}) \tag{9}$$

Hypothesis 3. *Longer wait times have a negative effect on intention to donate,* $\hat{\beta}_i < 0$.

Overall, we hypothesize that wait times negatively affect all outcomes. Donors who wait longer are more likely to report feeling less satisfied, less likely to intend to donate again and more likely to have adverse return behavior, either a delayed return or a cessation of donation activities.

Consistent with laboratory (Andreoni and Vesterlund, 2001), empirical (Andreoni et al., 2003) and field evidence (Conlin et al., 2003) which find that females are less responsive to price changes in altruistic settings, we hypothesize that female return behavior will be less responsive to wait time than male return behavior.

Hypothesis 4. *Male return behavior is more sensitive to wait time than female return behavior.*

1.3 Results

1.3.1 Main Findings

Table A.1 reports estimates of the effect of wait time from equations 7-9 on our three outcomes of interest. The dependent variable in the first column, "Likelihood to Return", is the probability of returning at time t to give whole blood or plasma given no return prior to time t. The dependent variables in columns (2) and (3) are the probability of reporting a higher level of satisfaction and intention to donate, respectively. The marginal effects are calculated at the means and represent the change in the probability of reporting the highest level of satisfaction or intention.[19]

The negative coefficients on $\widetilde{Wait}$ displayed in Table A.1 support hypotheses 1, 2, and 3. Column (1) estimates the likelihood of return using the Gompertz distribution.[20] Wait time has a negative effect on the return behavior of donors. Conditional on being eligible, but having not returned to donate, we estimate that a donor who experiences a wait that is 20 minutes (one standard deviation) longer than average is 12% (=-0.006*20) less likely to return on any given day.[21]

Result 1. *The return behavior of whole blood donors is negatively affected by longer wait times. An increase in wait time of one standard deviation (20 minutes) above average reduces the likelihood that a donor returns on any given day by 12%.*

Column (2) of Table A.1 shows the negative effect of wait time on reported satisfaction. Converting the parameter estimate to its marginal effect, we find that an increase in wait time of one standard deviation results in a decrease in the likelihood of reporting the highest level of satisfaction by 8 percentage points.[22]

[19] We do not cluster standard errors at the center level because there are only four donation centers with an imbalance in observations due to two of the centers having the vast majority of the observations (Cameron and Miller, 2013). In estimates not presented here, in which we nonetheless clustered standard errors at the center level, all of the significance levels reported in Table 4 are stronger (since the estimated standard errors are smaller).

[20] See Table A.1 in Appendix A for estimation using the Log-Logistic distribution.

[21] Column (2) also suggests that donors face a decreasing baseline hazard (estimated shape parameter, $\hat{p} = .5 < 1$, and significant at the 5% level). Specifically, the probability that a donor returns at time t, conditional on having not yet returned, is decreasing in t. This means that for each day a donor does not return, the probability that he returns on a given day decreases.

[22] Given the propensity for positivity biases in satisfaction surveys (Peterson and Wilson, 1992), we feel this estimate is reasonable.

Result 2. *The satisfaction of donors is negatively affected by longer wait times. An increase in wait time of one standard deviation (20 minutes) above average reduces the likelihood of a donor reporting the highest level of satisfaction by 8 percentage points.*

Column (3) reports similar effects of wait time on the donor's intention to return–an increase in one standard deviation above the average wait time corresponds to a 6 percentage point decrease in the probability that a donor is 'Completely certain' he will donate again in the next six months.

Result 3. *Intentions of donors are negatively affected by longer wait times. An increase in wait time of one standard deviation (20 minutes) above average reduces the likelihood of a donor reporting that he is 'Completely certain' to donate again by 6 percentage points.*

Table A.1 shows that the negative, significant effect of wait time on both satisfaction and intention to return are overall consistent with the effect on actual return behavior. However, observing the actual return behavior lets us, for the first time, also detect the magnitude of this effect. Moreover, Table A.1 shows similar effects of past donation history and age on satisfaction, intentions and actual return behavior, but a notable gender difference; women stated being both more satisfied and having a greater intention to return, but indeed have a lower propensity to actually return. Thus, the survey response data masks potentially important heterogeneity that we further explore below.

1.3.2 Instrumenting Wait Time

In order to implement the IV strategy discussed in Section 3.2 we discretize the return data and estimate a discrete time hazard model. The return data was discretized as follows: donors who returned during the first year are grouped by the week of their return, donors who returned in years 2-4 following the survey are grouped by year. The probability of return is then estimated as a stacked logit regression with the same set of variables as equation 7 and a dummy for each potential return group (Cameron and Trivedi, 2005).

The IV estimators are obtained with the logit regression via the general method of moments (GMM) and the control function approach (CF). The CF approach estimates the first stage via OLS and the second stage via maximum likelihood with bootstrapped standard errors (Cameron and Trivedi, 2013). The results of the discrete time hazard, and the IV estimated by GMM and CF are displayed in columns (1)-(3) of Table 1.5, respectively and provide qualitatively similar estimates to those shown in Table A.1. In the discrete time hazard and the two estimated IV models, we find that a longer wait significantly delays the time until a donor returns, and on average a one standard deviation increase in the wait time reduces the probability of returning at any t by 12% to 14%.

1.3.3 Competing Risks

After making a whole blood donation, donors are eligible to give another whole blood donation 12 weeks later and a plasma donation 3 weeks later. Table A.1 did not separately analyze the return to whole blood versus the return to plasma. To do this, we estimate a competing risks model, where at any time t a donor is "at risk" to return to give plasma or return to give whole blood. This allows for the estimated baseline hazard to vary depending on the type of return the donor experiences. In this specification, each donor has two observations, one for each potential type of return, but can only return to donate either whole blood or plasma. For this reason, we cluster the standard errors at the donor-level.

The calculated duration for each donor takes into account the differences in eligibility of the two types of return. For example, if a donor returns to give whole blood 14 weeks after his initial donation then he had been eligible to give plasma for 11 weeks and had been eligible to give whole blood for 2 weeks. On the other hand, if a donor returns to give plasma after 4 weeks, then he had been eligible to give plasma for 1 week, but was never eligible to give whole blood. In this case, the donor will not have an observation that tracks his duration of time for whole blood since he was never "at risk" to give whole blood.

Column (1) of Table 1.6 allows the baseline hazard and the coefficient on $\widetilde{Wait}$ to vary by the type of return and specifies that all other regressors do not vary by the type of return. Wait time has a negative effect on a whole blood donor's return to whole blood and plasma. Although the effect of wait time on the return to donate plasma is larger (-.02) than the return to donate whole blood (-.007), a statistical test cannot reject the null that the coefficients are equal (p-value=.22).

Column (2) allows all of the regressors to vary by the type of return. Yearly donation rates and gender have the same effect on return behavior to plasma as on the return behavior to whole blood. On the other hand, older donors return more quickly to whole blood and less quickly to plasma. There are also interesting differences in return behaviors across blood types. AB Positive donors (whose whole blood donations can only be given to other AB Positive donors) return more quickly to make a plasma than whole blood donation (p-value$<$.08). On the other hand, O Negative donors (whose blood can be given to anyone) return more quickly to make a whole blood than plasma donation (p-value$<$.09). These behaviors most likely reflect the Blood Service's efforts to direct O Negative donors to give whole blood and AB Positive donors to give plasma rather than any inherent differences in preferences between donors with different blood types.

Social cost of longer wait times Data from the Blood Service estimates that there were roughly 330,290 whole blood donors in Australia in 2009, resulting in approximately 604,000 donations. This section explores the effect of longer waits on the whole blood supply.

The estimates in Tables A.1 and 1.6 suggest that increasing the expected cost to donate can have large implications on the blood supply. Of the 848 whole blood donors surveyed in July 2009, only 72 returned to give plasma and 649 eventually returned to give whole blood. In light of this propensity to return to give whole blood, this section explores the social costs of longer waits on the whole blood supply. To do this, we will exlude the 72 donors who returned to donate plasma and focus the analysis on the remaining 776 donors.

Column (1) of Table 1.7 estimates the same model as column (1) of Table A.1 with the 776 whole blood donors who returned to give whole blood or did not return. Again, longer waits negatively affect return behavior of whole blood donors.[23] Using these estimates, we calculate

[23]Table A.1 in Appendix A estimates the effect of wait using the semi-parametric Cox Proportional Hazard Model.

the effect an increase in the average wait by 20 minutes (1 standard deviation) would have on the whole blood supply in Australia.

Figure 1.7 plots the survival function estimated in column (1) of Table 1.7 at the average wait time and at a wait time that is one standard deviation (20 minutes) longer than average. The survival function gives the probability that a donor has not returned to donate by time t. Alternatively, $1 - S(t)$ gives the probability that a donor has returned by time t; $1 - S(t)$ can also be interpreted as the proportion of donors who have returned at time t.

One way to calculate the change in donations due to a longer wait is to consider the change in behavior of the median donor–the donor who returns after 50% of the other donors have already returned. From the survival function, it is possible to impute the number of days the median donor returns conditional on his wait time. With an average wait time, the median donor returns 66 days after he is eligible to return. With a wait that is one standard deviation longer than average, the median donor returns 81 days after becoming eligible. Thus, the median donor delays his return by 15 days due to the increased wait time. If a donor systematically returns 66 days after eligibility then he can make 2.43 donations per year, whereas returning 81 days after eligibility results in 2.21 donations per year. This is an estimated loss of .22 donations per donor per year in Australia, resulting in a loss of 73,064 donations per year.

However, Figure 1.7 indicates that the difference between the survival functions widens as time increases, suggesting that donors who are among the first 25% to return have a shorter delay due to increased wait time than the median donor, while the donors who are among the last 25% to return have a longer wait-induced delay than the median donor. Thus, to obtain a more accurate estimate of the number of lost donations, we consider donors in three categories: those among the first 25% to return, those donors who are the last 25% to return and those in the middle 50% to return. We estimate that donors who return among the first 25% will donate 3 or more times per year, while donors who are among the last 25% to return will donate once per year. The donors

The coefficient estimate on $\widetilde{Wait}$ is qualitatively equivalent, which provides evidence that the parametrization of the baseline hazard is appropriate.

who are among the middle 50% to return will donate 1-3 times per year.

The three sets of parallel vertical lines in Figure 1.7 indicate the extra days of delay estimated for donors who return among the first 25%, the middle 50% and the bottom 25% of donors, respectively. A 20 minute increase in the wait of the most frequent donors results in an estimated four day delay in their return donation. However, for the middle 50% and the bottom 25% of donors, a 20 minute increase in the average wait results in a delay of 15 and 122 days, respectively.

In Table 1.8, we calculate the number of lost donations due to wait-induced delays. We estimate that a one standard deviation increase in wait time results in 88,730 fewer donations per year. This implies that an increase in wait time by 38% corresponds to a decrease in donations by 14%, resulting in an estimated elasticity of -.36.[24] Similarly, a decrease in wait time by one standard deviation (62.5% decrease in wait time) corresponds to an expected increase in donations by 11% and results in an estimated elasticity of -.17. Our estimated elasticities are similar in magnitude to the elasticities estimated in Karlan and List (2007) and Eckel and Grossman (2008). Karlan and List (2007) vary the size of a matching donation in the field and estimate a price elasticity of giving at -.30. Eckel and Grossman (2008) study the effects of rebates and matches on charitable donations to the National Public Radio and estimate elasticities of giving between -.35 and -1.03.

One potential concern in calculating the effect of wait time on the whole blood supply is the possibility that whole blood donors are substituting away from whole blood and into another blood product, like plasma, after a long wait for whole blood. However, Table 1.6 showed that waiting for whole blood delayed returns to both plasma and whole blood, suggesting that plasma donation is not viewed as a substitute but rather a complement to whole blood donation. Moreover, not only are whole blood donors delaying their return to donation in response to a long wait, they are also less likely to convert to plasma. Column (2) of Table 1.7 estimates a probit model in which the dependent variable takes a value of 1 if the whole blood donor returned to give plasma on his subsequent donation and 0 otherwise. While the effect of wait time on plasma conversion is small

[24] Given the pro-social context, no alternative blood collection agencies and the lack of a close substitute for donating blood, it is not surprising that the calculated elasticity of demand to donate appears inelastic when compared to standard consumer theory contexts.

in magnitude (an additional 20 minute wait reduces the likelihood of converting to plasma by 1.6 percentage points), the negative relationship suggests that our estimate on the whole blood supply is a lower bound. Not only are whole blood donors delaying their return to whole blood, but they are less likely to convert to plasma.

Longer wait times not only reduce the expected number of donations per year, but the time spent waiting is also valuable as it could be allocated to alternative activities. In fact, the main insights of Becker (1965) apply; the social cost of requiring a donor to wait 20 minutes longer per donation on average has two components–a loss in future donations and a loss of about 12 million minutes of time (equivalent to about 97 years of full time work).

1.3.4 Heterogeneity in Wait Time Effects

Effect of Gender This section considers whether men are more responsive to time costs than women and examines the robustness of Andreoni and Vesterlund's (2001) laboratory results not only in the field,[25] but also for a change in wait time costs (rather than monetary costs), to return to make a blood donation (rather than to make a monetary donation) and time horizon of several years (rather than a few minutes in the laboratory).

We present estimates of the Gompertz proportional hazard models presented in Tables A.1, 1.6 and 1.7, but interact wait times by gender. Table 1.9 shows that men and women respond to longer wait times differently, contributing to the growing literature on gender differences (Croson and Gneezy, 2009). Columns (1) and (2) show that both men and women are dissatisfied by longer waits and longer waits reduce their intention to donate. In fact, in column (1), the coefficient on wait time for women is more negative than it is for men, suggesting women are experiencing more

[25] In some studies, behavior in the field has been quite different than in the lab (see for instance Kessler (2013) for an extensive discussion of gift exchange experiments in the lab and field). There are many potential reasons why behavior may differ in the lab and in the field (e.g., experimental procedures, payoff differences, and relative costs and benefits). In the context of blood donations, Lacetera et al. (2013) points out that the extensive survey and laboratory evidence finds that incentives have a negative effect on pro-social behavior, whereas the recent the field evidence robustly finds that incentives increase donations. Whether gender differences in response to differential monetary costs in a laboratory dictator game are robust to different wait time costs in blood donations is thus a tough robustness test.

dissatisfaction from longer wait times than men.

However, columns (3) and (4) corroborate previous findings on gender differences: men are significantly more elastic in their response to times costs than women. The estimates in column (4) suggest that a 38% increase in the time cost of donation corresponds to a 16% reduction in the number of whole blood donations made by men, resulting in an elasticity of -.40. On other hand, the estimates indicate that we cannot reject that women are perfectly inelastic; women do not change the number of whole blood donations in response to the change in time cost.

In columns (5) and (6), we estimate the competing risk model presented in Table 1.6 and find that both men and women are responsive to time costs, but along different dimensions. In response to longer waits, male whole blood donors delay their return to whole blood and do not significantly alter their return to plasma. In contrast, female whole blood donors do not significantly delay their return to whole blood, but respond to the longer waits by reducing their propensity to convert to plasma and, upon conversion, delaying their return to a plasma donation.

Interestingly, the effect of wait for men is not significantly different across the two types of returns, but it is for women. Female donors who return to give whole blood respond significantly different to longer waits than females who return to give plasma and males who return to donate plasma or whole blood.

In sum, longer waits cause men to delay their return overall, and we cannot reject that this delay is different for making a subsequent whole blood and plasma donation. However, overall, women are insensitive to wait time, and longer waits only delay time until donating plasma.

Result 4. *Longer waits times have negative effect on male and female return behavior. In response to a longer wait, males delay their overall return to donate any blood product, while females only delay their return to donate plasma.*

Effect of Experience This section explores heterogeneity in wait time effects across donors with varying donation frequencies. If donors update their expectation about costs according to Bayes rule, then a frequent donor's expectation about a future wait time will be impacted less by a single wait time. In this case, we would expect frequent donors to be less responsive to the current wait time since the current wait time is only one of many. To explore this, Table 1.10, Column (1) interacts wait times with a dummy variable that takes a value of 1 if a donor has made more than 7 (median) lifetime whole blood donations. As expected, the coefficient on the interaction is positive, suggesting that more frequent donors are less responsive to longer waits, but the coefficient is not significantly different than zero. Finally, column (2) interacts wait time with a dummy that takes a value of 1 if the donor is a first-time donor. The coefficient suggests that first-time donors are more sensitive to long waits than repeat donors, however, again, the coefficient is also not significant.[26]

The estimates in Table 1.10 suggest that experience does not significantly affect a donor's responsiveness to longer waits. That is, regardless of donation history, donors respond similarly to their current wait times. This is suggestive evidence that while expectations about wait times might be a weighted average of all previous wait experiences, the most current wait time is weighted heavily, while previous wait experiences are substantially discounted or forgotten.[27] This observation is consistent with an adaptive learning model where the weight on past observations is negligibly small. Using laboratory data, Erev and Roth (1998) fit a learning model to interactive play and find that the model that best fits the data places 90% of the weight on the most recent event, and 10% on past expectation.

1.4 Conclusion

This paper estimates the effect of wait time on the satisfaction, intention to donate and actual return behavior of blood donors. We estimate that whole blood donors have a time cost elasticity of -.36: for a 38% increase in wait time there is a 14% decrease in whole blood donations. Thus, longer wait times entail substantial social costs.

Our main contribution is the use of actual return data, which is only possible given our context–

[26]The insignificant effect of the interaction of Wait by New Donor in column (2) may be due to an issue of low power (e.g., N=80) since the estimated effect is larger than the main effect of wait.

[27]Recency can be attributed to either discounting past information or events or to limited memory. Our data do not permit an exploration of the mechanism, but Fudenberg and Levine (2013) show, that under certain criteria, there is an equivalence between learning models with limited memory and those with information discounting.

the Blood Service's monopoly on blood collection implies that we are able to precisely track and measure individual donation behavior and need not worry about donors substituting across alternative blood collection organizations. This means that our data allows us to go beyond measures of satisfaction and intention to estimate the effect of wait time on subsequent donations.

The effect of an increase in the cost to donate is estimated using individuals who have revealed a preference for blood donation. Thus, we expect that our results underestimate the population effect since only individuals who are not sufficiently time-pressured choose to donate blood and individuals for whom the time cost is most restrictive are not active donors. Additionally, we expect our results would underestimate the population effect if the most time-pressured donors strategically time their arrival to obtain a shorter wait, thereby curtailing the cost of donation.

Our estimates of the effects of wait time on blood donations might also substantially underestimate the effects in other contexts to the extent that there are few close substitutes for supplying blood products and that the benefits (saving lives) might make donors even less sensitive to costs than in other contexts where volunteering has closer substitutes and less value to beneficiaries.

Our results contribute to the literature on the external motivations for pro-social behavior. While the literature has mainly focused on the effects of a change in the benefits of such behavior, we examine the effect of a change in costs. Our results suggest that the management of the cost of pro-social behavior, in addition to the benefits, may be an additional or alternative tool for policy-makers and organizations to encourage pro-social behavior.

We have focused on wait time as an important cost that volunteers incur when donating blood products. There are, however, many other costs associated with volunteering that deserve attention in future research. In the context of blood products, reducing the distance donors have to travel and lowering discomfort and (perceived) safety risks may also be viable approaches to encourage blood donation. Moving beyond blood donation and examining the effect of costs in other contexts would also be a fruitful avenue to further our understanding of pro-social motivations.

1.5 Tables and Figures

TABLE 1.1: DONORS IN OUR SAMPLE

Survey respondents			1370
Matched to administrative data			1251
July 2009 Donation Type			
Whole Blood			916
Return Donation Type			
WB, Plasma or No Return		914	
No missing outcome data	848		
Return, whole blood	649		
Return, plasma	72		
No Return	127		
Other product		2	
Other			335
Plasma		245	
Autologous		3	
Apheresis Platelets		46	
Therapeutic		41	

TABLE 1.2: SUMMARY STATISTICS

	All donors	WB Return	Plasma Return	No Return
Actual Wait Time (min)	42.74	42.39	39.07	46.62
	(18.79)	(18.44)	(16.73)	(21.05)
Median Wait Time (min)	39	39	35.5	39
Yearly Donation Rate	1.35	1.39	1.39	1.15
	(.66)	(0.65)	(.72)	(.65)
Female	.46	.45	.43	.54
	(.50)	(.50)	(.50)	(.50)
Age	43.96	46.02	40.75	35.20
	(15.95)	(16.10)	(13.55)	(13.00)
AB Positive	.04	.03	.10	.05
	(.20)	(.18)	(.30)	(.21)
O Negative	.10	.11	.04	.07
	(.30)	(.31)	(.20)	(.26)
Center Locations:				
A	.60	.59	.68	.60
	(.49)	(.59)	(.47)	(.49)
B	.03	.02	.04	.03
	(.16)	(.16)	(.20)	(.18)
C	.03	.03	.01	.03
	(.17)	(.17)	(.11)	(.18)
D	.34	.35	.26	.34
	(.48)	(.48)	(.44)	(.48)
Morning Arrival (0700-1100)	.35	.36	.31	.33
	(.48)	(.48)	(.46)	(.47)
Lunch Hour Arrival (1100-1300)	.38	.36	.54	.35
	(.48)	(.48)	(.50)	(.48)
Afternoon Arrival (1300-1700)	.27	.27	.15	.32
	(.44)	(.45)	(.36)	(.47)
Observations	848	649	72	127

TABLE 1.3: INSTRUMENT RELEVANCE, OLS ESTIMATES

	Wait Time
Wait, previous donor	0.34***
	(0.04)
Wait, next donor	0.37***
	(0.04)
Yearly Donation Rate	-2.24***
	(0.77)
Female	0.42
	(1.01)
Older than 65 years	2.57
	(1.70)
Constant	-25.41***
	(3.59)
Observations	848
R^2	0.42
F statistic	32.1

OLS regression coefficients. Center fixed effects, time of day, day of week, and dummies for AB Positive and O Negative blood types included. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 1.4: AVERAGE EFFECT OF WAIT TIME ON ALL DONORS

	Likelihood to Return	Satisfaction with Experience	Intent to Donate
$\widetilde{Wait}$	-0.006***	-0.01***	-0.01***
	(0.002)	(0.003)	(0.003)
Yearly Donation Rate	0.22***	0.08	0.44***
	(0.06)	(0.07)	(0.08)
Female	-0.12*	0.18**	0.2**
	(0.07)	(0.09)	(0.09)
Older than 65 years	0.41***	0.19	0.45**
	(0.09)	(0.16)	(0.22)
AB Positive	0.05	0.13	0.01
	(0.2)	(0.23)	(0.26)
O Negative	0.11	0.05	-0.03
	(0.1)	(0.15)	(0.17)
Constant	-5.27***	.	.
	(0.21)		
Observations	848	848	848
Log Likelihood	-1313.31	-747.72	-733.1
Ancillary Parameter (p)	-0.004	.	.
Marginal effect at max outcome		-.004***	-.003***

Col (1) Coefficients of Survival model with Gompertz parametrization; Col (2) & (3) Coefficients of Order Probits (not marginal effects). Center fixed effects, time of day, day of week, and dummies for AB Positive and O Negative blood types included. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Given that we have a directional hypothesis for the effect of wait time, the estimates on $\widetilde{Wait}$ are one-tailed; all other coefficient tests are two-tailed.

TABLE 1.5: DISCRETE TIME HAZARD AND IV ESTIMATORS: LIKELIHOOD TO RETURN

	Discrete Time Hazard	IV Estimator Control Function Estimation	IV Estimator GMM Estimation
$\widetilde{Wait}$	-0.007***	-0.007**	-0.007**
	(0.002)	(0.004)	(0.004)
Donation History	0.28***	0.28***	0.28***
	(0.08)	(0.06)	(0.06)
Female	-0.17**	-0.16*	-0.16**
	(0.12)	(0.08)	(0.08)
Older than 65 years	0.55***	0.55***	0.56***
	(0.13)	(0.13)	(0.13)
AB Positive	0.07	0.07	0.07
	(0.22)	(0.20)	(0.21)
O Negative	0.13	0.13	0.13
	(0.12)	(0.13)	(0.13)
Residual	.	-.0009	.
		(0.004)	
Constant	-2.55***	-2.28***	-2.27***
	(0.32)	(0.45)	(0.39)
Observations	19,442	20,504	20,504
Log Likelihood	-2670.39	.	.

Col (1) Coefficients of the discrete time hazard model estimated via logistic regression. Col (2) Coefficients from second stage of the IV estimation, using the control function approach and standard errors bootstrapped with 199 replications. Col (3) Coefficients from IV estimation, using a one-step GMM estimation. Center fixed effects, time of day, and day of week. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Given that we have a directional hypothesis for the effect of wait time, the estimates on $\widetilde{Wait}$ are one-tailed; all other coefficient tests are two-tailed.

TABLE 1.6: PROPORTIONAL HAZARDS WITH COMPETING RISKS

	Likelihood to Return	Likelihood to Return
$\widetilde{Wait}\times$ Return to WB	-0.007*** (0.003)	-0.007*** (0.003)
$\widetilde{Wait}\times$ Return to P	-0.02** (0.007)	-0.01* (0.007)
Yearly Donation Rate	0.33*** (0.08)	.
Female	-0.17* (0.09)	.
Older than 65 years	0.71*** (0.16)	.
Yearly Donation Rate $\times$ Return to WB	.	0.32*** (0.09)
Yearly Donation Rate $\times$ Return to P	.	0.33* (0.17)
Female $\times$ Return to WB	.	-0.16* (0.09)
Female $\times$ Return to P	.	-0.29 (0.25)
Age 65 or older $\times$ Return to WB	.	0.83*** (0.17)
Age 65 or older $\times$ Return to P	.	-1.68* (1.01)
AB Positive $\times$ Return to WB	.	-0.19 (0.26)
AB Positive $\times$ Return to P	.	0.63 (0.41)
O Negative $\times$ Return to WB	.	0.26* (0.15)
O Negative $\times$ Return to P	.	-0.6 (0.6)
Constant	-4.67*** (0.28)	-4.65*** (0.29)
Observations	1649	1649
Log Likelihood	-2083.52	-2063.19
$\hat{p}$ Return to Plasma	-.006***	-.006***
Constant	-.008***	-.008***

Coefficients of Survival model with Gompertz parametrization. Center fixed effects, time of day, day of week, and dummies for AB Positive and O Negative blood types included. Robust Standard Errors clustered at the donor-level in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Given that we have a directional hypothesis for the effect of wait time, the estimates on $\widetilde{Wait}$ are one-tailed; all other coefficient tests are two-tailed. Donors who returned to give plasma before they were eligible to return to give whole blood are never "at risk" of returning to whole blood.

TABLE 1.7: EFFECT OF WAIT TIME ON THE WHOLE BLOOD SUPPLY

	Likelihood to Return for WB	Likelihood to Convert for Plasma
$\widetilde{Wait}$	-0.008*** (0.003)	-0.0008** (0.0005)
Yearly Donation Rate	0.33*** (0.09)	0.009 (0.01)
Female	-0.15* (0.09)	-0.01 (0.02)
Older than 65 years	0.75*** (0.17)	-0.07*** (0.01)
AB Positive	-0.05 (0.26)	0.11* (0.07)
O Negative	0.25 (0.15)	-0.04* (0.02)
Constant	-4.60*** (0.29)	.
Observations	776	843
Log Likelihood	-1669.15	-224
Ancillary Parameter (p)	-0.008	.

Col (1) Coefficients of Survival model with Gompertz parametrization. Col (3) Marginal effects of Probit Model, outcome variable is 1 if the donor converted to plasma on his subsequent visit and 0 otherwise. Center fixed effects, time of day, day of week, and dummies for AB Positive and O Negative blood types included. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Given that we have a directional hypothesis for the effect of wait time, the estimates on $\widetilde{Wait}$ are one-tailed; all other coefficient tests are two-tailed.

TABLE 1.8: SOCIAL COST OF WAITING, WHOLE BLOOD DONORS ONLY

	TOTAL 330,290	75% (3+/YR)	50% (1-3/YR)	25% (0-1/YR)
# DONORS	330,290	27,666	182,596	120,028
# DONATIONS, AVE.WAIT	689,410	93,501	444,317	151,593
# DONATIONS, + 20 MIN WAIT	600,680	90,162	403,924	106,594
# LOST DONATIONS	88,730	3,339	40,392	44,998
DAYS DONATION DELAYED		4	15	122
TOTAL DONATIONS LOST 88,730				
ESTIMATED ELASTICITY -.36				

TABLE 1.9: PROPORTIONAL HAZARDS COEFFICIENT, GENDER EFFECTS

	Satisfaction With Experience All donors	Intent to Return All donors	Likelihood to Return All donors	Likelihood to Return No Plasma	Likelihood to Return All donors	Likelihood to Return All donors
$\widetilde{Wait}$ × Male	-0.009*** (0.003)	-0.01*** (0.004)	-0.01*** (0.003)	-0.01*** (0.004)	.	.
$\widetilde{Wait}$ × Fem	-0.02*** (0.004)	-0.009** (0.004)	-0.002 (0.004)	-0.0008 (0.004)	.	.
$\widetilde{Wait}$× Male × Return to WB	.	.	.	.	-0.01*** (0.004)	-0.01*** (0.004)
$\widetilde{Wait}$× Male × Return to P	.	.	.	.	-0.01 (0.009)	-0.006 (0.009)
$\widetilde{Wait}$× Female × Return to WB	.	.	.	.	-0.0003 (0.004)	-0.0003 (0.004)
$\widetilde{Wait}$× Female × Return to P	.	.	.	.	-0.02*** (0.01)	-0.03** (0.01)
Yearly Donation Rate	0.09 (0.07)	0.44*** (0.08)	0.32*** (0.08)	0.33*** (0.09)	0.33*** (0.08)	.
Female	0.2** (0.09)	0.2** (0.09)	-0.15* (0.09)	-0.14 (0.09)	-0.17* (0.09)	.
Older than 65 years	0.18 (0.16)	0.45** (0.22)	0.73*** (0.16)	0.77*** (0.16)	0.73*** (0.16)	.
AB Positive	0.11 (0.23)	0.01 (0.26)	0.02 (0.22)	0.02 (0.27)	0.003 (0.22)	.
O Negative	0.05 (0.15)	-0.03 (0.17)	0.22 (0.14)	0.26* (0.15)	0.22 (0.14)	.
Yearly Donation Rate × Return to WB	.	.	.	.	.	0.32*** (0.08)
Yearly Donation Rate × Return to P	.	.	.	.	.	0.32* (0.17)
Female × Return to WB	.	.	.	.	.	-0.15 (0.09)
Female × Return to P	.	.	.	.	.	-0.38 (0.26)
Age 65 or older × Return to WB	.	.	.	.	.	0.85*** (0.17)
Age 65 or older × Return to P	.	.	.	.	.	-1.70* (1.00)
AB Positive × Return to WB	.	.	.	.	.	-0.14 (0.26)
AB Positive × Return to P	.	.	.	.	.	0.57 (0.42)
O Negative × Return to WB	.	.	.	.	.	0.28* (0.15)
O Negative × Return to P	.	.	.	.	.	-0.62 (0.6)
Constant	.	.	-4.59*** (0.27)	-4.64*** (0.29)	-4.70*** (0.28)	-4.69*** (0.29)
Observations	848	848	848	776	1649	1649
Log Likelihood	-746.21	-733.07	-1820.57	-1665.49	-2079.6	-2058.93
Ancillary Parameter (p)	.	.	-0.008	-0.007	.	.
χ^2 test: Wait× Male=Wait× Fem	2.43	.00	3.62*	4.90**		
(p-value)	(.12)	(.99)	(.06)	(.03)		
χ^2 test: Wait× Male WB=Wait× Male P					.01	.33
(p-value)					(.92)	(.56)
χ^2 test: Wait× Female WB=Wait× Female P					5.66	4.70
(p-value)					(.02)	(.03)

Coefficients of Survival model with Gompertz parametrization. Center fixed effects, time of day, day of week, and dummies for AB Positive and O Negative blood types included. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Given that we have a directional hypothesis for the effect of wait time, the estimates on $\widetilde{Wait}$ are one-tailed; all other coefficient tests are two-tailed.

TABLE 1.10: DONATION FREQUENCY AND WAIT TIME EFFECTS

	Likelihood to Return All	Likelihood to Return All
$\widetilde{Wait}$	-0.006*** (0.002)	-0.004** (0.002)
$\widetilde{Wait}\times$ Frequent Lifetime Donor	0.005 (0.004)	.
Frequent Lifetime Donor (More than 7 lifetime WB donations)	0.32* (0.18)	.
$\widetilde{Wait}\times$ New Donor	.	-0.005 (0.006)
New Donor	.	-0.36** (0.14)
Yearly Donation Rate	.	.
Female	-0.12* (0.07)	-0.17** (0.07)
Older than 65 years	0.25*** (0.09)	0.47*** (0.09)
AB Positive	0.09 (0.19)	0.16 (0.19)
O Negative	0.13 (0.09)	0.13 (0.1)
Constant	-5.19*** (0.2)	-4.91*** (0.2)
Observations	848	848
Log Likelihood	-1298.11	-1311.43
Ancillary Parameter (p)	-0.004	-0.004

Hazard model with Gompertz parametrization. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Given that we have a directional hypothesis for the effect of wait time, the estimates on $\widetilde{Wait}$ are one-tailed; all other coefficient tests are two-tailed.

FIGURE 1.1: SATISFACTION AND INTENTION, SURVEY RESPONSES

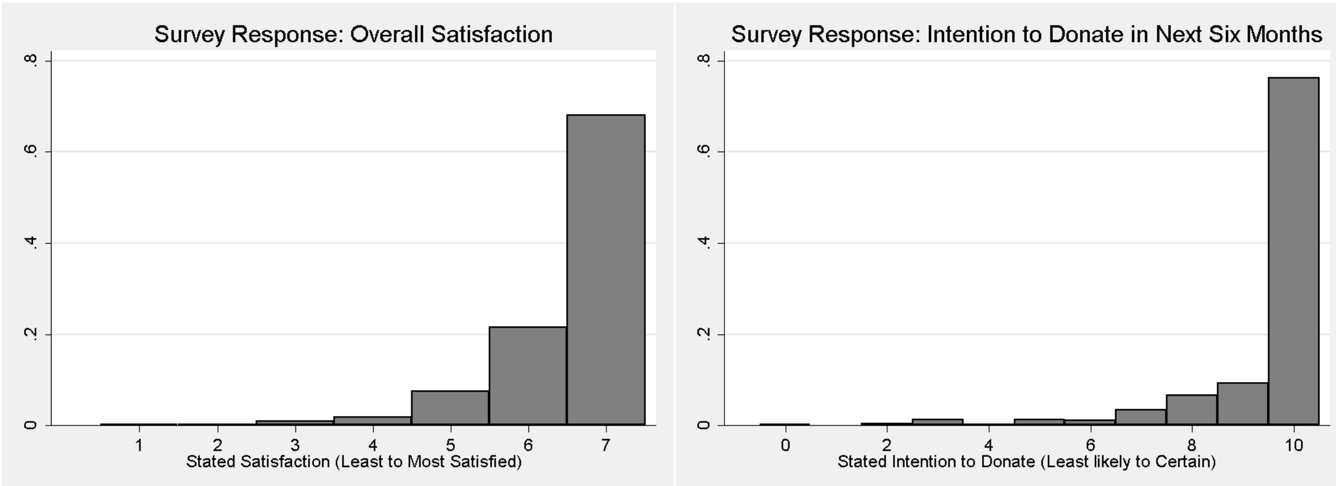


FIGURE 1.2: DISTRIBUTION OF WAIT TIME

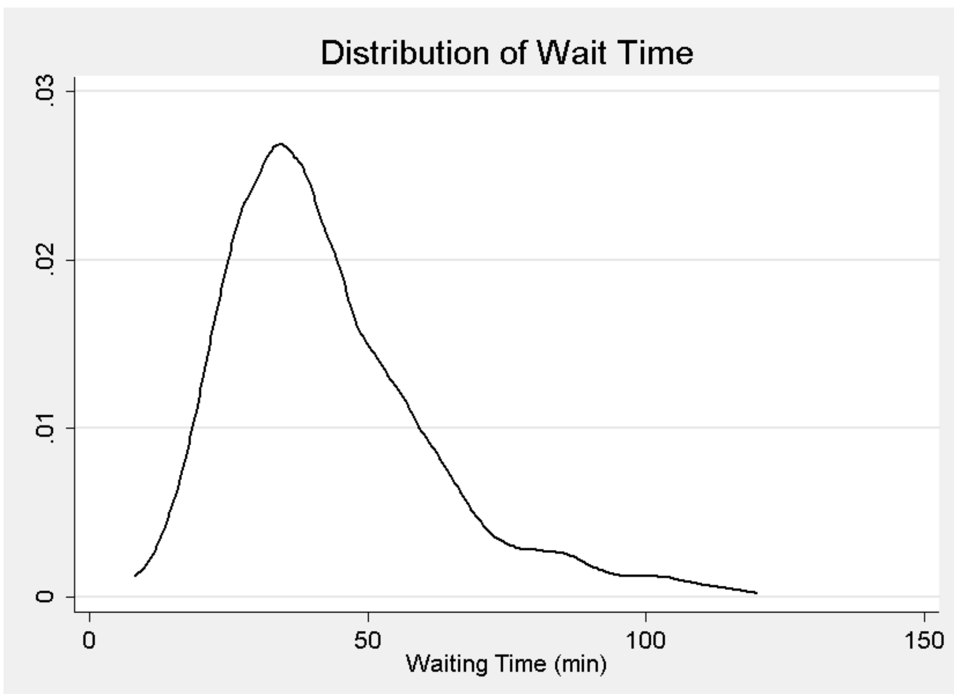
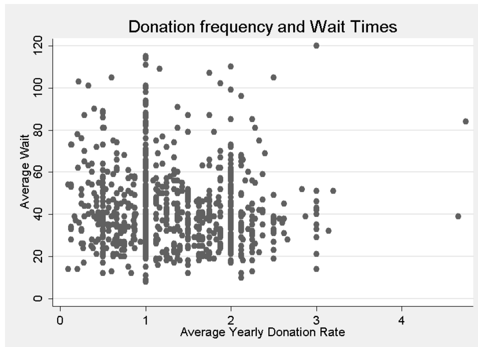
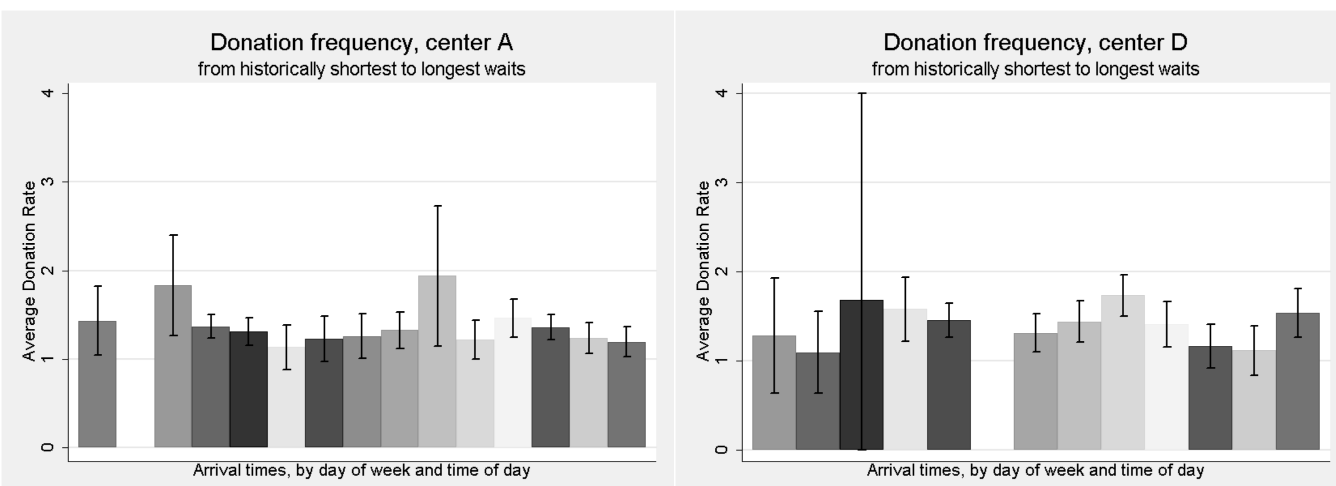


FIGURE 1.3: DONATION FREQUENCY AND WAIT TIMES

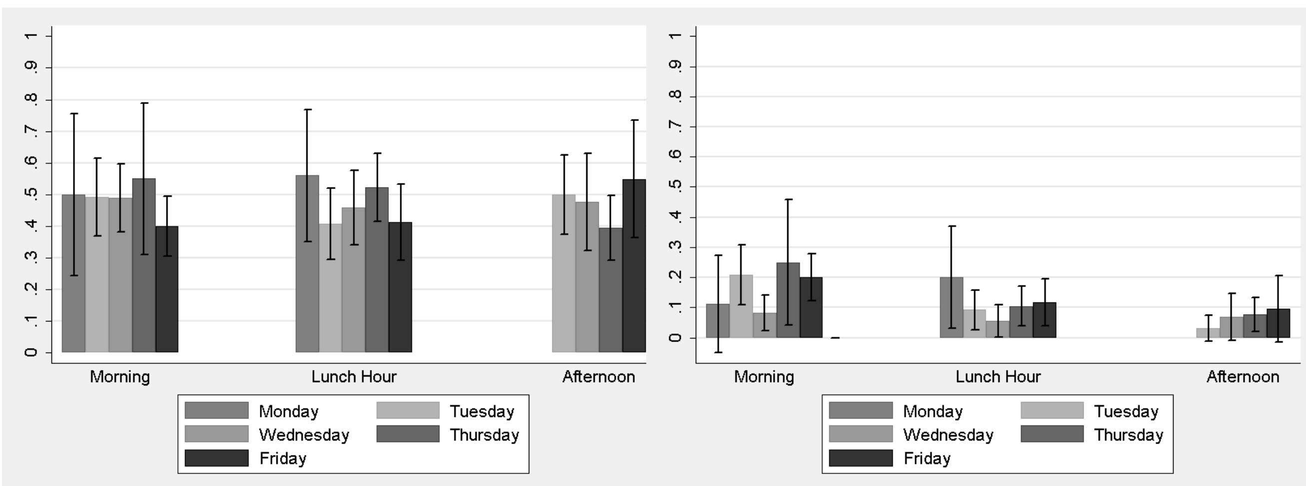


The y-axis is wait time and the x-axis is the donor's yearly donation rate.

FIGURE 1.4: DONATION FREQUENCY AND STRATEGIC ARRIVALS

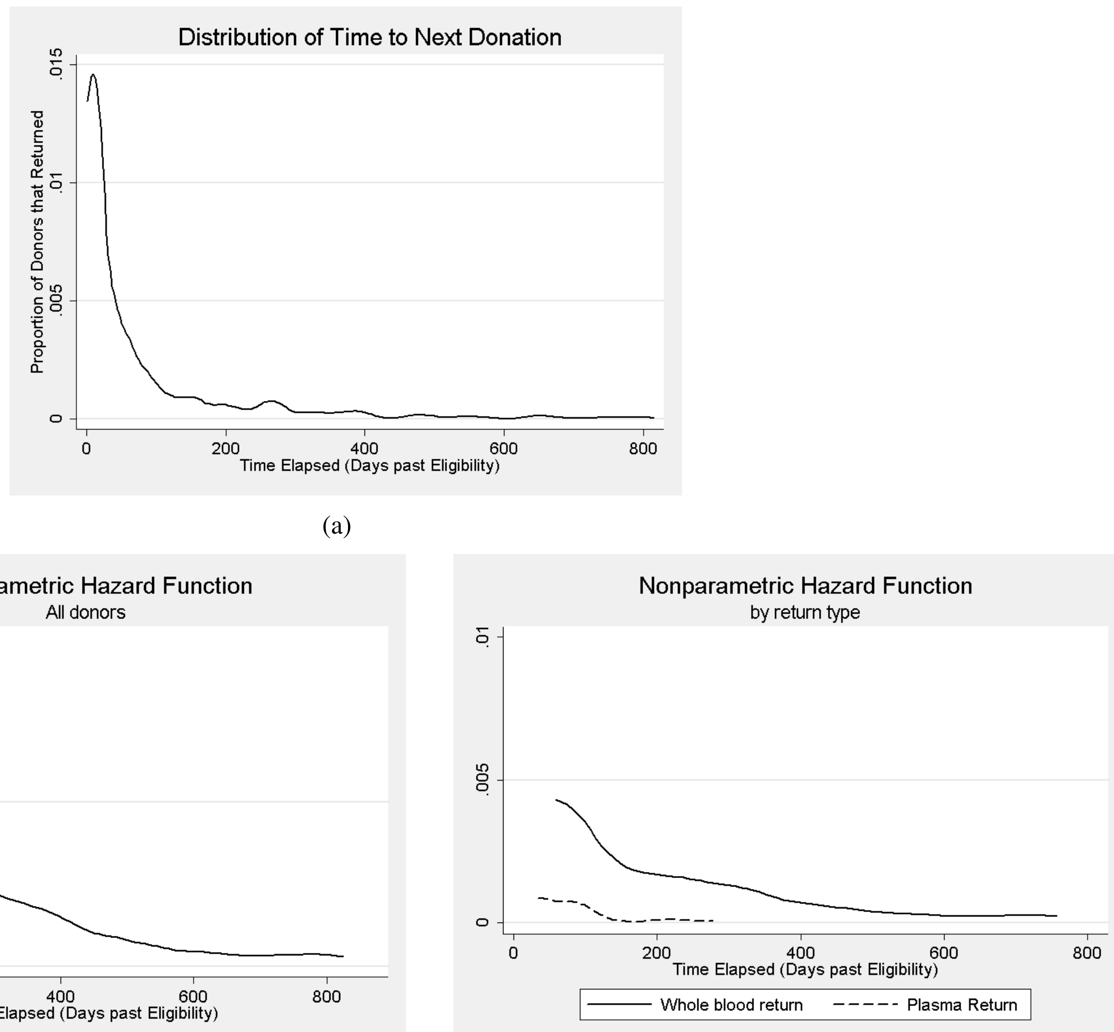


Each bar represents a day of week-time of day combination, listed in order from the shortest historical wait times to the longest historical waits times. The y-axis is the average yearly donation rate of donors in our sample who arrived to donate at each day-time combination.



(a) (b)

FIGURE 1.5: Figure A.1 PERCENT OF FEMALE DONORS, POOLED ACROSS CENTERS. Figure A.2 AVERAGE AGE, POOLED ACROSS CENTERS.



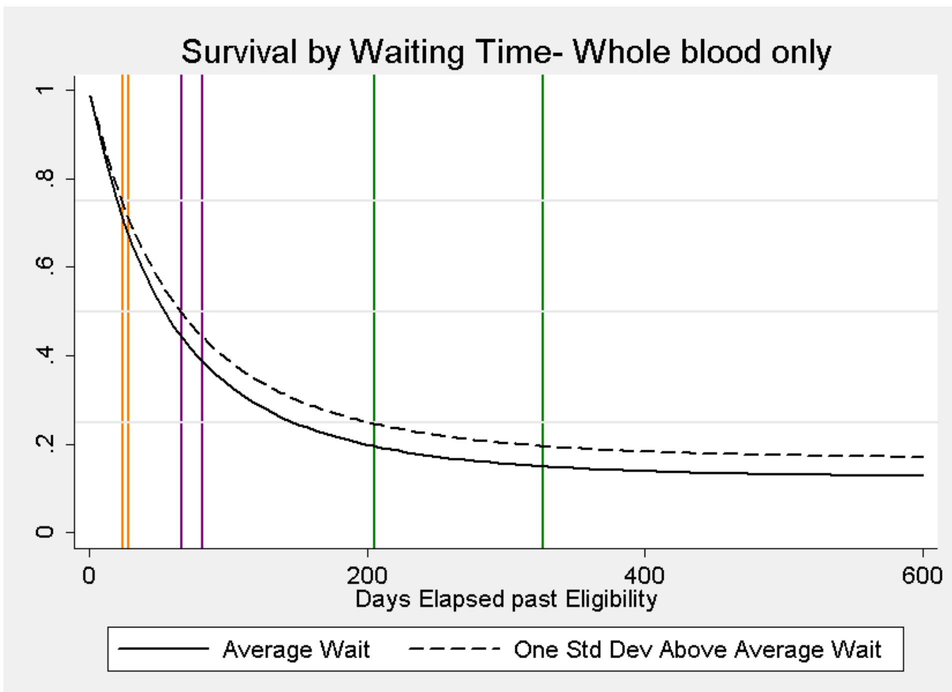
(a)

(b)

(c)

FIGURE 1.6: Figure 6(a) DURATION UNTIL NEXT DONATION. Figure 6(b) ESTIMATED NON-PARAMETRIC HAZARD FUNCTION OF ALL DONORS. Figure 6(c) ESTIMATED NON-PARAMETRIC HAZARD FUNCTION OF ALL DONORS, STRATIFIED BY TYPE OF RETURN DONATION.

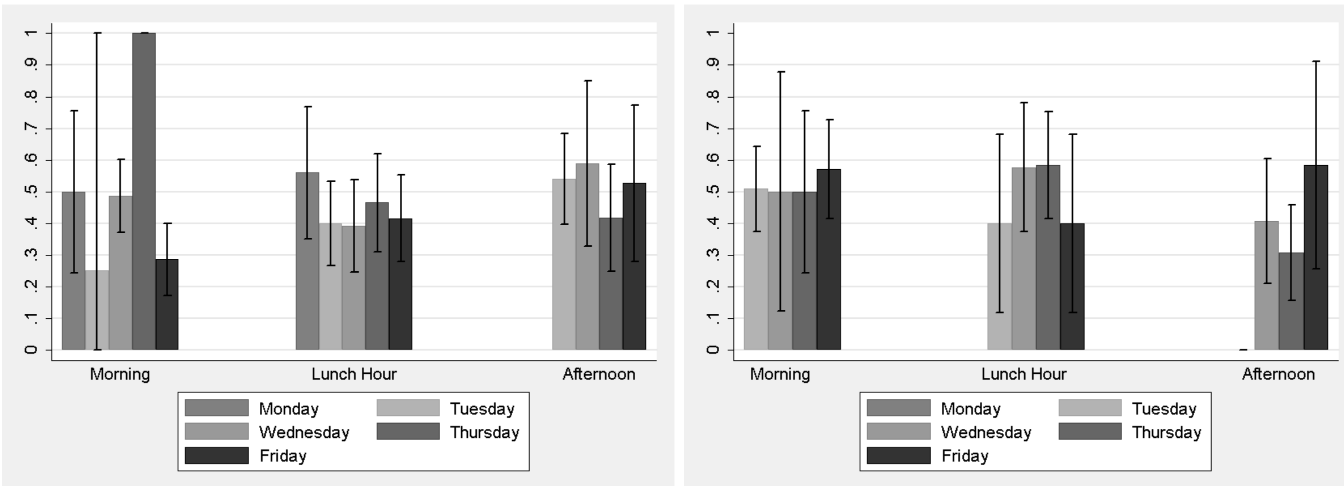
FIGURE 1.7: ESTIMATED SURVIVAL CURVE



The estimated survival curves at the average (42 min) and one standard deviation above average (+ 20 min). Vertical lines indicate the estimated day of return for the first 25%, the middle 50% and the bottom 25% of donors.

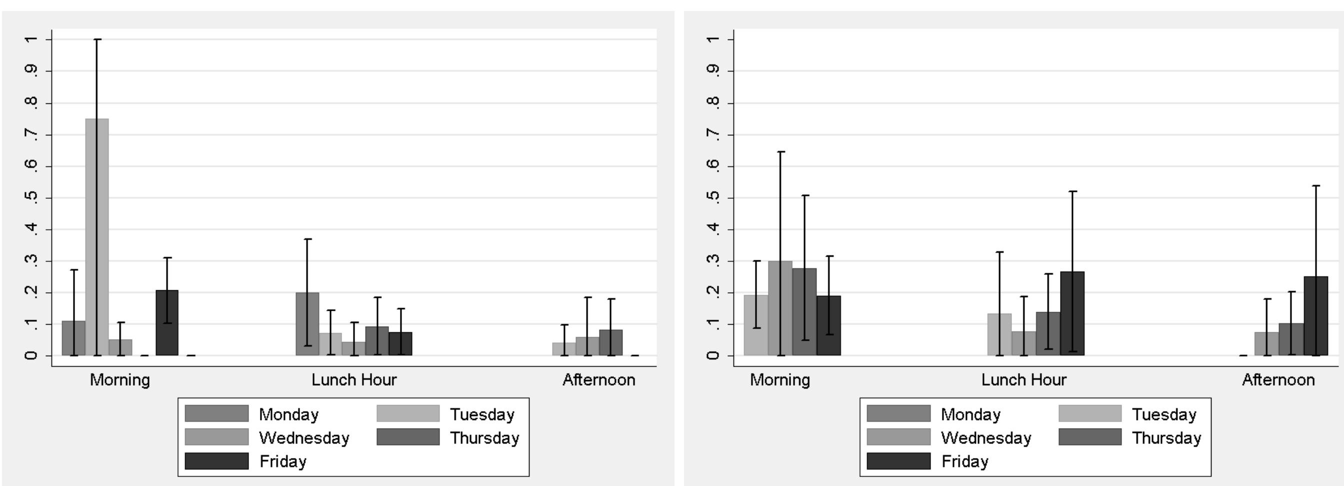
1.6 Appendix A

The Appendix contains two sections. The first two pages present the Figures A.1 & A.2 and Tables A.1. Pages three and four present more details on the comparative statics of the conceptual model. The survey is available upon request.



(a) (b)

FIGURE A.1: Figure 1(a) PERCENT OF FEMALE DONORS, CENTER A. Figure 1(b) PERCENT OF FEMALE DONORS, CENTER D.



(a) (b)

FIGURE A.2: Figure 2(a) AVERAGE AGE, CENTER A. Figure 2(b) AVERAGE AGE, CENTER D.

TABLE A.1: EFFECT OF WAIT TIMES, ROBUSTNESS TO SPECIFICATION

	Likelihood to Return All Donors Log-Logistic Parametrization	Likelihood to Return No Return Plasma Donations Semi-Parametric (Cox PH Model)
$\widetilde{Wait}$	0.007** (0.003)	-0.007*** (0.002)
Yearly Donation Rate	-0.32*** (0.07)	0.28*** (0.08)
Female	0.12 (0.08)	-0.14* (0.08)
Older than 65 years	-0.34*** (0.08)	0.62*** (0.12)
AB Positive	-0.15 (0.23)	-0.05 (0.24)
O Negative	-0.11 (0.11)	0.19 (0.12)
Constant	5.28*** (0.25)	.
Observations	848	776
Log Likelihood	-1374.95	-3867.08

Col (1) Replicates Table 4 in main text with log-logistic parametrization, Time Ratios Reported; (2) Replicates Table 7 of main text using a semi-parametric model (Cox Proportional Hazard Model). Center, day of week, time of day fixed effects included and dummies for AB Positive and O Negative blood types. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

1.6.1 Conceptual Model

Equation 10 is the first order condition resulting from the maximization of Equation 3 in the main text.

$$ln(\beta)\left[1-(\beta\delta)^{t^*}\right]-\delta^{t^*}ln(\beta\delta)\left[1-\beta^{t^*}\right]=\frac{f(c_0^i)(1-\beta\delta)ln(\beta)}{u(b^i)} \tag{10}$$

Implicitly differentiating 10, it is straightforward to show that t^* increases as the cost of the last donation c_0^i increases and the benefits of donating decrease:

$$\frac{\partial t^*}{\partial c_0^i}=-\frac{f'(c_0^i)(1-\beta\delta)ln(\beta)}{u(b^i)\delta^t ln(\beta\delta)ln(\delta)(1-\beta^{t^*})}>0 \tag{11}$$

$$\frac{\partial t^*}{\partial b^i}=\frac{f(c_0^i)u'(b^i)(1-\beta\delta)ln(\beta)}{u(b^i)^2\delta^t ln(\beta\delta)ln(\delta)(1-\beta^{t^*})}<0 \tag{12}$$

Comparative Statics Recall, $f'(c_0)>0$, $0<\delta,\beta<1$, $b>0$, $t\geq 1$.

In this section, we drop the $*$ superscript on t, as well as the i superscripts on b and c. In order to obtain comparative statics for the parameters of the model we use implicit differentiation. First, we are interested in the effect of an increase in costs on t^*. This comparative static is obtained through implicit differentiation of equation 10. To simplify notation, I will drop the superscript on t. Thus, I'm interested in $\frac{\partial t}{\partial c_0}$.

$$D\left[ln(\beta)\left[1-(\beta\delta)^{t^*}\right]-\delta^{t^*}ln(\beta\delta)\left[1-\beta^{t^*}\right]-\frac{f(c_0)(1-\beta\delta)ln(\beta)}{u(b)}\right]=D\left[0\right]$$

$$D\left[-ln\beta(\beta\delta)^t\right]-D\left[\delta^t ln(\beta\delta)\right]+D\left[(\beta\delta)^t ln(\beta\delta)\right]-D\left[\frac{f(c_0)(1-\beta\delta)ln(\beta)}{b}\right]=0$$

$$\partial t \delta^t ln(\beta\delta)\left[-\beta^t ln(\beta) - ln(\delta) + \beta^t ln(\beta\delta)\right] = \frac{f'(c_0)(1-\beta\delta)ln(\beta)}{u(b)}\partial c_0$$

$$\frac{\partial t}{\partial c_0} = -\frac{f'(c_0)(1-\beta\delta)ln(\beta)}{u(b)\delta^t ln(\beta\delta)ln(\delta)(1-\beta^t)} > 0 \tag{13}$$

It is then straightforward to find an expression for $\frac{\partial t}{\partial b}$

$$\frac{\partial t}{\partial b} = \frac{f(c_0)u'(b)(1-\beta\delta)ln(\beta)}{\left(u(b)\right)^2 \delta^t ln(\beta\delta)ln(\delta)(1-\beta^t)} < 0 \tag{14}$$

Expressions for $\frac{\partial t}{d\beta}$ and $\frac{\partial t}{\partial\delta}$ can also be obtained via implicit differentiation. $\frac{\partial t}{\partial\delta}$ can be obtained as follows from equation 10:

$$\begin{aligned} &t'\left[-(\beta\delta)^t\delta ln(\beta\delta) - \delta\delta^t ln(\beta\delta)ln(\delta) + \delta(\beta\delta)^t ln(\beta\delta)ln(\beta\delta)\right] \\ &= -\frac{f(c_0)\beta\delta ln(\beta)}{u(b)} + t\left[(\beta\delta)^t + \delta^t ln(\beta\delta) - (\beta\delta)^t ln(\beta\delta)\right] + \delta^t(1-\beta^t) \end{aligned}$$

Rearranging and simplifying the righthand side of the equation yields:

$$\begin{aligned} &t'\delta\delta^t ln(\beta\delta)\left[\beta^t(ln(\beta)-1) - ln(\delta)(1-\beta^t)\right] \\ &= -\frac{f(c_0)\beta\delta ln(\beta)}{u(b)} + t\left[(\beta\delta)^t + \delta^t ln(\beta\delta) - (\beta\delta)^t ln(\beta\delta)\right] + \delta^t(1-\beta^t) \end{aligned}$$

Finally, solving for $t' = \frac{\partial t}{\partial\delta}$

$$\frac{\partial t}{\partial\delta} = \frac{1}{\delta\delta^t ln(\beta\delta)\left[\beta^t(ln\beta - 1) - ln\delta(1-\beta^t)\right]}\left[-\frac{f(c_0)\beta\delta ln\beta}{u(b)} + t\left[(\beta\delta)^t + \delta^t ln(\beta\delta) - (\beta\delta)^t ln(\beta\delta)\right] + \delta^t(1-\beta^t)\right] \tag{15}$$

$\frac{\partial t}{\partial\delta} > 0$ when two conditions are met:

1. $\beta^t(ln(\beta)-1) - ln(\delta)(1-\beta^t) > 0 \rightarrow \frac{\beta^t}{1-\beta^t} < \frac{-ln(\delta)}{1-ln(\beta)}$
2. $t\left[(\beta\delta)^t + \delta^t ln(\beta\delta) - (\beta\delta)^t ln(\beta\delta)\right] > 0 \rightarrow \frac{\beta^t}{1-\beta^t} < -ln(\beta\delta)$

When these two conditions hold, $\frac{\partial t}{\partial\delta} > 0$. This relationship between t^* and δ is intuitive: the more quickly the benefits (e.g., the warm glow) from donating wear off, then the more quickly a donor will return to donate in order to reset his benefits.

Again, use implicit differentiation to obtain $\frac{\partial t}{\partial \beta}$ from equation 10

$$t' \left[-\beta(\beta\delta)^t ln(\beta\delta) ln\beta - \beta\delta^t ln\delta ln(\beta\delta) + \beta(\beta\delta)^t ln(\beta\delta) ln(\beta\delta) \right]$$
$$= \frac{f(c_0^i)\left[1 - \beta\delta - \beta\delta ln\beta\right]}{u(b)} - (1 - \delta^t) - t(\beta\delta)^t ln\delta$$

Simplifying the left-hand side of the equation yields:

$$t'\beta\delta^t ln(\beta\delta)\left[(\beta^t - 1)ln\delta\right] = \frac{f(c_0^i)\left[1 - \beta\delta - \beta\delta ln\beta\right]}{u(b)} - (1 - \delta^t) - t(\beta\delta)^t ln\delta$$

Solving for $t' = \frac{\partial t}{\partial \beta}$ yields:

$$\frac{\partial t}{\partial \beta} = \frac{-1}{\beta\delta^t ln(\beta\delta)\left[(1 - \beta^t)ln\delta\right]} \left[\frac{f(c_0^i)\left[1 - \beta\delta - \beta\delta ln\beta\right]}{u(b)} - (1 - \delta^t) - t(\beta\delta)^t ln\delta\right] \quad (16)$$

$\frac{\partial t}{\partial \beta} > 0$ when $\frac{f(c_0^i)[1-\beta\delta-\beta\delta ln\beta]}{u(b)} - (1 - \delta^t) - t(\beta\delta)^t ln\delta < 0$ and $\frac{\partial t}{\partial \beta} < 0$ if $\frac{f(c_0^i)[1-\beta\delta-\beta\delta ln\beta]}{u(b)} - (1 - \delta^t) - t(\beta\delta)^t ln\delta > 0$.

The benefits of donating are discounted by beta in every period, whereas the costs are discounted only once every t^* periods. An increasing relationship between t^* and β occurs when, as β increases, the increase in the present value of a donor's stream of benefits increases more than the discounted present value of future costs.

2 We Should *Totally* Open a Restaurant: How Optimism and Overconfidence Affects Beliefs

2.1 Introduction

A robust finding in experimental economics is that individuals tend to over-estimate the probability of high-payoff outcomes (De Bondt and Thaler, 1995). This type of bias is concerning if it affects decisions. An example that has received considerable attention is over-entry into self-employment arising from systematically biased beliefs on the success of business ventures. Indeed, fully 80% of nascent entrepreneurs believe their chances of success are at least 70%, but roughly two-thirds will fail within the first few years (Cooper et al., 1988). If individuals start businesses that are unprofitable or destined to fail—and if they choose to do so because they systematically over-estimate the probability of success—then they make inefficient use of their personal resources, such as time and effort, and possibly forgo higher earnings in paid employment. They also potentially waste publicly-funded resources, including government-sponsored subsidies, which could presumably be more productively allocated elsewhere.

Previous literature explaining why individuals over-estimate the probability of high-payoff outcomes has typically focused on *overconfidence*, defined here as the tendency to over-estimate one's own performance.[28] An alternative and distinct explanation is *optimism* or *wishful thinking*, defined as the tendency to over-estimate the probability of preferred outcomes (Irwin, 1953; Weinstein, 1980). Earlier studies have examined optimism and overconfidence as isolated phenomena, which is problematic for two reasons. First, in many decision-making scenarios, individuals facing uncertainty are prone to both. For example, an individual deciding to open a business must assess her expected performance as a business-owner and also has preferences over the outcome, presumably preferring to earn more money rather than less money. Therefore, if she over-estimates the payoff

[28]Moore and Healy (2008) identify three types of overconfidence: (1) over-estimation: believing one's own performance or ability is better than it actually is; (2) over-placement: over-estimating one's own performance or ability relative to a reference group; and (3) over-precision: over-estimating the precision of one's knowledge.

to opening her own business, it might be because she is overconfident in her assessment of her own performance as business-owner, optimistic in her expectations about earnings or, as we propose, some combination of the two. Second, earlier studies examining optimism or overconfidence in isolation ignore how these two biases are potentially correlated at the individual level.

In this paper, we present results from an experiment designed to study optimism and overconfidence as distinct but potentially related phenomena. The goal is to understand the extent to which beliefs in settings such as the decision to open a business are driven by optimism, overconfidence or both. In doing so, we make two key contributions, which highlight the problems associated with studying optimism and overconfidence separately. First, we show that optimism and overconfidence are positively correlated at the individual level.[29] Second, we show that both optimism and overconfidence explain individual tendencies to over-estimate the likelihood of high-payoff outcomes in settings where (i) the individual's performance affects these outcomes and (ii) individuals have preferences over these outcomes. Our results cast doubt on earlier findings that explain biased beliefs as either optimism or overconfidence. The reason is that results may suffer from omitted variables bias. For example, if over-entry into entrepreneurship is explained solely as a function overconfidence, the role of optimism is omitted. Therefore, the estimated impact of overconfidence on entry is upwardly biased as it also captures the positive correlation between overconfidence and optimism. The impact of policies designed to mitigate the effects of overconfidence are likewise over-estimated if optimism is overlooked.

The experiment we design and conduct is outlined in detail in Subsection 2.3, but we explain its main features here using the example of a coin toss. To assess optimism, we first elicit an individual's probabilistic belief that a fair coin lands on heads. Second, we inform the individual that he will receive a side payment if heads occurs and again elicit his probabilistic belief about the likelihood of heads. Optimism is identified by comparing the individual's probabilistic beliefs when heads is payoff favorable versus when it is not. A subject that reports $\frac{1}{2}$ when heads is not payoff favorable and reports a number greater than $\frac{1}{2}$ when heads is payoff favorable is classified

[29] A finding that is similar in spirit is shown in Åstebro et al. (2007).

as optimistic. The reason is that the reported probability of the outcome was higher when that outcome was payoff favorable.

To identify overconfidence, we use a similar technique. First, we elicit the likelihood of heads in a fair coin toss. Second, the individual answers a trivia question. A correct answer results in a coin that has $\frac{2}{3}$ chance of heads and $\frac{1}{3}$ chance of tails, whereas an incorrect answer results in the fair coin. In other words, the individual's performance directly affects the distribution he faces—in this case increasing the probability of heads. Without feedback on his performance, the individual forms a belief about his performance and we elicit his belief about the probability of heads. Suppose he did not answer the trivia question correctly, but thinks there is some possibility that he might have. Then, when asked to report his belief of the probability of heads, his uncertainty may be reflected by a report between $\frac{1}{2}$ and $\frac{2}{3}$. If so, then we say he over-estimates his performance. Analogous to how we identify optimism, we identify overconfidence from within-individual individual shifts. Had the individual answered $\frac{2}{3}$ regardless of the role of performance, he would not be counted as having over-estimated his performance.

The economic environments we are interested in (e.g., entrepreneurship, investment strategies and decisions to compete) are those where the individual's performance affects the likelihood that a preferred outcome is realized. Thus, individual decisions may be influenced by overconfidence and optimism simultaneously. We simulate an environment in the laboratory where the individual can increase the probability of high payoff outcomes through better performance. This environment is called the *combined setting* since the subject can increase the probability that the coin lands on heads through his performance (as in the performance treatment) and receives an additional side payment when heads is realized (as in the payment treatment). Having examined performance over-estimation and optimism in isolation, we can examine to what degree beliefs in the combined setting are attributable to either optimism or performance over-estimation (or both).

In our experiment, we elicit beliefs over a more general set of distributions. We ask subjects to report beliefs about the number of white balls that will be drawn from jars containing various compositions of white and black balls. This experiment is described in detail in Subsection 2.3.[30] Our technical definitions are presented in Subsection 2.2.

2.2 Optimism and Overconfidence

The idea that individuals facing uncertainty make decisions based on their subjective beliefs and, further, that subjective beliefs may not correspond to objective probabilities of outcomes, is not new (Savage, 1954; Manski, 1993). This paper deals with two particular types of departures, optimism and overconfidence, and focus on the idea that they are distinct concepts that are often confounded. This highlights our contribution: to devise and implement an experiment to study optimism and overconfidence as potentially correlated phenomena that together drive beliefs over uncertain outcomes.

Broadly speaking, there are two types of models of optimism and overconfidence bias that are relevant to our discussion.[31] The first, recognizes that optimism breaks the independence between decision weights (or beliefs) and payoffs and allows decision weights to be determined by the decision-maker's preference ordering over outcomes, including theories of rank-dependence utility (Quiggin, 1982) and affective decision-making (Bracha and Brown, 2012). In these models, decision-makers only have preferences over the outcomes.

Alternatively, optimism and overconfidence biases are also modeled as belief-based preferences, which include models where decision-maker's beliefs enter the utility function and optimization is performed by choosing beliefs. Belief-based preferences include models of ego utility (Köszegi, 2006), and anticipatory utility (Brunnermeier and Parker, 2005; Caplin and Leahy, 2001). In models of belief-based preferences, decision-makers have preferences over their beliefs and over outcomes.

To fix ideas, consider that a decision-maker answers 10 IQ questions of which an unknown pro-

[30] The counterpart to the coin toss—one white ball and one black ball with a single draw—is one of the distributions subjects face.

[31] There are other belief formation models that show how overconfidence, in the sense of over-precision, can result from correlation neglect (Eyster and Rabin, 2010; Enke and Zimmermann, 2013).

portion q are answered correctly. Now, consider the following three scenarios. In scenario 1, a coin with known odds q is tossed. The decision-maker earns \$100 if heads is realized and 0 otherwise and is asked the probability of heads. In scenario 2, the decision-maker is asked the probability that he correctly answered a randomly drawn IQ question. In scenario 3, the decision-maker reports the probability that a randomly drawn IQ question was answered correctly; additionally, he earns \$100 if he answered the IQ question correctly and 0 otherwise. Over-estimating the probability in scenario 1, which we refer to as optimism, can occur if the decision-maker has preferences given by a rank dependent utility function or experiences anticipatory utility; over-estimation of the probability in scenario 2, which we refer to as overconfidence, can occur if the decision-maker has belief-based preferences that permit ego utility. Scenario 3 contains the possibility for both optimism and overconfidence.

Thus, if we observe that the decision-maker overestimates the probability in scenario 3, but do not observe his reports in scenario 1 or 2, then we can only conclude that he is optimistic, overconfident or both. Simply, in any context in which an individual is asked to assess his performance and he has preferences over the outcomes generated by his performance, both overconfidence and optimism may drive his assessment. However, throughout the literature, environments akin to scenario 3, which contain the possibility of both optimism and overconfidence, are studied and overestimation is attributed solely to overconfidence (Blavatskyy, 2009; Camerer and Lovallo, 1999; Hoelzl and Rustichini, 2005; Kirchler and Maciejovsky, 2002; Malmendier and Tate, 2008; Koellinger et al., 2007; Niederle and Vesterlund, 2007).

For example, Niederle and Vesterlund (2007) partially explain the over-willingness of men to compete (relative to women) by differences in overconfidence between the two genders. Men were more likely to over-estimate the probability of winning the tournament; additionally, winning the tournament entailed a higher payoff than not winning. Similarly, Malmendier and Tate (2008) show that more overconfident CEOs sub-optimally invest in their company. Overconfident CEOs believe their firm is under-valued by the market and are thus less likely to accept external financing and more likely to invest with internal funds to take advantage of the perceived arbitrage opportunity.

Camerer and Lovallo (1999) explain market over-entry with overconfidence: subjects are more likely to enter a laboratory industry when the ranking and therefore the subsequent payoff depends on performance than when it depends on luck.

These three examples, over-willingness to compete, suboptimal investment strategies and market over-entry, all share common features with scenario 3: not only are individuals tasked with making a probabilistic assessment of their own performance, but their performance directly affects payoffs. In other words, belief biases may operate by (1) inflating the probability of obtaining the high payoff, conditional on the subject's performance level (optimism); (2) inflating the decision-maker's own performance assessment due to ego or anticipatory utility (overconfidence) ; or (3) both.

The literature in optimism deals explicitly with environments similar to scenario 1, which systematically find optimism: subjects overweight the probability of payoff favorable outcomes (Coutts, 2014; Irwin, 1953; Ito, 1990; Mayraz, 2011; Weinstein, 1980). By contrast, our paper studies all three scenarios within the same context. This allows for a clean analysis of how optimism and overconfidence affect beliefs in environments when decision-makers are prone to both as in scenario 3.

2.2.1 Conceptual Framework

The agent in our setting faces two dimensions of uncertainty: uncertainty about his performance represented by a random type $\theta \in \Theta$ and uncertainty about the outcome of a lottery X with support $[0, N]$, where N is a positive integer. The outcome of the lottery, denoted x, depends on the agent's performance type and is described by a distribution, which we denote:

$$G_X\left(x|\theta\right) = P\left(X \leq x|\theta\right). \tag{17}$$

We assume that the measure of performance and the outcome of the lottery are ordered and discrete. The link between performance type, θ, and the distribution $G_X\left(x|\theta\right)$ is given by the following: if $\theta' > \theta''$ then $G_X(x|\theta = \theta')$ first order stochastically dominates $G_X(x|\theta = \theta'')$. In other words, better performance is associated with a "better" distribution, in the sense of stochastic dominance. The agent has a true performance type, $\theta_o \in \theta$, and the distribution Θ is degenerate at θ_o, but θ_o is unknown to the agent. The agent has beliefs about his true performance type, θ_o, given by the distribution $\tilde{\Theta}$ over θ.

There is also a non-decreasing map from lottery outcomes to monetary payoffs, $m(\cdot)$, meaning that higher values of x have weakly larger monetary payoffs. Moreover, we assume that the agent's preferences can be described by a utility function, such that if $x' > x''$ then $u(m(x')) > u(m(x''))$. The agent has subjective beliefs about G that are given by

$$F\left(x|m(\cdot);\tilde{\Theta}\right), \tag{18}$$

where we explicitly condition on $m(\cdot)$ to capture that an agent's beliefs may be affected by the payoff function.

Next, we will characterize beliefs if four settings. First, consider the case where there is no performance uncertainty and the monetary payoff is constant (does not depend on x), thus we write $m(x) = m$. Then the agent has subjective beliefs given by

$$F\left(x|m(x) = m;\tilde{\Theta}\right) = F(x), \tag{19}$$

where we do not conditional on $m(\cdot)$ since the payoff is independent of x and we do not condition on $\tilde{\Theta}$ since there is no performance uncertainty and thus no uncertainty regarding the distribution the agent faces. Call this set of beliefs the agent's Baseline beliefs.

Second, if there is no performance uncertainty and the monetary payoff is a weakly increasing in x, then the agent has subjective beliefs given by

$$F\left(x|m(\cdot);\tilde{\Theta}\right) = F(x|m(\cdot)), \tag{20}$$

where we explicitly conditional on $m(\cdot)$ since the payoff changes with x and might therefore influence beliefs about x. Call this set of beliefs the agent's Payment Only.

For the third and fourth beliefs, we drop the assumption that there is a single performance type and allow for subjective uncertainty regarding performance type. Recall, θ_o denotes the agent's true type, which is unknown to the agent. $\tilde{\Theta}$ denotes the agent's beliefs about the degenerate distribution over θ, Θ. The agent is tasked with forming beliefs over:

$$G(x|\theta_o) \tag{21}$$

In this case we allow G to change with performance as described above: if $\theta' > \theta''$ then $G(x|\theta = \theta')$ stochastically dominates $G(x|\theta = \theta'')$. In other words, when an agent performs better, he faces a better distribution in the sense of stochastic dominance. The distribution is therefore endogenously determined by the agent's level of performance. The third setting for which we characterize beliefs is when the agent faces performance uncertainty and a monetary payoff function that is constant, his beliefs are given by

$$F\left(x|m(x) = m; \tilde{\Theta}\right) = F\left(x|\tilde{\Theta}\right) \tag{22}$$

where we do not condition on $m(\cdot)$ as payoffs are constant and do not depend on x, but do allow F to be a function of the agent's performance beliefs $\tilde{\Theta}$. Call this set of beliefs the agent's Performance Only beliefs.

Fourth, when the agent simultaneously faces performance uncertainty and a monetary payoff that is weakly increasing in x, then his beliefs are given by

$$F\left(x|m(\cdot), \tilde{\Theta}\right). \tag{23}$$

These beliefs are called Combined beliefs since they reflect the agent's beliefs when both performance uncertainty and a preference for larger realizations x are present. It is important to note that in this setting, the agent can affect the lottery he faces with his performance and that larger values of x are payoff favorable. This means that the agent increases the likelihood of a larger monetary payoff through better performance.

Definition 2.1. *An agent displays a shift towards optimism (pessimism) when*

$$\frac{1}{N}\Sigma_{x=0}^{N}[F\left(x|m\left(x\right)=m\right)-F\left(x|m\left(\cdot\right)\right)]>\left(<\right)0. \tag{24}$$

Definition 2.2. *An agent displays a shift towards performance overestimation (underestimation) when*

$$\frac{1}{N}\Sigma_{x=0}^{N}[F\left(x|m\left(x\right)=m\right)-F\left(x|m\left(x\right)=m;\tilde{\Theta}\right)]>\left(<\right)0. \tag{25}$$

Definition 2.3. *An agent displays a shift towards overestimation and/or optimism (underestimation and/or pessimism) in the combined setting when*

$$\frac{1}{N}\Sigma_{x=0}^{N}[F\left(x|m\left(x\right)=m\right)-F\left(x|m\left(\cdot\right),\tilde{\Theta}\right)]>\left(<\right)0. \tag{26}$$

2.3 Experimental Design

The purpose of our experimental design is to separately identify and measure optimism and overconfidence and to relate these isolated measures to individual decisions that involve both. To do so, we employ a 2×2 within-subject experimental design; thus each subject completes a common task facing each of the four treatment combinations.

2.3.1 Overview

The common task that subjects face across treatments consists of reporting probabilistic beliefs about realizations from the six distributions summarized in Table 2.2. The distributions are presented as computerized jars with various compositions of white and black balls. Subjects know the number of white and black balls in each jar and the number of balls that will be drawn from the jar and they are asked to report cumulative probabilities about the likelihood of white balls being drawn. In doing so, we elicit subjects' beliefs about the entire distribution.[32] To incentivize reports of probabilistic beliefs, we pay subjects according to the quadratic scoring rule (QSR) (Brier, 1950; Murphy and Winkler, 1970).

$$\text{SCORE} = \begin{cases} 10 - 10 * [\text{reported belief} - 1]^2 & \text{if event occurs} \\ 10 - 10 * [\text{reported belief} - 0]^2 & \text{if event does not occur.} \end{cases}$$

2.3.2 Treatments

The experiment consists of two treatments at two levels, resulting in four treatment combinations: the Baseline Treatment, the Payment Only Treatment, the Performance Only Treatment and the Combined (Payment + Performance) Treatment. The Baseline Treatment elicits beliefs about known distributions and pays subjects for the accuracy of those probabilistic beliefs. Similarly, the Payment, Performance and Combined Treatments also pay subjects for the accuracy of beliefs, but each have an additional feature that will be described below and are summarized in Table 2.1.

In the Payment Only Treatment, in addition to being paid for the accuracy of beliefs, subjects are induced to prefer that white balls, instead of black balls, are drawn from the jar. This is operationalized by giving subjects a side payment that is independent of their payment for belief accuracy and increases in expected value when more white balls are drawn. More specifically, when the Payment Treatment is applied, $m(x)$ is weakly increasing x, where x is the number of white balls drawn during the treatment and $m(x)$ is given by

$$\text{m(x)} = \begin{cases} 100 & \text{with probability } \frac{\text{total white}}{\text{max white}} \\ 0 & \text{with probability } \left(1 - \frac{\text{total white}}{\text{max white}}\right). \end{cases}$$

In the Performance Only Treatment, in addition to being paid for the accuracy of their beliefs, subjects can influence the number of white balls in the jar by correctly answering IQ questions.

[32] On each screen, the computerized jar is displayed on the left side and a series of questions about the jar on the right side. Subjects move the cursor to indicate a percent chance of a certain number of white balls being drawn from the jar. The numerical value indicated by position of the cursor is displayed next to the number line. Figure **??** in **??** is a screen shot of the computerized interface the subject uses during the experiment.

For example, a subject starts facing distribution 1 (1 white, 1 black and 1 draw) and is given an IQ question and told that if he answers correctly then a white ball will be added to his jar, in which case he faces distribution 2 (2 white, 1 black, and 1 draw). Without feedback on the IQ question, subjects report their belief about the likelihood that the one draw from the jar is a white ball. This is repeated one more time, but with a different IQ question. Subjects also repeat this same process, but start facing distribution 3 (1 white, 1 black and 3 draws). When subjects start in distribution 3, they answer 3 IQ questions and a white ball is added to the jar for each correct IQ question, resulting in a final distribution that corresponds to distribution 3, 4, 5 or 6. Again, without feedback, subjects are asked about the likelihood that 0, 1, 2, or 3 of the draws from the jar consist of white balls. This is repeated one more time, but with a different set of 3 IQ questions. In summary, subjects start in distribution 1 twice and distribution 3 twice in the both the Performance Only and Combined Treatments and the order within each treatment is randomized.

To gauge performance in the Performance Treatment, subjects answer multiple choice IQ questions from the Mensa Quiz book (Grosswirth et al., 1999).[33] Multiple choice questions are chosen to avoid open-ended questions and subject confusion. The Mensa Quiz book also reports the percentage of quiz takers that answered a given question correctly. This allows us to select questions of similar difficulty level, controlling for any complications that may arise from the documented "hard-easy" effect (Lichtenstein and Fischhoff, 1977). One potential concern is that a subject might purposefully give an incorrect answer to the IQ question to increase his certainty about the distribution he faces. However, we pay subjects $2 for each correct IQ question so that this behavior is not incentive-compatible.

In the Combined Treatment, we simultaneously apply both the Payment Only and Performance Only Treatment. Not only can subjects expect to make more money when more white balls are drawn from the jar (via the same side payment as in the Payment Treatment), but they can also influence the number of white balls in the jar by correctly answering IQ questions in the same manner as in the Performance Treatment. Thus, in the Combined Treatment, subjects can increase

[33] This task was also used in Owens et al. (2012); Grossman and Owens (2012).

the likelihood of a higher payoff outcome. In this sense, the Combined Treatment contains the elements that are similar to scenarios outside of the laboratory. In many contexts, such as starting a business, investing, engaging in competition allow individuals to increase their likelihood of achieving the high payoff outcome.

Key Features of the Experimental Design In this subsection we will further elaborate on two key features of our experimental design: (1) the within subject design and (2) the single unified task used across treatments.

First, the within subject design allows us to study belief changes at the individual level. In particular, we are interested in whether and how beliefs change when the potential for optimism or overconfidence is present. In order to do this, we must have an accurate measure of the individual's belief when neither bias is present, which is achieved in the Baseline Treatment. Thus, our measure of optimism and overconfidence will always be a comparison between the treatment beliefs (payment only, performance only, and combined treatments) and the Baseline belief.

The use of an individual-level control in our analysis, as Subsection 2.4.2 will make clear, means that any factor that affects individual reports uniformly across treatments, including poor mathematical skills or curvature of the utility function, do not drive our results. For example, if poor math skills lead a subject to over-estimate a probability, then the over-estimation induced by poor math skills occurs in all treatments, including the Baseline Treatment and thus we are able to "net out" this characteristic.

Further, we chose to incentivize beliefs using the QSR because of its simplicity, although it is only incentive-compatible under the assumption of risk-neutrality. Risk aversion causes subjects' probabilistic reports to tend towards 0.5. This tendency towards 0.5 would occur in each treatment as subjects are incentivized with the QSR throughout the experiment. A binary lottery implementation of the quadratic scoring rule is theoretically incentive compatible and robust to risk preferences (McKelvey and Page, 1990), but experimental evidence suggests that it does not successfully induce risk-neutrality (Selten et al., 1999) and the cognitive burden imposed on subjects may result in less reliable reports than the deterministic quadratic scoring rule (Rabin and Thaler, 2001).

While a within subject design allows for clean identification of optimism and overconfidence, there is a potential for order effects due to the order in which subjects face each of the four treatments. Accordingly, we have run sessions in 5 different orders. We find no evidence that order drives our results.

Second, we have designed the experiment so that the variable of interest in each treatment is the subject's probabilistic belief about white balls drawn from a jar. This allows us to make comparisons between the magnitudes of optimism and overconfidence at the individual level, as well as to directly decompose the probabilistic belief in the combined treatment into its optimistic component and its overconfident component.

We never directly ask subjects about their performance on the IQ questions because it is possible to impute the subject's belief about the probability of having correctly answered. Consider when the subject has a starting distribution of 1. If he answers the IQ question correctly, he moves to distribution 2 and otherwise remains in distribution 1. From the baseline treatment, we know his belief about the probability of 1 white ball drawn from distribution 1 and distribution 2, which we denote z^b_{d1} and z^b_{d2}, respectively. Let $\hat{p}$ be the probability the subject places on having answered the IQ question correctly and let z^{perf} be his elicited belief in the performance only treatment about the probability that 1 white ball is drawn from the jar. Then, the only unknown is $\hat{p}$, which can be found from

$$z^{perf} = \hat{p} \times z^b_{d2} + (1 - \hat{p}) \times z^b_{d1} \tag{27}$$

In Subsection **??**, we impute the subject-specific $\hat{p}$ in the single-draw distribution. Alternatively, it is possible to elicit $\hat{p}$ and then impute z^{perf}, but we chose to maintain a uniformity across treatments in order to emphasize their similarity and reduce the subjects' cognitive burden.

2.4 Data Construction and Preliminary Data Analysis

In this subsection, we describe the data generated by the experiment and conduct a preliminary data analysis. We emphasize one of the key strengths of our experimental design: that it generates a subject-level control against which all experimentally induced shifts are compared.

2.4.1 Raw Data

125 individuals across 15 sessions were asked to report beliefs about the number of white balls being drawn from six different distributions and under four different experimental treatments. Beliefs were elicited 20 times for each individual, which means we begin with 2,500 observations. Table 2.3, described in the previous subsection, shows the combination of experimental treatments and initial distributions faced by each individual. Recall that we distinguish between the initial distribution and the distribution the subject actually faces, which in the performance and combined treatments is determined by the number of correctly answered IQ questions. For each individual and distribution dyad, subject reports of their beliefs consist of one moment for Distributions 1 and 2 and three moments for Distributions 3-6.

We drop 52 observations where individual reports are not consistent with positive marginal probabilities.[34] Also, a number of individuals face the same distribution under the same treatment more than once. For example, suppose an might answer zero IQ questions correctly in each round that he starts by facing distribution 3 in the performance treatment. If so, he reports beliefs under the performance treatment and facing distribution 3 twice. In such cases, we average over the individual's responses.[35] Averaging in this manner means we lose an additional 204 observations. This leaves us with 2,244 observations. In Table 2.4, we record the total number of remaining observations we have for each treatment and distribution.

[34]For example, if a subject reports that the probability of drawing either one or two white balls is 20% and that the probability of drawing one white ball is 40%, answers are not consistent with probabilistic beliefs. These observations can be re-coded in various ways to make them consistent with probabilities. Doing so leaves results unchanged and so we prefer to drop them from our main analysis.

[35]Alternatively, we could randomly choose one set of beliefs. Main results are robust to these changes.

2.4.2 Measuring Optimism and Overconfidence

For each individual and for each distribution, we elicit beliefs under the baseline treatment, where individuals are incentivized to report their beliefs. The baseline treatment establishes a subject level control, against which we compare beliefs in the other treatments. We use the baseline belief to control for individual-level unobserved heterogeneity, including differences across individuals in their computational ability and heterogeneity in risk preferences. We measure optimism and overconfidence as within-subject shifts (relative to baseline beliefs) in the remaining experimental treatments: the payment and performance, respectively.

Formally, for individual i facing distribution d under treatment τ, we define shifts relative to baseline beliefs as follows:

$$\overline{shift}_{i,d,\tau} \equiv \frac{1}{M_d} \sum_{m=1}^{M_d} \left[Beliefs_{i,d,m,\tau} - Truth_{d,m}\right] - \left[Beliefs_{i,d,m,\tau=B} - Truth_{d,m}\right], \qquad (28)$$

where M_d is the number of moments for distribution d, $Truth_{d,m,\tau}$ is the objective probability for moment m of distribution d, and $\tau = B$ refers to beliefs elicited under the baseline treatment. Notice that we can rewrite equation (28) as

$$\overline{shift}_{i,d,\tau} = \frac{1}{M_d} \sum_{m=1}^{M_d} \left[Beliefs_{i,d,m,\tau} - Beliefs_{i,d,m,\tau=B}\right]. \qquad (29)$$

The variable $\overline{shift}$ is therefore the average difference between beliefs reported under treatment τ and beliefs reported under the baseline treatment ($\tau = B$) for the same individual and distribution. In the payment treatment, $\overline{shift}$ captures optimism by measuring within-subject shifts in beliefs due to changes in side payments for white balls. In the performance treatment, $\overline{shift}$ captures overconfidence by measuring within-subject shifts in beliefs due to changes in how trivia answers affect the distribution of white balls. In the combined treatment, $\overline{shift}$ captures shifts in beliefs when subjects face uncertainty, can affect the distribution using through their performance and also receive side payments for each white ball that is drawn.

Our definition of $\overline{shift}$ nets out baseline beliefs. Therefore, we only define it for

$$\tau \in \{Payment, Performance, Combined\}$$

This also means that the sample size is reduced since, for each distribution, each individual loses the baseline beliefs observation. The result is a sample reduction of 726 observations and leaving 2,244−726=1,518 observations for which $\overline{shift}$ is defined. These observations are comprised of 738 within-subject shifts comparing the payment treatment to the baseline control, 385 for the performance treatment and 395 for the combined treatment. Table 2.5 describes the number of observations in each treatment by gender and by number of correctly answered trivia questions in the experiment. Of the 125 individuals in the sample, 59 are male and 66 are female. Throughout the experiment, subjects are asked to answer 16 IQ questions, where Figure **??** is a histogram showing the distribution of total correctly answered IQ questions among sample subjects, where the mean is 9.23 and the standard deviation is 0.53.

2.4.3 Measuring Within-Subject Correlation

The main analysis in subsection 2.5 focuses on how optimism, overconfidence and over-estimation are related at the individual-level. Doing so places additional burden onto the data. In particular, we need to observe the same individual in multiple treatments for the same distribution, which is not always the case in the performance treatments given that the distribution subjects face depends on his answers to the IQ questions. Returning to Table 2.5, consider the final two lines. In the second-to-last line, we report that 383 individuals are observed in the same distribution in both the payment and the performance treatments. In the bottom line, we report that 247 individuals are observed in the same distribution in all three treatments. These are the sample sizes we use when comparing within-subject correlations in responses to treatments. From Table 2.5, we note that these samples, though small, are composed nearly evenly of males versus females and of low versus high IQ individuals, which helps to dispel concerns that our main results are identified off of a non-randomly selected sample.

2.4.4 Average Treatment Effects

In this subsection, we study average treatment effects. In particular, we provide a preliminary analysis of the 1,518 observations of the variable $\overline{shift}$ defined in equation (28).[36] In Figure 2.3, we plot histograms of $\overline{shift}$ for all 1,518 observations and then separately for the payment, performance and combined treatments. First, note that the mode in all four panels is zero meaning that a plurality of subjects show no significant departures in their treatment reports than in their baseline reports. However, there are non-zero observations, which means that some subjects' are optimistic (pessimistic) and overconfident (under-confident).

Next, we ask if observed treatment-induced shifts are systematically related to observable covariates. In Table 2.6, we present estimates from OLS regressions where the outcome variable is $\overline{shift}$ and explanatory variables include experimental treatments (payment, performance or combined), gender, correctly answered trivia questions. The specification we use is

$$\overline{shift}_{i,d,\tau} = \sum_{\tau} \mathbf{1}[treatment = \tau]\psi_\tau + X_{i,d}\delta + e_{i,d,\tau} \tag{30}$$

We also include distribution and order dummy variables. In the first specification (Column [1]), we only control for treatments. Doing so, we see that the payment only treatment induces no average shift, but that the performance and combined treatments lead people to over-estimate the number of white balls (relative to the baseline). This is consistent with what we see in Figure 2.3 and indicates that the subjects are overconfident, on average.

Next, we control for possible order effects by adding dummy variables for each order (Column [2]). Doing so increases the size of the treatment effects, though this increase is only significant for the payment-only treatment.[37] In Column [3], we also control for distribution dummy variables.

[36] In the appendix, we repeat our analysis of average treatment effects for the subsample of individuals who are used in our main analysis since they are observed. Main patterns are the same, which helps to dispel concerns that our main results are driven by bias in the selection of the individuals off whom we estimate main effects.

[37] This change reflects that subject deviations from the objective distribution grow larger toward the end of the

This further raises the estimated coefficients on the treatment effects. It reflects how, on average, the more complex distributions lead to larger shifts. Our results suggest that optimism is more likely when forming beliefs amounts to more difficult computational task. Finally, we add a gender dummy in Column [4] and find that it has no impact. In other words, on average, men and women are equally likely to over-estimate the number of white balls that are drawn.

In Column [5], we add a variable for the total number of correctly answered IQ questions. We show that treatment effects are larger for people who answer few trivia questions, but decline for people who answer more trivia questions correctly. One possibility is that answering more IQ questions correctly is indicative of a stronger ability to calculate complex probabilities, which means that individuals might be less prone to shift in response to experimental treatments. However, this relationship could also reflect that individuals facing uncertainty who answer more IQ questions correctly are more likely to face distributions with higher numbers of white balls. We have controlled for distribution dummy variables, which should address the second possibility. In Column [6], we go further, interacting total correctly-answered IQ questions with each treatment. The idea is that the payment treatment keeps the distribution fixed so that any variation in the treatment effect by correct IQ answers in not an artifact of the impact of IQ answers on the distribution. We find that the impact of correctly answered trivia questions is present in the payment treatment. This suggests that individuals who answer fewer IQ questions correctly are also more likely to exhibit optimistic beliefs.

2.5 Main Results

In this subsection, we establish two main results. First, optimistic people tend to be overconfident. Second, optimism and overconfidence help to explain why individuals facing uncertainty over-estimate high-payoff outcomes. The converse is also true. Pessimism and under-confidence are related at the individual level and both explain why some individual under-estimate the likelihood of high-payoff outcomes. We also decompose the explanatory power of optimism and overconfi-

experiment, which is consistent with fatigue.

dence for different subsets of subjects.

2.5.1 How Optimism Relates to Overconfidence

In this subsection, we relate $\overline{shift}$ for the payment and performance treatments. The former captures optimism since performance plays no role, but individuals are experimentally induced to prefer some outcomes over others. The performance treatment captures overconfidence since subjects must form beliefs over their ability to answer trivia questions and, in so far as they over-estimate this probability, believe there are more white balls in the urn than are actually there. In Figure 2.5, we plot within-subject shifts in beliefs in the payment treatment and compare it to within-subject shifts in the performance treatment. The Figure shows clear evidence of a positive correlation.

Next, we ask if this correlation is robust when we control for different sets of covariates. We use OLS to estimate equations of the following form:

$$\overline{shift}_{i,d,performance} = \overline{shift}_{i,d,payment}\phi_1 + X_{i,d}\beta_1 + \epsilon_{i,d,\tau} \tag{31}$$

The key identifying assumption is that once we have controlled for total number of white balls added, the baseline and gender, selection on who reaches what distribution is random. Results are presented in Table 2.7. We do this for 383 observations where the individual is observed in the baseline, payment and performance treatments for the same distribution. In the first four specifications, we add controls. We consistently find a strong correlation. Column [1] of Table 2.7 suggests that a 10 percentage point increase in a subject's optimism is associated with 6.6 percentage point increase in his overconfidence.

We show that gender and the number of correctly answered IQ questions do not affect the relationship.[38] In the fourth column, we limit attention to the 247 observations that we use in subsequent analysis, where we observe the individual in the same distribution for all four treatments.

[38] We also fully interact optimistic shifts with order effects. There is some variation, especially the fifth order finds a weaker correlation that is not significantly different from zero.

2.5.2 How Optimism and Overconfidence Affect Beliefs

Next, we relate shifts in the performance and payment treatments related to shifts in the combined treatment. Here, the goal is to assess how optimism and overconfidence relate to beliefs in a setting where both are possible. We begin by plotting shifts in the payment and combined treatments (Figure 2.6) and the performance and combined treatments (Figure 2.7). In both cases, there is clear evidence of positive correlation.

Next, we regress shifts in the combined treatment onto shifts in the payment and performance treatments, again relating within individual shifts (relative to each individual's baseline). We limit attention to the 247 observations where the same individual is observed in all four treatments. The aim is to understand how beliefs in the combined setting decompose into its optimism and overconfidence components.

$$\overline{shift}_{i,d,combined} = \overline{shift}_{i,d,payment}\phi_2 + \overline{shift}_{i,d,performance}\phi_3 + X_{i,d}\beta_2 + \eta_{i,d,\tau} \tag{32}$$

Results are in Table 2.8. First, we find that shifts in beliefs in the payment and performance treatments are both positively correlated. Similar for the payment treatment. In other words, optimistic shifts are correlated to shifts where optimism and overconfidence are possible. Next, because they are positively correlated, we are able to show that they impact is attenuated when we control for both. The coefficient falls. We also interact both fully with order for robustness.

2.5.3 Explaining Variation in Over-estimation

Table 2.9 presents the estimates of the squared semi-partial correlations obtained by estimating equation 2.6.1 (**?**).[39] The squared semi-partial correlations estimate the proportion of variance in $\overline{shift}_{i,d,combined}$ that is due to variations in $\overline{shift}_{i,d,performance}$ (overconfidence) and $\overline{shift}_{i,d,payment}$ (optimism), respectively. Column (1) shows that 16% of the variation in the combined treatment is

[39]The meaningfulness of these estimates depends heavily on whether the model is correctly specified as a linear model. In the appendix, we show that the relationship between over-estimation, optimism and overconfidence is highly linear.

explained by overconfidence only, while 3% of the variation in explained by optimism only. The third line of column (1) accounts for the positive correlation between optimism and overconfidence and shows that an estimated 36% of the variation in beliefs in the combined treatment can be attributed to overconfidence and optimism jointly. By comparison, only 4% of the variation can be explained by gender and IQ.[40] In subsection 2.7 we discuss the potential policy implications of these results.

Columns (2)-(7) compares the decomposition of variance across three sub-population: male versus female, 1-draw distributions versus 3-draw distributions, and low IQ versus high IQ subjects. However, we find no significant differences in how overconfidence only and optimism only explain variation within each of the sub-populations.

2.6 Robustness of Main Results

Here, we ask whether our results are robust. First, we consider alternative ways to define shift variables. One way allows for more flexibility. The second is a much stricter definition. Next, we discuss mis-calibration.

2.6.1 Alternative Specification

In this subsection, we present robustness checks. Some details are relegated to the appendix. First, we discuss alternative measures of optimism and overconfidence, which amounts to re-defining the variable $\overline{shift}_{i,d,\tau}$. We consider two alternative ways to measure shifts. First, we allow more flexibility in the relationship between baseline beliefs and other beliefs. Second, we conduct our analysis using stricter definitions of optimism and overconfidence, requiring first-order stochastic dominance. We show that our main results are robust to both.

Alternative 1:

Relating optimism and overconfidence using equation (29) is possible over-restrictive. An

[40]This was calculated by comparing the difference in pseudo-R^2 when the variables are included in the model and when they are omitted.

alternative is to define it as follows.

$$\widetilde{shift}_{i,d,m,\tau} \equiv Beliefs_{i,d,m,\tau} \tag{33}$$

In this definition, a shift is not relative to an individual's own baseline beliefs, but is measured relative to the objective probability only. To account for individual heterogeneity in how they respond to questions about beliefs, we include baseline beliefs relative to the truth ($\widetilde{shift}_{i,d,m,baseline}$) as additional regressors. This definition of shifts is more flexible than the one used in our main analysis. In particular, this definition allows the relationship between baseline beliefs and beliefs elicited in other treatments to vary across treatments. Using this definition, we compare treatment responses in the payment and performance treatments and then assess how beliefs in the combined treatment relate to responses in the payment and performance treatments. We estimate

$$\widetilde{shift}_{i,d,performance} = \widetilde{shift}_{i,d,payment}\phi_1^{A1} + \widetilde{shift}_{i,d,baseline}\phi_2^{A1} + X_{i,d}\beta_1^{A1} + \epsilon_{i,d,\tau}^{A1} \tag{34}$$

and

$$\begin{aligned} \widetilde{shift}_{i,d,combined} &= \widetilde{shift}_{i,d,payment}\phi_3^{A1} + \widetilde{shift}_{i,d,performance}\phi_4^{A1} \\ &+ \widetilde{shift}_{i,d,baseline}\phi_5^{A1} + X_{i,d}\beta_2^{A1} + \eta_{i,d,\tau}^{A1} \end{aligned} \tag{35}$$

Estimating equation (34) is comparable to estimating equation (31) where the goal is to assess within-individual correlation between optimism and overconfidence. Equation is comparable to , where the aim is to assess how optimism and overconfidence jointly drive beliefs under uncertainty, where individuals are potentially prone to both biases. In running these regressions, we work with a sample of 1,732 observations, where each observation is not an individual-distribution-moment tryad.[41] Results are in 2.10 and 2.11 and are similar to our main results.

Alternative 2:

Another possibility when defining shifts under different experimental treatments is to require that individual beliefs stochastically dominate the true, objective distribution in order to categorize

[41] We arrive at our sample in the following manner.......

them as optimistic or overconfidence. This might seem like the more natural way to do things. However, we do lose in some sense what it means to be optimistic or overconfidence since it might be that people are optimistic with regards to a distribution for one moment, but pessimistic for another. In any case, having showing that our results hold under a more flexible definition of a shift, we now show that our results hold under a stricter definition. In particular, we now define our shift variable as follows:

$$\widehat{shift}_{i,d,\tau} \equiv \begin{cases} 1 & \text{if} \quad [Beliefs_{i,d,m,\tau} < Beliefs_{i,d,m,B})] \ \forall m \in \{1,\ldots,M_d\} \\ -1 & \text{if} \quad [Beliefs_{i,d,m,\tau} > Beliefs_{i,d,m,B})] \ \forall m \in \{1,\ldots,M_d\} \\ 0 & \text{otherwise} \end{cases} \tag{36}$$

According to this definition, the shift variable takes the value of 1 if individual beliefs about the distribution first-order stochastically dominate the objective distribution and the value -1 beliefs are first order stochastically dominated by the true, objective distribution. In contrast to the other shift variables, the individual's beliefs must lie to the right or the left of the objective distribution for all moments.[42] Average treatment effects are plotted in **??** (Figure **??**).

As before, our aim is to compare treatment responses in the payment and performance treatments and then assess how beliefs in the combined treatment relate to responses in the payment and performance treatments. We estimate

$$\widehat{shift}_{i,d,performance} = \widehat{shift}_{i,d,payment}\phi_1^{A2} + X_{i,d}\beta_1^{A2} + \epsilon_{i,d,\tau}^{A2} \tag{37}$$

and

$$\widehat{shift}_{i,d,combined} = \widehat{shift}_{i,d,payment}\phi_2^{A2} + \widehat{shift}_{i,d,performance}\phi_3^{A2} + X_{i,d}\beta_2^{A2} + \eta_{i,d,\tau}^{A2} \tag{38}$$

[42]We note that some individuals face the same distribution more than once and, among these, some are categorized differently. Our results are robust to several ways to categorize these. One possibility is to average them (so that some distribution-individual dyads take values of -0.5 or 0.5. Alternatively, these individuals can be assigned 0, which makes our shift definition even stricter. These observations can also be dropped. Results are robust to these alternatives.

These are, as before, analogous to equations (31) and , respectively. We estimate them using ordered probits. Results are in 2.12 and 2.13 and are similar to our main results.[43]

2.6.2 Measuring Overconfidence as Miscalibration

In this subsection, we show that our main results are robust to other measures of overconfidence. Recall, we do not explicitly elicit the subject's probabilistic report about the likelihood of giving a correct answer to the IQ questions, but it is straightforward to impute the subject's belief that he gave a correct answer, $\hat{p}$, in the single-draw distributions from equation 27. Currently, if a subject's probabilistic reports imply $\hat{p} = .55$ and, in reality, his answer was incorrect, then our measure classifies him as being overconfident. However, if the subject answers, on average, 55% of the IQ questions correctly, then a $\hat{p} = .55$ is well-calibrated (Lichtenstein et al., 1977).

Figure 2.8 shows the distribution of $\hat{p}$ in the single-draw distribution. Figure 9(a) shows that subjects who answered incorrectly have a mean belief of .53, but are likely to either believe their answer was incorrect $\hat{p} = 0$) or believe with certainty that their answer was correct ($\hat{p} = 1$). On the other hand, Figure 9(b) shows that among subjects who answered correctly, the mean belief is .81 while the majority of subjects believe they answered correctly ($\hat{p} = 1$).

To measure calibration, we subtract the subject's overall proportion of correct IQ answers, q, from the imputed probabilistic report of a correct IQ answer, $\hat{p}$. If a subject's imputed report of a correct answer, $\hat{p}$, is 64% and he answered 40% (70%) of the IQ questions correctly, then we classify him as over-calibrated (under-calibrated). Figure **??** shows the distribution of the calibration measure, which has a mean .10 and standard deviation .42.

Next, we replicate equation 31 using the calibration measure as our measure of overconfidence. We find a significant positive correlation between miscalibration and optimism: subjects who are over-calibrated (under-calibrated) are also more likely to be optimistic (pessimistic).

Finally, we replicate equation 31 and equation 2.6.1 for a restricted sample: subjects for whom

[43] In results available upon request, we also estimate these equations using OLS instead of ordered probits. Results are qualitatively similar.

$| \hat{p} - q | > 0.1$.[44] Results are reported in Table 2.14 and show qualitatively similar relationships to results in Tables 2.7 and 2.8.

2.7 Discussion of Results

In summary, our two main findings are that optimism and overconfidence are positively correlated at the individual level and that both explain beliefs in the combined setting. Together, these results have various implications.

One implication of the positive correlation structure between optimism and overconfidence is that attributing overestimation solely to overconfidence results in an omitted variables bias and inflates the explanatory power of overconfidence. The common view in both psychology and economics is that men are more overconfident than women,[45] which results in differences in willingness to compete (Niederle and Vesterlund, 2007), as well as differences in trading and investment strategies (Barber and Odean, 2001). Men would also appear more overconfident than women if the correlation between optimism and overconfidence is stronger for males than females. However, the data do not support this hypothesis (p-value=.89).

There is a second implication for the design of policy and information interventions. The design of cost-effective information interventions aimed at changing behavior by changing beliefs crucially depends on the structural relationship between beliefs. Table 2.9 shows that 36% the variation in beliefs in the combined setting is explained by optimism or overconfidence, while only 4% is explained by IQ and gender. This has finding has potentially positive implications for policy. If the majority of the variation was explained by gender or IQ (or other non-malleable characteristics) then information interventions may be fruitless.

However, information interventions can only have an impact if beliefs, like optimism and overconfidence, are predictably malleable. There is evidence that individuals update differently when receiving objective information versus self-relevant information (**??**). In fact, **?** finds that sub-

[44] This result is robust to various thresholds.

[45] See Croson and Gneezy (2009) for a short review.

jects update in as a Bayesian when receiving objective information, but do not update according to Bayes rule when they receive self-relevant (e.g., performance-related) information. Further, **?** show that when subjects receive information about their IQ score they put full weight on their prior belief, update asymmetrically (weighting favorable information more heavily than unfavorable information) and are increasingly averse to receiving information the more over-confident they are. These findings are potentially problematic for information interventions aimed at changing beliefs about self-relevant characteristics: individuals respond in less consistent, predictable ways. However, our findings suggest that the positive correlation between optimism and overconfidence could potentially be leveraged in such a way to render more predictable and effective information interventions.

Our findings suggest that when individuals over-estimate the probability of a high pay-off outcome, simply providing information meant to address optimism (i.e., market demand for an entrepreneur's good or service) will not fully rectify their belief because they are also likely to be overconfident. Unless, optimism causes overconfidence. In this case, providing information targeted directly at the individual's optimism would be sufficient. Conversely, providing the individual with information meant to address overconfidence (i.e., technical expertise or specialist training) will have zero impact since it doesn't address the cause of the overconfidence. Thus, an interesting next step would be to establish whether there is a causal relationship between optimism and overconfidence.

2.8 Tables and Figures

TABLE 2.1: TREATMENT, BELIEFS AND TREATMENT EFFECTS

Treatments	Payment for Belief Accuracy	Side Payment for White Balls Drawn	White Balls Added to Jar for Correct Answers
Baseline	Yes	No	No
Payment Only	Yes	Yes	No
Performance Only	Yes	No	Yes
Combined	Yes	Yes	Yes

TABLE 2.2: EXPERIMENTAL DESIGN AND DISTRIBUTIONS

	DISTRIBUTION DETAILS			PERFORMANCE
DISTRIBUTION	# OF WHITE	# OF BLACK	# OF DRAWS	TREATMENT
1	1	1	1	↓
2	2	1	1	
3	1	3	3	↓
4	2	3	3	
5	3	3	3	
6	4	3	3	

Subjects face 6 distributions in the Baseline Treatment and Payment Only Treatment. In the Performance Only Treatment and Combined Treatment subjects start in Distribution 1 twice and Distribution 3 twice and one white ball is added to the starting distribution for each correctly answered IQ question. Subjects starting in distribution 1 answer 1 IQ question, adding 1 white ball if correct and therefore facing distribution 2. If they answer the question incorrectly, no white ball is added and they face distribution 1. When subjects start with distribution 3, they answer 3 IQ questions and may add 0, 1, 2 or 3 white balls, therefore facing distributions 3, 4, 5, or 6.

TABLE 2.3: DATA GENERATION

	TREATMENTS			
STARTING DISTRIBUTION	No Payment & No Performance	Payment Only	Performance Only	Payment & Performance
1	1	1	2	2
2	1	1	0	0
3	1	1	2	2
4	1	1	0	0
5	1	1	0	0
6	1	1	0	0
Σ	6	6	4	4

This table shows what information is gathered from each subject. There are six distributions and four treatments. Each subject is asked about a total of 20 distributions. In the No-Payment, No-Performance treatment, the subject is asked about all six distributions. In the Payment Only treatment, the subject is asked about all six distributions. If the Performance distribution, the subject begins facing distribution 1 twice and distribution 3 twice. In the Payment and Performance treatment, the subject begins facing distribution 1 twice and distribution 3 twice. Recall that in the performance treatments the actual distribution subjects face is endogenous to the number of trivia questions they answer correctly and so may differ from the starting distribution.

TABLE 2.4: OBSERVATIONS

	TREATMENTS				
DISTRIBUTION	No Payment & No Performance	Payment Only	Performance Only	Payment Performance	Σ
1	125	125	86	88	424
2	125	125	92	102	444
3	110	117	22	24	273
4	119	122	40	62	343
5	123	125	94	74	416
6	124	124	51	45	344
Σ	726	738	385	395	2,244

This table shows the how many observations are collected for each distribution and experimental treatment pair.

TABLE 2.5: SUMMARY STATISTICS: SAMPLE SIZE OF WITHIN SUBJECT SHIFTS

				Trivia	
	Total	Male	Female	Low	High
Subjects	125	59	66	61	64
Observations (Treatment-Induced Shifts)					
Total	1,518	730	788	746	772
Payment	738	352	386	360	378
Performance	385	184	201	191	194
Combined	395	194	201	195	200
Sample for Main Analysis					
Payment and Performance	**383**	184	199	189	194
Combined, Payment and Performance	**247**	129	118	118	129

The sample sizes for the main analysis are determined by the number of subject-distribution pairs that are observed for the relevant treatments. In Table 2.7 we only require that subject-distribution pairs be present in the Payment only and Performance only treatments, resulting in 383 observations. For the analysis in Table 2.8 we apply an additional restriction and require subject-distribution pairs to also be observed in the Combined Treatment, resulting in 247 observations.

TABLE 2.6: AVERAGE TREATMENT EFFECTS: REGRESSIONS

	[1]	[2]	[3]	[4]	[5]	[6]
Payment Only	0.003	0.01*	0.06***	0.07***	0.11***	0.1***
Performance Only	0.03***	0.04***	0.09***	0.09***	0.14***	0.16***
Pay + Perf	0.02***	0.04***	0.09***	0.09***	0.14***	0.16***
Male	.	.	.	-0.007	0.0005	0.0006
Correct IQ Answers	.	.	.	.	-0.006***	.
IQ $\times$ Pay	.	.	.	.	.	-0.004*
IQ $\times$ Perf	.	.	.	.	.	-0.008**
IQ $\times$ Pay + Perf	.	.	.	.	.	-0.008**
Order Dummies	[N]	[Y]	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[Y]	[Y]	[Y]	[Y]

OLS regression. Outcome variable: Baseline belief minus treatment belief, cumulative probabilities.

TABLE 2.7: CORRELATION BETWEEN OPTIMISM AND OVERCONFIDENCE

	[1]	[2]	[3]	[4]
Optimism	0.66^{***}	0.65^{***}	0.64^{***}	0.62^{***}
Male	.	0.01	0.006	0.02^{*}
Correct IQ Answers	.	-0.009^{***}	-0.003	-0.004
Constant	0.03^{***}	0.11^{***}	0.12^{***}	0.13^{***}
Observations	383	383	383	247
R^2	0.32	0.34	0.41	0.46
Order Dummies	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[Y]	[Y]
Smaller Sample	[N]	[N]	[N]	[Y]

OLS regression. Outcome variable: Baseline belief minus Performance Only treatment belief, cumulative probabilities.

TABLE 2.8: THE ROLE OF OPTIMISM AND OVERCONFIDENCE

	[1]	[2]	[3]	[4]	[5]
Overconfidence	0.65^{***}	.	0.5^{***}	0.56^{***}	0.54^{***}
Optimism	.	0.59^{***}	0.27^{***}	0.25^{***}	0.25^{***}
Male	.	.	.	0.02	0.02
Correct IQ Answers	.	.	.	-0.002	-0.001
Constant	0.05^{***}	0.11^{***}	0.06^{***}	0.04	0.05
Observations	247	247	247	247	247
R^2	0.51	0.41	0.54	0.52	0.53
Order Dummies	[Y]	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[N]	[N]	[Y]

OLS regression. Outcome variable: Baseline belief minus Combined treatment belief, cumulative probabilities.

TABLE 2.9: DECOMPOSING VARIATION IN BELIEFS IN THE COMBINED TREATMENT

	All	Males	Females	Simple	Complex	Low IQ	High IQ
Overconfidence only	16%***	16%***	15%***	10%***	13%***	12%***	27%***
Optimism only	3%***	2%**	6%***	4%***	3%**	4%***	3%**
Overconfidence & Optimism	36%	20%	41%	28%	47%	34%	38%
All other variables, jointly	4%	9%	5%	8%	2%	8%	4%
Observations	247	129	118	144	103	156	91

TABLE 2.10: CORRELATION BETWEEN OPTIMISM AND OVERCONFIDENCE

	[1]	[2]	[3]	[4]	[5]	[6]
Optimism Only	0.82***	0.53***	0.53***	0.53***	0.42***	0.42***
Baseline Belief	.	0.35***	0.35***	0.37***	0.26***	0.22***
Male	.	.	-0.001	0.001	-0.001	-0.02
Correct IQ Answers	.	.	0.0009	-0.004	-0.004	-0.003
Observations	778	778	778	778	778	450
R^2	0.69	0.72	0.72	0.74	0.76	0.77
Order Dummies	[Y]	[Y]	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[N]	[Y]	[Y]	[Y]
Moment Dummies	[N]	[N]	[N]	[Y]	[Y]	[Y]
Smaller Sample	[N]	[N]	[N]	[N]	[N]	[Y]

OLS regression. Raw Beliefs.

TABLE 2.11: THE ROLE OF OPTIMISM AND OVERCONFIDENCE

	[1]	[2]	[3]	[4]	[5]	[6]
Performance Only	0.61***	.	0.48***	0.47***	0.45***	0.37***
Optimism Only	.	0.55***	0.28***	0.29***	0.29***	0.23***
Baseline Belief	0.25***	0.29***	0.13*	0.13*	0.14**	0.06
Male	.	.	.	-0.03*	-0.03*	-0.03*
Correct IQ Answers	.	.	.	0.001	-0.0004	-0.0006
Constant	0.06***	0.06***	0.05***	0.05	0.04	0.15***
Observations	450	450	450	450	450	450
R^2	0.69	0.65	0.71	0.72	0.72	0.74
Order Dummies	[Y]	[Y]	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[N]	[N]	[Y]	[Y]
Moment Dummies	[N]	[N]	[N]	[N]	[N]	[Y]

OLS regression. Raw Beliefs.

TABLE 2.12: CORRELATION BETWEEN OPTIMISM AND OVERCONFIDENCE

	[1]	[2]	[3]	[4]
Optimism Only Shift	0.29*	0.29*	0.36**	0.14
Male	.	0.23**	0.22*	0.41***
Correct IQ Answers	.	-0.03	-0.001	-0.02
Constant	.	.	.	.
Observations	383	383	383	247
Pseudo R^2	0.02	0.03	0.07	0.07
Order Dummies	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[Y]	[Y]
Smaller Sample	[N]	[N]	[N]	[Y]

oprobits for categorical vars.

TABLE 2.13: THE ROLE OF OPTIMISM AND OVERCONFIDENCE

	[1]	[2]	[3]	[4]	[5]
Performance Only Shift	0.6^{***}	.	0.6^{***}	0.68^{***}	0.56^{***}
Optimism Only Shift	.	0.52^{**}	0.51^{**}	0.44^{*}	0.47^{**}
Male	.	.	.	0.02	0.05
Correct IQ Answers	.	.	.	0.01	0.04
Constant	.	.	.	.	.
Observations	247	247	247	247	247
Pseudo R^2	0.1	0.07	0.11	0.08	0.11
Order Dummies	[Y]	[Y]	[Y]	[Y]	[Y]
Distribution Dummies	[N]	[N]	[N]	[N]	[Y]

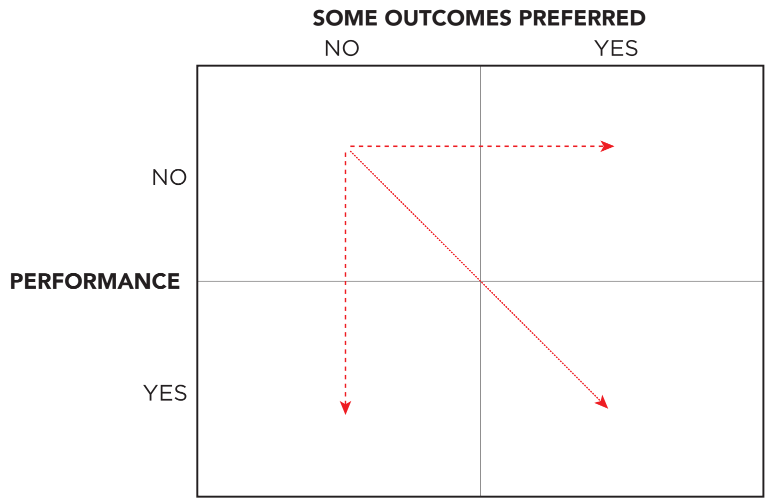
oprobits for categorical vars.

TABLE 2.14: ROBUSTNESS TO MISCALIBRATION

	[1]	[2]	[3]
Optimism Only	0.35^{*}	0.57^{***}	0.26^{**}
Overconfidence Only	.	.	0.5^{***}
Male	0.05	0.04^{*}	0.02
Correct IQ Answers	-0.06^{***}	-0.02^{***}	-0.003
Constant	0.74^{***}	0.25^{***}	0.06
Observations	159	170	137
R^2	0.23	0.39	0.54
Order Dummies	[Y]	[Y]	[Y]

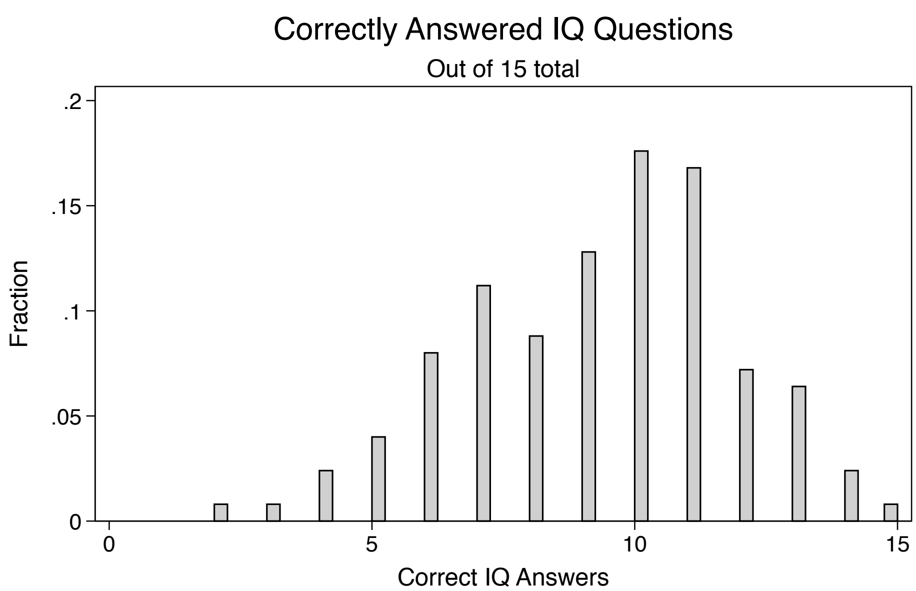
OLS regression. Outcome variable: Baseline belief minus treatment belief, cumulative probabilities.

FIGURE 2.1: EXPERIMENTAL TREATMENTS



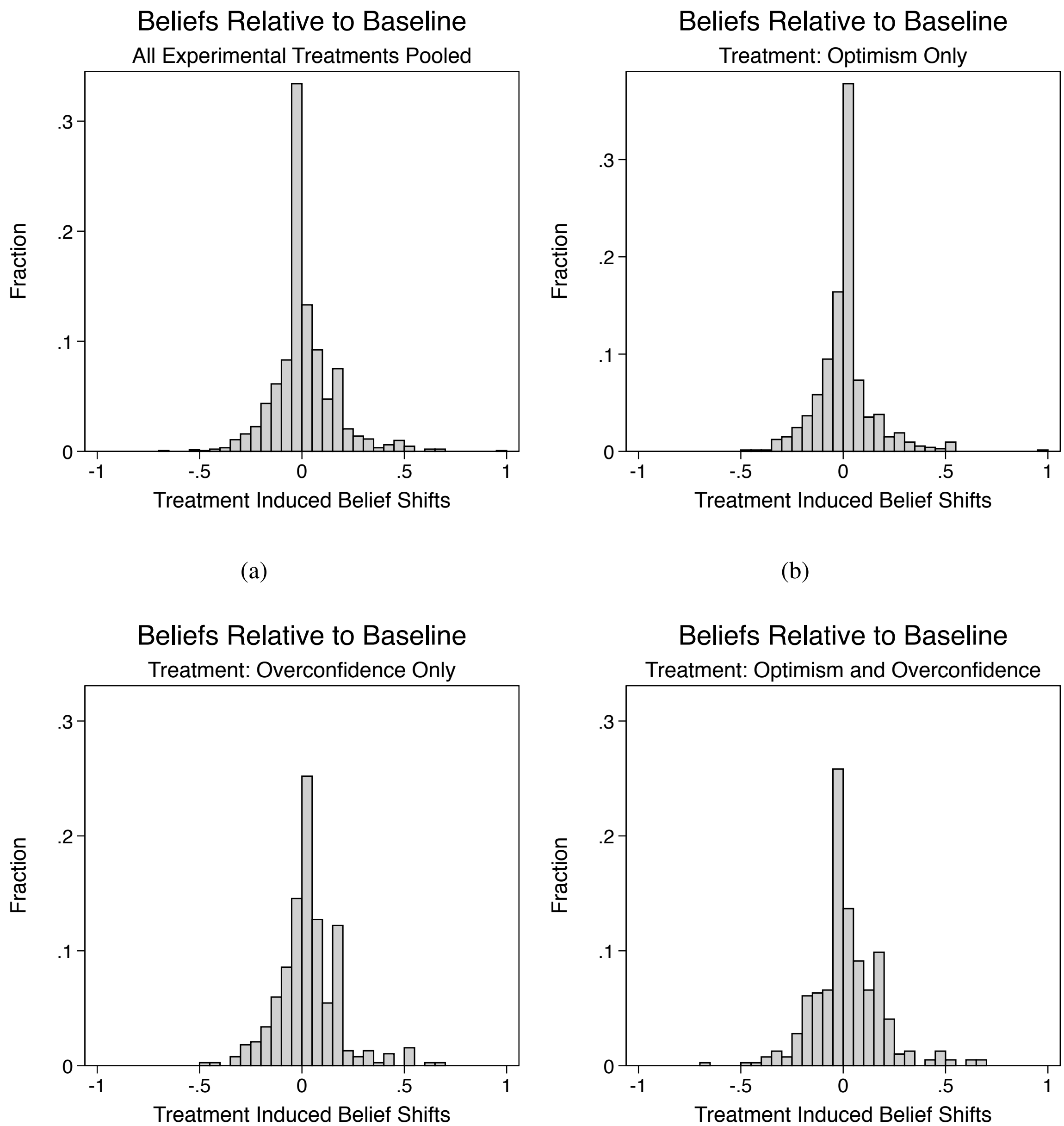
Each cell in the box represents a level of one of the experimental treatments and the arrows represent the treatments. The *payment treatment* varies whether white balls are payoff favorable. The *performance treatment* varies whether the distribution is exogenously determined or endogenously determined by the subject's performance (correctly answered trivia questions).

FIGURE 2.2: DISTRIBUTION OF PROXY IQ



Histogram of correctly answered IQ questions, by individual.

FIGURE 2.3: AVERAGE TREATMENT EFFECTS



AVERAGE TREATMENT EFFECTS: We plot histograms where each observation is a within-subject shift relative to the baseline deviation from the objective distribution. 4(a): All treatment pooled. 4(b): Payment only treatment. 4(c): Performance only treatment. 4(d): Combined treatment.

3 The Innovative Personality

3.1 Introduction

The role of the individual entrepreneur in fostering innovation and economic growth has obtained nearly folkloric stature. Schumpeter (1947) notes that producing "caviar from sawdust" is the

FIGURE 2.4: OPTIMISM AND OVERCONFIDENCE

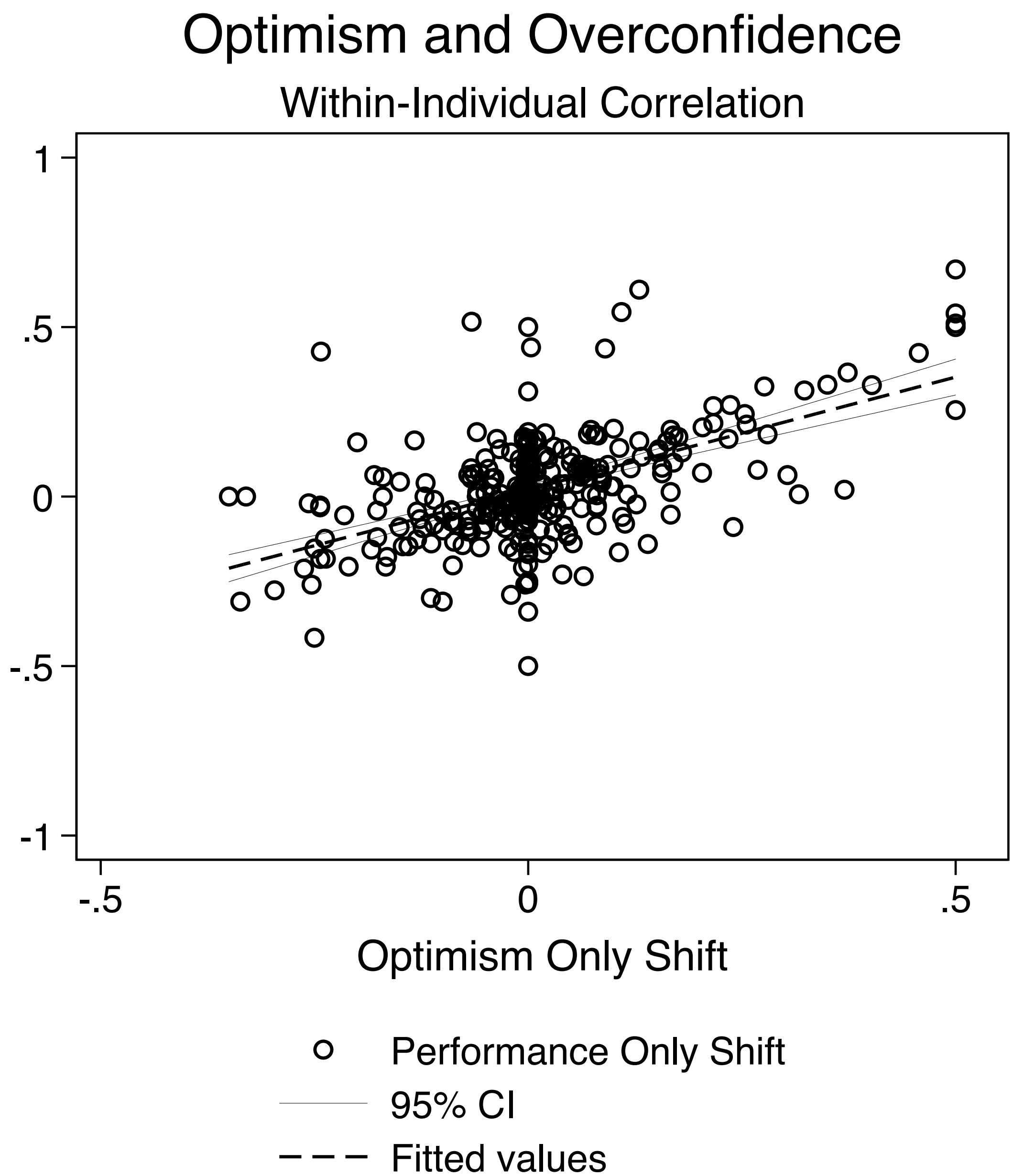
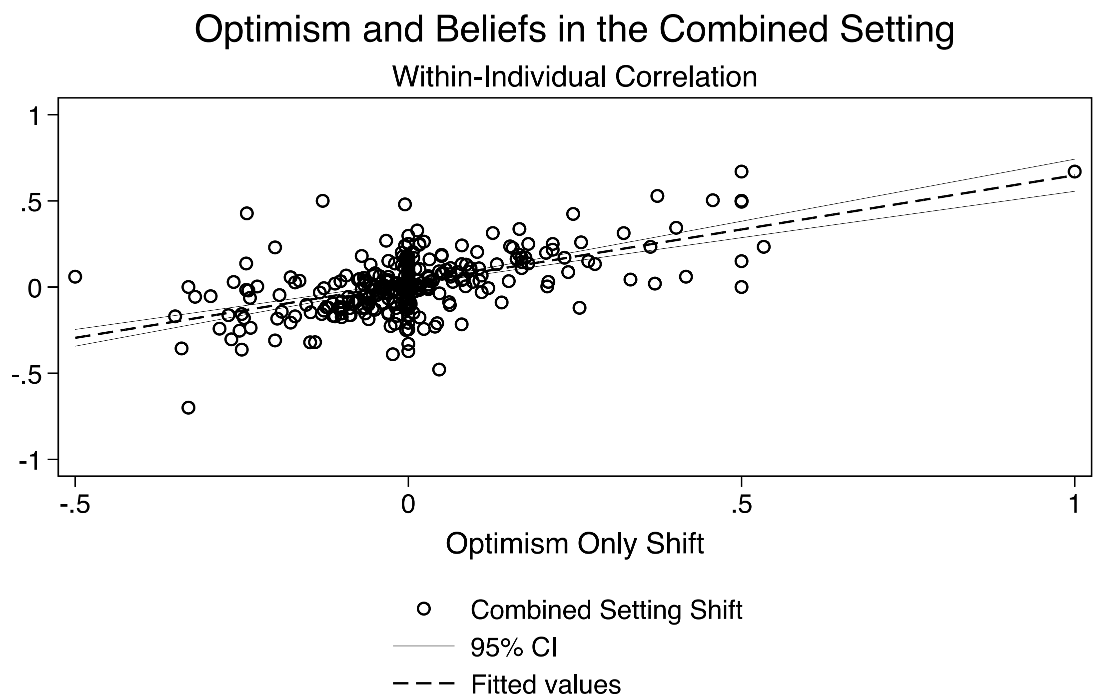


FIGURE 2.5: This figure relates shifts in beliefs in the payment and performance treatments. This plot shows evidence that optimistic individuals also tend to be overconfident.

result of "only one man or a few men who see the new possibility". Knight (1921) echoes this sentiment, stating that a society's economic fortune rests upon its supply of "entrepreneur qualities". Thus, these early economists ignited a large and growing literature in economics, psychology and

FIGURE 2.6: OPTIMISM AND BELIEFS IN THE COMBINED SETTING



This figure relates shifts in beliefs in the payment and combined treatments. This plot shows suggestive evidence that optimistic individuals also tend to over-estimate high-payoff outcomes in the combined treatment, where individuals have preferences over outcomes and performance plays a role in the distribution individuals face.

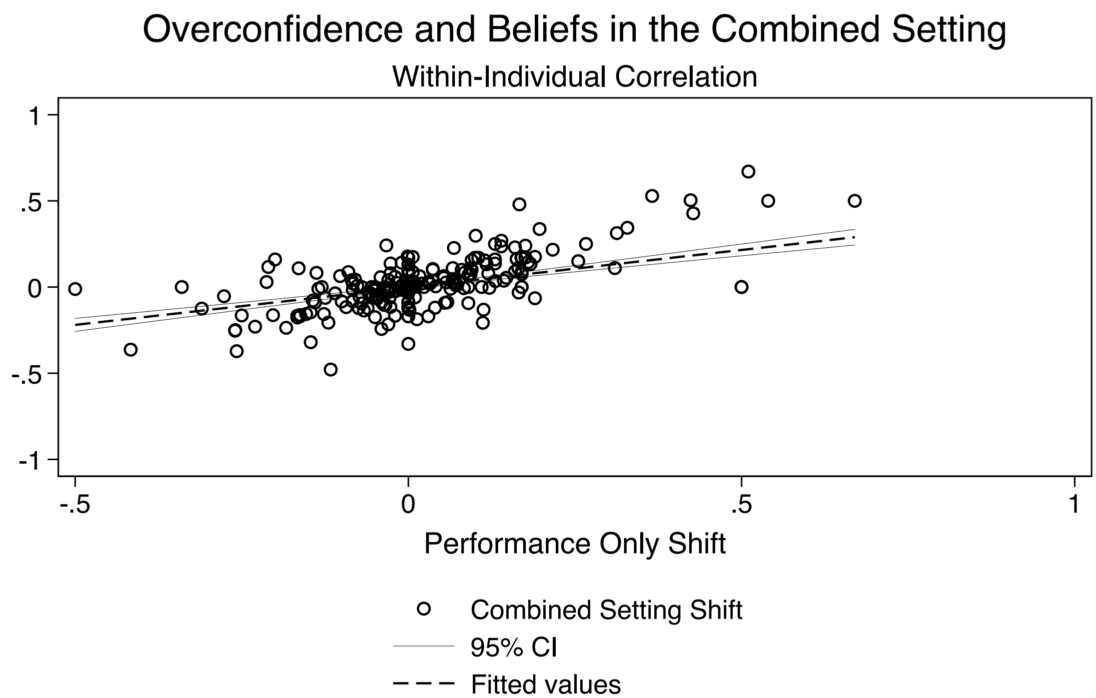
neuroscience that attempts to characterize the preferences, personality and even the biological underpinnings of the entrepreneur and innovative behavior (see Åstebro et al. (2014) for a current review).

Knight (1921) particularly emphasized the role of risk tolerance as a defining characteristic of the entrepreneur, a notion later formalized by Kihlstrom and Laffont (1979).[46] More recent work examines a link between personality and entrepreneurship (Brandstätter, 1997; Caliendo et al., 2011; Evans and Leighton, 1989; Fairlie and Holleran, 2012; Hamilton et al., 2014).

A related literature examines the role that human capital accumulation and information demand play in encouraging innovative behavior. Lazear (2004) proposes a "Jack of All Trades" theory of

[46]While intuitive, there is a lack of empirical evidence that entrepreneurs are less risk-averse than non-entrepreneurs (Elston et al., 2006).

FIGURE 2.7: OVERCONFIDENCE AND BELIEFS IN THE COMBINED SETTING



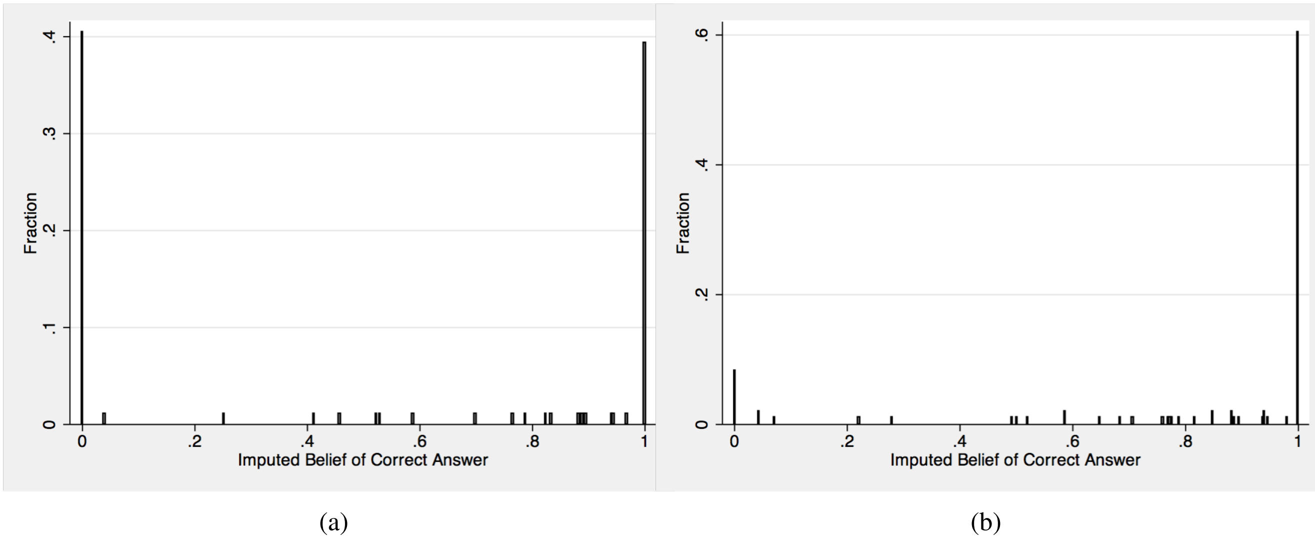
This figure relates shifts in beliefs in the payment and combined treatments. This plot shows suggestive evidence that overconfident individuals also tend to over-estimate high-payoff outcomes in the combined treatment, where individuals have preferences over outcomes and performance plays a role in the distribution individuals face.

entrepreneurship, which claims that individuals who accumulate a general skill set are most likely to become entrepreneurs. Similarly, Gompers et al. (2005) suggest that small firms spawn entrepreneurs because employees of smaller firms gain a wider breadth of human capital.[47] However, Åstebro and Thompson (2011) point out that observing entrepreneurs who look like "Jacks of All Trades" is also consistent with an individual who has a "Preference for Variety" (Ghiselli, 1974).[48] Elfenbein et al. (2010) find that while small firms may foster a human capital accumulation that is particularly useful for entrepreneurs, they find that individuals significantly sort on preferences: in-

[47]There are other forms of information accumulation. The literature in economics and entrepreneurship identifies several channels through which innovation-inducing information may be acquired: formal education, peers (Lerner and Malmendier, 2011; Minniti, 2005; Nanda and Sørensen, 2010), and government-sponsored programs (Fairlie et al., 2014).

[48]While Wagner (2003) finds support in favor of the Jack of All Trades theory of entrepreneurship,Silva (2007) does not and Åstebro and Thompson (2011) find evidence that supports the "Preference for Variety" theory.

FIGURE 2.8: IMPUTED BELIEFS



IMPUTED BELIEF: 9(a): Incorrect Answer. 9(b): Correct Answer.

dividuals who have a strong preference for autonomy have a preference for working for a smaller firm where they can exercise more decision-making power and are also more likely to become entrepreneurs.

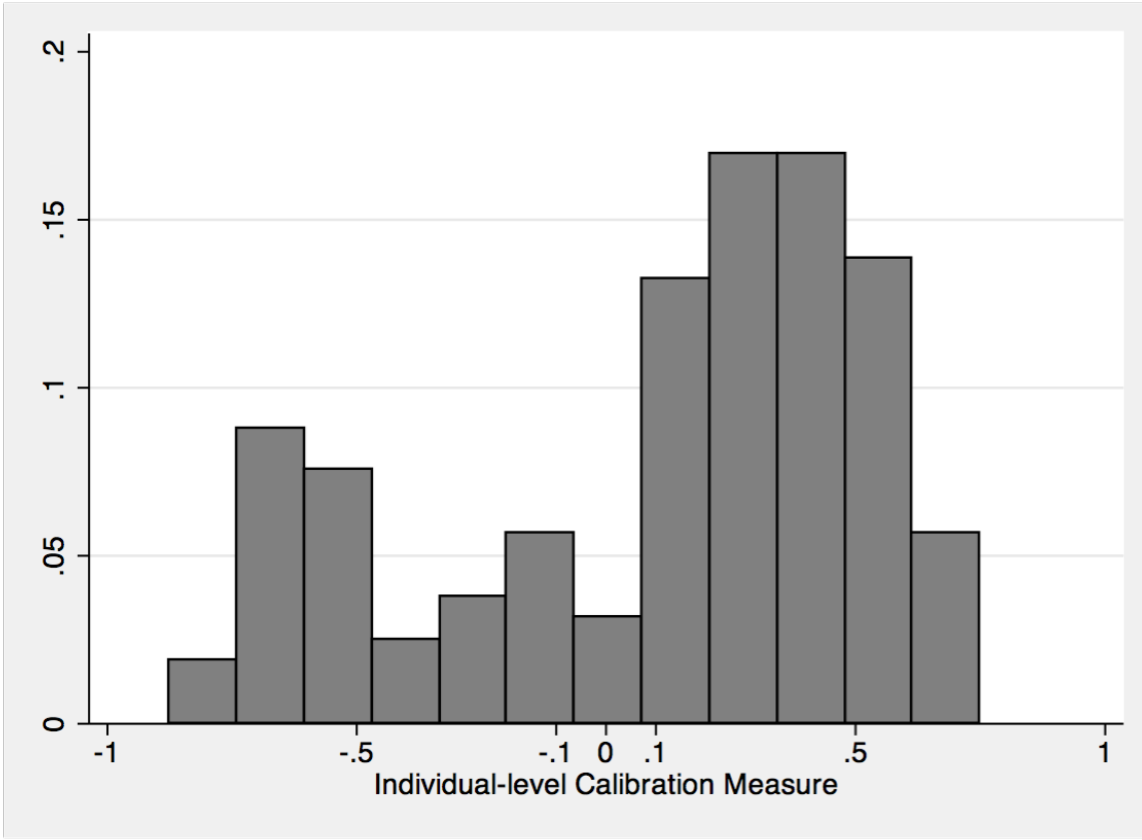
In this paper, we examine how information and individual traits affect innovative behavior. We depart from most previous studies and examine innovation in the laboratory.[49] We do this for two reasons. First, our sample is not subjected to a survivor bias. This allows us to observe how the innovative process unfolds and distinguish clearly between exploration versus successful innovation.[50] Second, the lab allows control over the information acquisition process. Outside of the laboratory, individuals accumulate capital and knowledge of their choosing. Fréchette et al. (2011) shows that individual traits affect preferences for demand of information, which present a challenging problem for studying entrepreneurship.

Since we are interested in the interaction between personality and information acquisition and use, we must first have a clear idea of how information affects innovative process when it is not en-

[49]Notable exceptions include Charness and Grieco (2013); Ederer and Manso (2013); Herz et al. (2013); Meloso et al. (2009).

[50]Lerner and Malmendier (2011) differentiate between entrepreneurial activity and successful entrepreneurial activity. They find that increased exposure to entrepreneurial peers reduces the likelihood of starting a business, but increases the successfulness of the business that are started.

FIGURE 2.9: AVERAGE CALIBRATION



This figure shows the average calibration at the subject-level, which is measured as the difference between the subject's imputed belief and the subject's proportion of correctly answered IQ questions.

dogenously acquired. Fairlie et al. (2014) is the only other study that looks at the effect of randomly assigning information to entrepreneurs. They report results from a large-scale field experiment in which potential entrepreneurs are randomly assigned to a training program. Thus, in addition to studying how individuals sort into different forms of information, we also conduct treatments in which we randomly assign individuals to receive different types of information.

The main task we use in our experiment, the Industry Game, is adapted from Ederer and Manso (2013) and Herz et al. (2013). The task consists of a trade-off between exploration and exploitation (March, 1991). Specifically, subjects take on the role of a manager in which they must decide which Industry to enter and how to invest their money in the Industry's three products. There is an optimal product mix that maximizes the subject's investment in the Industry. Moreover, there is a fixed cost for operating in each Industry. Subjects are also provided with an outside option, which we call Industry D, with a known and fixed expected value that is unaffected by the subject's actions.

Our main treatment manipulation in the Industry Game is information or feedback. We follow Ederer and Manso (2013) and Herz et al. (2013), and provide all subjects with immediate profit feedback after each round. In addition to the Control Treatment in which subjects only receive profit feedback, there are two additional types of information. Investment Information consists of unbiased signal about the optimal industry-specific investment level relative to their current investment strategy, whereas Cost Information consists of an unbiased signal about their industry-specific fixed cost.

Our main treatment, Information Choice Treatment, allows subjects to choose the type of information that want to receive. However, we first establish a set of baseline treatments to help guide our hypothesis for the Information Choice Treatment. In total, we conduct four treatments. The first treatment, the Control Treatment, provides subjects only with profit feedback after each round. In the Investment Information and Cost Information Treatments, we randomly assign subjects to receive either Investment Information feedback or Cost Information, in addition to profit feedback. Profit feedback is given for all 20 rounds of the Industry game, whereas the Investment Information and the Cost Information feedback is given only during the first 10 rounds.

We also examine how personality traits, risk preferences and cognitive ability directly drive innovative behavior and indirectly drive behavior through information. We thus join a growing literature that looks at the role of or personality traits on economic outcomes (see Almlund et al. (2011) for an overview of this literature). Previous literature suggests a role for locus of control (see (Rotter, 1971)) and the Big Five personality traits (see (Norman, 1963)) on labor market outcomes and entrepreneurship (Barrick and Mount, 1991; Brandstätter, 1997; Caliendo et al., 2011; Evans and Leighton, 1989; Fletcher, 2013; Hamilton et al., 2014).

Individuals with an internal locus of control view the outcomes and events of their life as under their direct control and influence, a trait that is linked to need for high achievement and a preference for autonomy (McClelland, 1965) and subsequently to a preference for entrepreneurship (Brandstätter, 1997; Caliendo et al., 2011; Evans and Leighton, 1989).

The Big Five is a five-factor model of personality, which we describe in more detail in Section 3.5. Two of the factors, Extroversion and Openness, have consistently been found to play an important role in the choice to become and the success of entrepreneurs (Caliendo et al., 2011; Hamilton et al., 2014). Moreover, both traits are linked to propensity for creativity and successfully managing exploration-exploitative problems. Literature in psychology suggests that increased Openness is associated with a paradoxical frame (Amabile and Pillemer, 2012); that is, an individual is better able to cognitively manage the contradictory goals that define an exploration-exploitation problem (Amabile, 1983; Smith and Tushman, 2005).

There are also biological underpinnings that support the idea that exploration-exploitation problems involve competing cognitive processes (Aston-Jones and Cohen, 2005). Daw et al. (2006) find that the fronto-polar prefrontal cortex is involved in exploratory decision-making, while the ventromedial prefrontal cortex regulates exploitative decision-making.

We present three sets of preliminary results. We begin with a brief discussion of the role of exogenous information. First, exogenously-given information affects the innovative process. Upon completing the first 10 rounds, subjects in the Cost Information Treatment have explored more industries, explored a wider variety of ideas (mixes between industries and investment strategies) and have a larger variance in industry-specific investment strategies than subjects in the Investment Information Treatment. Because the Cost Information Treatment conveys a wider breadth of knowledge and information to its recipients, we view subjects in the Cost Information Treatment as "Jacks of All Trades". By round 10, subjects in the Investment Information Treatment explore fewer industries and explore a more narrow set of ideas and can thus be viewed as "Specialists". Ultimately, we find that while "Jacks of All Trades" explore more than "Specialists", "Specialists" innovate more successfully and subsequently earn more money than "Jacks of All Trades".

Next, we generate predictions about the endogenous information treatment (i.e., which individuals will prefer Investment Information versus Cost Information) by interacting individual traits with the exogenous information treatments. Our second finding is that individual traits have a heterogeneous effect on the outcomes of “Jacks of All Trades” and “Specialists”. In particular, increased Openness is associated with a preference for entrepreneurship for both “Jacks of All Trades” and “Specialists”, but is only an asset for “Jacks of All Trades”. Additionally, we find that Extroversion and Risk tolerance play different roles for “Jack of All Trades” and “Specialists”: increased Extroversion is predictive of successful innovation for “Jacks of All Trades”, but not “Specialists” and risk tolerance is a liability for “Specialists”, but not for “Jacks of All Trades”. In summary, we find that Open, Extroverted, Risk tolerant innovate most successfully of the “Jacks of All Trades”, while Introverted, Risk-averse innovate most successfully of the “Specialist”.

Third, the insights gained from the exogenous information treatments generate predictions about which subjects will prefer Investment Information versus Cost Information. We do not find strong evidence in favor of the “Preference for Variety” story of entrepreneurship, which suggests that the factors that encourage entrepreneurship (Openness) should also encourage a preference to acquire a more general skill set (Cost Information). Instead, we find that more risk-averse introverted individuals are more likely to choose Investment Information. These findings support a sector-specific selection hypothesis; certain traits are more profitable for “Specialists”, while other traits are more profitable for “Jack of All Trades” and individuals sort into the sectors that are most profitable.

Fourth, individual traits affect innovative behavior through information acquisition, increased Openness and an Internal Locus of Control are associated with strong non-pecuniary benefits of entrepreneurship. In particular, we find that Open and Internal individuals are more likely to forego a higher payoff in Industry D (i.e., paid employment) in order to explore more entrepreneurial industries. Our finding on Openness is consistent with **?** who find that increased Openness is associated with a preference for entrepreneurship, but that it is also a liability for entrepreneurs. That is, more Open individuals are more likely to select into entrepreneurship, but are also likely to make less.

3.2 Design and Data

This section describes the main experimental task, the Industry Game, as well as the tasks used to elicit risk preferences, cognitive ability, the Big 5 personality traits and locus of control. We will also discuss our measures of innovation and successful innovation which will be used in our analysis presented in Section 3.3. During the experiment, subjects can earn money during the Industry Game (20 Rounds), the lottery task (45 lottery choices) and the cognitive test (answer up to 12 questions, earn $5 per correct question). This means, there are 66 items (20+45+1) for which the subject can earn money. At the end of the experiment we randomly choose one of these decisions for payment.

3.2.1 The Industry Game

The Industry Game, to be described below, consists of three key features. The first is that it contains an allocation problem within an exploration-exploitation framework (March, 1991). Second, the Industry Game captures the idea that innovative activity often involves finding new ways to combine existing resources that exploit complementarities to generate profit (Meloso et al., 2009; Schumpeter, 1947). In each Industry, there are three investment products in which the subject must choose to invest and the optimal investment strategy involves a certain combination of investments across the three products. Galenson (2004) refers to this type of creativity as experimental innovation, where innovation comes from trial and error and occurs, as opposed to a "stroke of a genius". The notion of experimental innovation also highlights the third key feature of the Industry game, the idea that the type of innovation we are interested in occurs through learning and experience.

In our Industry game, subjects take on the role of a manager who must decide how to invest his resources for 20 rounds. In each round, subjects choose one of the four industries in which to operate (Industry A, Industry B, Industry C, or Industry D). Each subject i has an unknown industry-specific fixed cost drawn randomly from a uniform distribution between 50 and 100, which remains fixed throughout the 20 rounds of the Industry game, $f_{i,I} \sim U\,[50, 100]\;\; \forall I \in \{A, B, C, D\}$.

At the beginning of each round, subjects are endowed with 100 Australian dollars (AUD) and choose which of the four Industries to enter. The subject knows that if he enters Industry A, B, and C he will have to make an investment decision and allocate his money across three investment products, x, y and z. The profit function is defined so that within each Industry, there is an optimal investment strategy, (x_I^*, y_I^*, z_I^*) $\forall I \in \{A, B, C\}$, and there is a unique profit-maximizing bliss point for each Industry. Subjects do not know the exact profit function, but they do know that their earnings depend on the amount invested, the distance their investment is from the bliss point, and their industry-specific fixed cost.[51] Alternatively, subjects can exercise an outside option and enter Industry D. Industry D differs from the other three Industries in that there are no investment decisions to be made and subject always earns 100 minus his Industry D fixed cost. After an investment decision is made, the subject learns his earnings for the round and then proceeds to the next round.

There are two additional types of feedback subjects can receive. Investment Information provides subjects with feedback on their investment strategy during the first 10 rounds. Subjects are given truthful, unbiased information about the optimal investment product mix. For example, if a subject has over-invested in product x and product x is randomly chosen by the computer, then his signal will be to decrease his investment in product x. This information is equivalent to the "customer feedback" in Ederer and Manso (2013) and Herz et al. (2013).

A second piece of information, Cost Information, provides subjects with unbiased information about their industry-specific fixed cost during the first 10 rounds. The information is relevant to the Industry in which they are operating. Thus, if the subject is operating in Industry A, then he receives information about the fixed cost only in Industry A. For example, if a subject's fixed cost in Industry A is 62, then the computer will randomly draw a number, z, from $Z \sim U[50, 100]$. If z is greater than 62, then the subject will receive a signal that says his fixed cost is less than z.[52]

All subjects, regardless of treatment, receive profit feedback after each round for all 20 rounds.

[51] Appendix C shows the Industry-specific bliss points and profit functions.

[52] 3.6.2 formally describes the signals.

Additionally, depending on the treatment, subjects may also receive *either* Investment Information *or* Cost Information during rounds 1-10. In the Control Treatment, subjects only receive profit feedback.

Our main treatment, the Information Treatment, allows subjects to choose the type of information that want to receive during the Industry game. This treatment is designed to explore whether certain types of individuals prefer one type of information over the other and whether personality indirectly affects innovation through information choice. Before beginning the game, subjects are shown the information associated with Investment Information and Cost Information and then told that they can choose to receive No Information (analogous to the control), Investment Information or Cost Information.

However, before we can understand how information and personality interact to affect innovation, we must have an idea of how they affect behavior in the Industry Game independently. To do this, we conduct the Investment Information Treatment and the Cost Information Treatment, which randomly assigns subjects to receive *either* Investment Information *or* Cost Information during the first 10 rounds, respectively.

In rounds 1-10, subjects are in an accumulation phase, which we view as capital accumulation or information accumulation. Upon reaching Round 11, subjects assigned to the Investment Information Treatment have accumulated different knowledge than subjects in the Cost Information Treatment. Investment Information provides highly specialized feedback whereas Cost Information provides more general information. In this sense, Cost Information is valuable because the subject can quickly gain broad cross-industry information; whereas the value of Investment Information is that provides detailed industry-specific information.

3.2.2 Risk preferences, cognitive and non-cognitive skills

In addition to the Industry Game, we also elicited risk preferences, measured cognitive ability and personality traits.

Risk preferences The motivation for eliciting risk preferences is that while there is not overwhelming empirical support for the notion that entrepreneurs have significantly different risk profiles than non-entrepreneurs, we are interested in how risk preferences affect the subjects' propensity to innovate, success at innovating and choice of information.

To elicit risk preferences, we used the task introduced by Hey and Orme (1994) where subjects faced a series of 45 lottery choices in which the prizes and the probabilities of prizes varied. Subjects are asked to choose whether they prefer the "Left Lottery", the "Right Lottery" or "Don't Care". We follow Andersen et al. (2014) and estimate risk preferences at the individual-level, assuming CRRA utility, via maximum likelihood.

Cognitive Skills Next, we measure the subjects' cognitive ability. Models of entrepreneurial choice often stress the role of entrepreneurial ability, which includes intelligence that may affect the quality of the individual's ideas or how quickly or how well the individual learns from previous experience.

We use the Raven's Advanced Progressive Matrices test to measure cognitive ability (Raven and Court, 1998), an intelligence test that is designed to be culture-free since it does not rely on language or cultural references. The test consists of 12 questions, which each consist of a diagram with a missing piece and eight suggested answers to the missing piece. The subject's task is to choose one of the eight suggested answers. During the experiment, subjects have 12 minutes to complete 12 questions without feedback. We measure their cognitive ability as the number of correct answers from this test.

Personality Traits We contribute to a growing literature in economics that looks at the role of non-cognitive skills, or personality traits, on economic outcomes (see Almlund et al. (2011) for an overview of this literature). In particular, we choose to look at Locus of Control and the Big Five personality traits, focusing on Extroversion and Openness.

We use Rotter's External-Internal Locus of Control test (Rotter, 1971), which is designed to determine the extent to which an individual views that the events and outcomes of his life are under his control or are determined by forces external to him. The relationship between entrepreneurship and internal locus of control is empirically well-established Brandstätter (1997); Caliendo et al. (2011); Evans and Leighton (1989). Moreover, Psychology has found a strong link between an internal locus of control and the need for high achievement (McClelland, 1965; Phillips and Gully, 1997). The test consists of 29 pairs of statements and subjects are asked to indicate which of the two statements are consistent with their own views. The contemporary scoring system, which is the opposite of Rotter's original scoring rule, associates higher scores with a more internal locus of control.

The push to create a taxonomy of personality began with McDougall (1932). While different taxonomies have been proposed, there is broad support for the five-factor personality taxonomy first suggested by Norman (1963) and popularized to its current form by Costa and McCrae (1985). The Big 5 are widely used in economics and psychology and are believed to be stable over the life-cycle (Cobb-Clark and Schurer, 2012).

The Big Five personality traits include Extroversion, Openness, Conscientiousness, Neuroticism, and Agreeableness. Extroversion, also referred to as Surgency, is associated with high energy, assertiveness, and positive affect. Openness, also referred to as Intellect or Culture, reflects the degree of intellectual curiosity, creativity and is associated a preference for a variety. Conscientiousness is associated with a tendency to be organized, efficient, dependable, and self-disciplined. Agreeableness is associated with the tendency to seek compromise and cooperation. Neuroticism is associated with being emotionally unstable and a tendency to experience anxiety and anger.

The Big Five have been linked to both labor market outcomes and entrepreneurship (Barrick and Mount, 1991; Caliendo et al., 2011; Fletcher, 2013; Hamilton et al., 2014). Barrick and Mount (1991) finds that the effect of the Big Five varies across different occupational groups and job-related task. Their most striking findings are the roles played by Extroversion and Openness. In particular, they find that increased Extroversion is associated with individuals in Managerial positions (leadership roles), while increased Openness was associated with training proficiency (positive attitudes towards learning). Caliendo et al. (2011) hypothesize and find a strong link between Extroversion and Openness (and so a lesser extent Agreeableness and Neuroticism) and preference for entrepreneurship and success in entrepreneurship.

Hamilton et al. (2014) estimate a model in which individuals choose between self-employment or paid employment and allow the Big Five to affect expected earnings and preferences over each sector. They find that Extroversion and Openness play a significant, nuanced role. Extroversion is associated with higher earnings in both paid employment and self-employment, but was a more profitable trait for the self-employed. Openness is associated with a preference for entrepreneurship, but was also a liability in terms of earnings in self-employment.

The role Openness plays in the choice to be an entrepreneur, success at entrepreneurship and innovate behavior in general is quite nuanced. Openness is associated with high levels of creativity and curiosity, but also high levels of intellect. These characteristics are not necessarily opposing, but suggest a careful balance between exploring new ideas and recognizing the benefits of exploiting the current opportunity. Psychologists refer to this as paradoxical framing and often link it to Openness (Amabile, 1983; Amabile and Pillemer, 2012).

The literature in management and strategy refer to a firm that is able to manage competing processes as organizational ambidexterity (Tushman et al., 1996). Smith and Tushman (2005) suggest that individual managers who can engage in paradoxical thinking are a key component for organizational ambidexterity.

Neuroscientists have also explored the potential biological underpinnings that affect management of the exploration-exploitation trade-off (Aston-Jones and Cohen, 2005). Daw et al. (2006) have subjects complete a multi-armed bandit while under an fMRI, providing insights into which regions of the brain are most active during different phases of the game. They find that the frontopolar prefrontal cortex is significantly more active when subjects deviated from the bandit algorithm (exploration), while activity in the ventromedial prefrontal cortex was associated with the magnitudes of the reward that was predicted by the bandit algorithm (exploitative).

There are various instruments to measure the Big 5 personality traits. In our last experimental task, we use the 120 item short form, developed by Johnson (2014).

3.2.3 Data

Our data come from experiments run at the University of Sydney in May and October 2014. Our sample consists of 131 subjects recruited through Greiner (2004) and he experiment was programmed using Z-Tree (Fischbacher, 2007). Sessions lasted approximately 90 minutes and the average earnings were approximately 33 AUD.

Table 3.1 presents summary statistics of our sample. Note that the sample size is 117, this is due to technical difficulties in a session in which data from the Industry Game was collected, but data from the risk elicitation, cognitive test and personality surveys were lost. The Big Five personality test is designed so that the median score for each trait is 50, with a standard deviation of 10. Also consistent with other findings, the subjects in our experiment are weakly risk-averse, with an average estimated CRRA coefficient of .89. Half of our subjects are female and the average age is just under 23 years.

The Industry Game is designed to measure preferences for entrepreneurship, propensity to explore and successful innovation. We claim that a subject has a preference for entrepreneurship when he chooses to operate in any industry other than Industry D, since Industry D does not require any investment and the subject always receives his endowment minus his Industry D fixed cost.

We use four measures of exploration. Our first measure follows Ederer and Manso (2013) and Herz et al. (2013), measuring exploration as the subject's average industry-specific standard deviation in investment strategies. This measure captures the variance in the subject's investment strategies, but does not capture the frequency with which the subject changes industries. A change in industry is perhaps the biggest exploration since it requires an entirely new and unknown investment strategy and unknown fixed cost.

Our second measure of exploration is the frequency with which a subject changes industries. While this may capture one aspect of exploration, it will not always provide an clear distinction between imitation and exploration. For example, this measure would consider an individual who switches back and forth between two Industries (possibly using the same investment strategy each time he enters an industry) as more exploratory than an individual who spends 5 periods in each of the 4 industries. Our third measure is a count of the total number of industries the individual enters during the 20 rounds.

Our fourth measure, the Exploration Index, is the most nuanced and attempts to capture the degree of change in investment strategies and industry switches into a single measure. The Exploration Index scores the subject's industry choice and investment strategy by how similar it is to all previous investment choices within the industry and assigns a score based on the how different it is from the most similar, previously used strategy. This allows us to identify when a subject returns to a previously tried idea (even when that choice happened several rounds before), which is an important aspect to capture. We normalize the index between 0 and 1, inclusive. If a subject exactly replicates a previously used industry-investment choice or enters Industry D, then his Exploration Index in this round is 0. When a subject enters an Industry for the first time, his Exploration Index is 1.

We obtain the Exploration Index for subject i in period n in the following way. Define $I_{i,n}$: $\{n' : n' \leq n \cap Industry_{i,n'} = I\}$ and let $\varpi_{I,i,n} = (x_{I,i,n}, y_{I,i,n}, z_{I,i,n})$ be a vector of subject i's investment strategy in period n in Industry I.

$$= \begin{cases} 1 & \text{if } n = \min I_{i,n} \\ 0 & \text{if Industry}_{i,n} = D \\ \kappa \times \min_{I_{i,n}} \mid \varpi_{I,i,n} - \varpi_{I,i,n'} \mid & \text{otherwise.} \end{cases}$$

where $\kappa = \frac{1}{200}$, which is the maximum deviation possible between two investment strategies, normalizes the Exploration Index so that it is between 0 and 1.[53]

Figures 3.1 and 3.2 show the distributions of our various exploration measures for our entire sample. Where applicable, we show how the distributions differ during the first 10 rounds of the game versus the entire Industry Game. Typically, there is more innovation during the first 10

[53]For example consider an investment strategy in period 1, $\varpi_{I,i,1} = (100, 0, 0)$ and an investment strategy in period 2 of $\varpi_{I,i,2} = (0, 100, 0)$ in Industry I. Then, the Exploration Index is given by $\frac{200}{} \times \kappa = 1$.

rounds as subjects are trying new ideas to maximize their profit.

We also measure the degree to which subjects successfully innovate. We have two measures of successful innovation: (1) whether the subject operates in the industry with the lowest fixed cost; and (2) the distance the subject's investment strategy is from the optimal investment strategy.

Figure 3.3 displays the distribution of successful innovation for our entire sample. Figure 3(a) shows the average distance the subjects were from the optimal investment strategy during the first 10 rounds and during the entire Industry Game. As expected, subjects were further from the optimal investment strategy during the first 10 rounds. Figures 3(b) and 3(c) show the frequency with which subjects operate in their minimum cost industry during the entire game and during the first 10 rounds only, respectively.

3.3 Main Findings

This section reports findings from the laboratory experiment. In order to analyze how individual traits directly and indirectly affect innovative behavior we begin with an analysis of the effect of exogenous information. This allows us to establish differences generated by information that i independent of the choice to acquire the information. Next, we investigate how individual traits interact with exogenously given information. This allows us to generate predictions about which types of individuals are more likely to acquire each kind of information (Investment or Cost Information). Finally, we test our hypotheses in the Information Choice Treatments.

3.3.1 Effects of Information

Our first set of findings examines differences in preferences for entrepreneurship, exploration and successful innovation across the No Choice Treatments. First, Table 3.2 shows that during the first 10 rounds, subjects who are randomly assigned to the Cost Information Treatment switch industries and experiment with a wider range of investment strategies than subjects in either the Investment Information Treatment and the Control Treatment. Thus, during the first 10 rounds a gap in experience and breadth of knowledge emerges between the subjects in the Cost Information Treatment and subjects in the other two treatments that cannot be attributed to preferences.

Second, Tables 3.3 & 3.4 shows that subjects in the Investment Information Treatment are more successful innovators than subjects in both the Cost Information Treatment and the Control Treatment. While subjects in all treatments were equally likely to operate in the industry with the minimum fixed cost, subjects in the Investment Information Treatment had investment strategies that were significantly closer to the optimal investment strategy.

Tables 3.2-A.1 suggest that Cost Information encourages more exploration than Investment Information. Further, Cost Information results in less successful innovation than Investment Information. And while Investment and Cost Information do not differ in encouraging entrepreneurship, subjects receiving Investment Information explore less, but their innovation is more successful.

However, this analysis does not account for potential heterogeneity across subjects. In what follows, we investigate if and how personality traits, cognitive skills and risk preferences interact with information to affect preferences for entrepreneurship, propensity to explore and successful innovation. In particular, we examine whether there are differences in the cognitive and non-cognitive traits of individuals who prefer entrepreneurship and successfully innovate as "Jack of All Trades" versus "Specialists".

Preference for Entrepreneurship First, since we cannot observe the subject's preference for entrepreneurship, we assume there is an underlying preference, y_i^*, that can be inferred from his choice of Industry. Recall that in Industry D, the subject does not make an investment decision and always receives 100AUD minus his fixed cost. Thus, Industry D represents the outside option in the Industry game and is analogous to choosing paid employment. When a subject i does not choose Industry D in round j, $y_{i,j} = 1$, he is expressing a preference for entrepreneurship, $y_i^* > 0$.

$$\begin{aligned} Pr\left[y_{i,j}=1\right] &= \alpha_0 + \alpha_{\text{Cost}} \times \mathbf{1}[\text{Cost Information Treatment}] \\ &+ \alpha_{\text{Investment}} \times \mathbf{1}[\text{Investment Information Treatment}] \\ &+ \mathbf{P}_{\text{Traits}} \times \mathbf{X}_j \\ &+ \alpha_{\text{Payoffs}} \times \text{Industry D Payoff}_{j,i} + \varepsilon_{i,j}, \end{aligned}$$

the variable $\mathbf{X}_i$ is a vector individual-level traits including the subject's cognitive score from the Raven's Advanced Matrix test, estimated risk tolerance, locus of control, the Big Five personality traits, and gender. We also control for the subject's potential earnings if he enters Industry D, which is fixed for all rounds. We estimate this choice with a probit regression.

Column (1) presents marginal effects from the probit regression where the dependent variable takes a value of 1 if the subject did not enter Industry D and a value of 0 otherwise. There are no differences across information treatments in preference for entrepreneurship: in our setting, "Jacks of All Trades" and "Specialists" do not express different preferences for entrepreneurship.

As hypothesized, increased Openness is associated with a preference for entrepreneurship. An increase in one standard deviation in Openness increases the probability of choosing entrepreneurship by 1 percentage point, from a baseline of 99%. Also, risk preferences and cognitive ability play no role in the decision to choose entrepreneurship.

Propensity to Explore Second, we examine the effect of individual traits on the propensity of a subject to be exploratory. However, an individual can only be exploratory when he chooses to operate outside of Industry D and so we must account for this selection into entrepreneurship. To account for this selection, we estimate a Heckman selection model (Heckman, 1976).

We model the propensity of subject i to innovate in round j as

$$\begin{aligned} ExplorationIndex_{i,j} &= \beta_0 + \beta_{\text{Cost}} \times \mathbf{1}[\text{Cost Information Treatment}] \\ &+ \beta_{\text{Investment}} \times \mathbf{1}[\text{Investment Information Treatment}] \\ &+ \mathbf{Q}_{\text{Traits}} \times \mathbf{X}_j \\ &+ \beta_{\text{Payoffs}} \times \text{Average Previous Pay}_{j,i} + \upsilon_{1,i,j}, \end{aligned}$$

which is only observed if he selects into entrepreneurship, which occurs when

$$\begin{aligned} &\gamma_0 + \gamma_{\text{Cost}} \times \mathbf{1}[\text{Cost Information Treatment}] \\ &+ \gamma_{\text{Investment}} \times \mathbf{1}[\text{Investment Information Treatment}] \\ &+ \mathbf{R}_{\text{Traits}} \times \mathbf{X}_j \\ &+ \gamma_{\text{Payoffs}} \times \text{Industry D Payoff}_{j,i} + \upsilon_{2,i,j} > 0, \end{aligned}$$

where $\upsilon_1 \sim Normal(0, \sigma)$ and $\upsilon_2 \sim Normal(0, 1)$ and the correlation between υ_1 and υ_2 is given by ρ.

Column(2) displays the estimates from the Heckman selection model of the propensity of an individual to explore. The most striking finding is that the lower the individual's average payment in all previous rounds, the more he explores in the current round. This is intuitive since the less successful a subject's past investment decisions, the less he will want to imitate previous decisions and the more incentive he has to explore.

Further, we see that increased Openness and a more Internal locus of control are associated with a lower propensity to explore. While these findings appear at odds with the description of Openness (and to a less extent an Internal Locus of Control), they highlight an important feature of exploration. There are two reasons why an individual might be more exploratory. The first is that he has a preference for exploration; he receives non-pecuniary utility from exploring new ideas.

The second is that he explores out of necessity and must explore because his previous ideas were not profitable. Thus, it is important to distinguish between exploration and successful innovation: successful innovation today typically leads to less exploration tomorrow. We discuss the role of traits in determining successful innovation in column (3).

Column (2) also show significant treatment effects. In particular, "Specialists" are less exploratory than "Jacks of All Trades". As in column (1), cognitive ability and risk preferences play no significant role in predicting exploration.

Successful Innovation Third, we estimate the effect of traits on successful innovation. The findings in column (2) suggest that it is important to distinguish between innovation and successful innovation. To do this, we estimate an OLS regression model where we regress the distance of subject i's investment strategy in round j from the optimum investment strategy on the same set of regressors as in equation 39.

$$\begin{aligned} InnovationIndex_{i,j} &= \delta_0 + \delta_{\text{Cost}} \times \mathbf{1}[\text{Cost Information Treatment}] \\ &+ \delta_{\text{Investment}} \times \mathbf{1}[\text{Investment Information Treatment}] \\ &+ \mathbf{R}_{\text{Traits}} \times \mathbf{X}_j \\ &+ \delta_{\text{Payoffs}} \times \text{Average Previous Pay}_{j,i} + \omega_{i,j}, \end{aligned}$$

In column (3), negative coefficients indicate an increase in success, since a subject is more successful the smaller is the distance between his investment strategy and the optimal investment strategy. Column (2) showed that increased Openness leads to less exploration, but Column (3) indicates that increased Openness is associated with more successful innovation. Column (3) also shows that subjects with higher cognitive skills are also more successful innovators, but again, there is no effect of risk tolerance and no significant differences between "Jacks of All Trades" and "Specialists".

Next, we interact the individual traits with the Information treatments. This allows us to investigate whether traits affect "Jack of All Trades" and "Specialists" similarly. Further, by understanding whether different traits predict differences in successful innovation for "Jacks of All Trades" and "Specialists" we can generate a set of hypotheses to predict which types of individuals are likely to choose either Investment Information or Cost Information. We present the estimates in Table 3.6.

Propensity to Explore Column (1) of Table 3.6 displays estimates from a linear regression model on the propensity of an individual to explore. As in Table 3.5, there are significant treatment effects: "Jacks of All Trades" explore more than "Specialists". Also as in Table 3.5, we find that increased Openness and a more Internal Locus of Control are associated with a lower propensity to explore, however when we interact traits with treatment effects we find that these relationships are not significant for "Specialists" (i.e., Investment Information).

Increased Extroversion also decreases exploration for both "Jacks of All Trades" and "Specialists" relative to the Control Treatment. Again, it is unclear whether these relationships represent a dis-utility for exploration or whether increased Extroversion, Openness and an Internal Locus of Control are associated with more successful innovation and the negative coefficients indicate that there is less need to explore. We address this next in column (2)

Successful Innovation Column (2) of Table 3.6 considers the interaction between traits and information on successful innovation. Tests of significance for various coefficients are presented in Table 3.7. First, we focus on Extroversion and Openness and their heterogeneous role in predicting the success of "Specialists" versus "Jacks of All Trades". Increased Openness and Extroversion are associated with more successful innovation for "Jacks of All Trades", but have no effect on the success of "Specialists". The results from column (2) for Extroversion shed light on the interpretation of the effect of Extroversion on exploration in column (1). Recall that in column (1) increased Extroversion was associated with a decrease in exploration for both "Jacks of All Trades" and

"Specialists". However, we see from column (2) that Extroversion is an asset for "Jacks of All Trades", and thus we can interpret the negative coefficient in column (1) as suggesting that more Extroverted "Jacks of All Trades" explore less because their initial ideas are more successful than less Extroverted "Jacks of All Trades". However, increased Extroversion is not significantly associated with increased success for "Specialists", but is associated with less exploration. One potential explanation is that among "Specialists", increased Extroversion may be associated with a dis-utility for exploration.

Second, the role of risk tolerance is heterogeneous. Increased risk tolerance is associated with less successful innovation for "Specialists", but not for "Jacks of All Trades". Third, increased cognitive ability plays a larger role in the success of "Jacks of All Trades" than for "Specialists".

In summary, column (2) in Table 3.6 offers substantial insight into the differences we might find between successful "Jack of all Trades" and successful "Specialist" entrepreneurs. In particular, Extroversion and Openness are associated with successful "Jacks of all Trades", while Introversion and risk-aversion is associated with successful "Specialists". Moreover, while increased Cognitive Ability increases the success of both types of entrepreneurs, it plays a larger role for "Jack of All Trades".

3.3.2 Information Choice

This next section investigates how individuals sort into different information treatments. In particular, the Information Choice Treatment asks subjects to choose to receive either the Cost Information or the Investment Information.[54] Table 3.6 shows that suggests that more Open, Extroverted individuals are successful innovators as "Jacks of All Trades", while more risk-averse individuals are more successful innovators as "Specialist".

Based on these findings, we hypothesize that increased Openness and increased Extroversion is associated with choosing Cost Information, while increased risk-aversion is associated a preference for Investment Information. Similarly, the "Preference for Variety" theory predicts that the factors

[54] They also had the choice to choose No Information (i.e., the Control Treatment), but not subject made this choice.

or traits that drive an individual to prefer entrepreneurship are the same traits that drive them to accumulate a wider breadth of information. Table 3.5 suggests that increased Openness is a predictor of a preference for entrepreneurship, and thus according to the "Preference for Variety" theory should also be predictive of choosing Cost Information.

To model the information choice problem, we estimate the following model via maximum likelihood,

$$Pr[\text{Investment Information} = 1] \;=\; \beta_0 + \mathbf{P}_{\text{Traits}} \times \mathbf{X}_j + \varepsilon_j,$$

where we assume $\varepsilon_j \sim \; Normal(\mu, \sigma)$ and thus specify a probit regression.

Table 3.8 reports the marginal effects of the probit regression that estimates the probability that an individual in the Choice Treatment chooses Investment Information. Consistent with our hypotheses, individuals who are more Risk Tolerant and more Extroverted are less likely to choose Investment Information. An increase in one standard deviation in Extroversion increases the probability of choosing Cost Information by nearly 20 percentage points. However, we do not find evidence that more Open individuals are more likely to choose Cost Information.

Table 3.9 shows that when the choice of information is endogenous the differences in exploration between the Investment Information Treatment and the Cost Information Treatment are greatly reduced. Subjects in the Cost Information Treatment explore more industries than subjects who choose to receive Investment Information, but there are no significant differences between the variance in their investment strategies or exploration indices.

After 10 rounds, subjects in the Cost Information Treatment still have a wider breadth of knowledge than subjects in the Investment Information Treatment, but this difference when information choice is endogenous is more attenuated than when information is exogenously chosen.

Table 3.10 shows that there are no differences in success between subjects choosing Cost Information and subjects choosing Investment Information. This is in stark contrast to Table 3.3, where information was exogenously given, and appears to be mostly driven by subjects who are randomly assigned Investment Information being significantly more successful than subjects in other treatments. One reason that subjects who endogenously choose Investment Information might be innovating less successfully than subjects who are exogenously assigned Investment Information is that they are exploring significantly more. A comparison of Table 3.2 and Table 3.9 shows that subjects who choose Investment Information explore at similar levels to subjects in both the endogenous and exogenous Cost Information Treatments. Thus, the finding that when information is endogenous that subjects who receive Cost and Investment Information are similarly successful might be explained by subjects who choose Investment Information exploring more than when information is exogenously given.

One reason this might occur is that subjects who choose Investment Information are more Introverted (see Table 3.8) and increased Introversion is associated with increased exploration for "Specialists" (see Table 3.6).

Table 3.11 replicates Table 3.5, but for the subjects in the Information Choice Treatment only. The estimates in Table 3.11 shows that none of the relevant individual traits predict either a preference for entrepreneurship, a propensity to explore, or successful innovation. In fact, it appears that personality affects the outcomes only through information choice. Subjects who choose Cost Information are no more likely to choose entrepreneurship, but are more likely to explore and to innovate less successfully.

Table 3.12 replicates Table 3.6 for the Information Choice Treatment only. We see that individual traits play almost no direct role in determining subjects' propensity to explore or their success in innovating. However, there is a very interesting relationship with Risk Tolerance. Recall, more Risk Tolerant subjects were more likely to choose Cost Information, which discourages exploration for subjects, but discourages exploration less among subjects who choose Cost Information. Similarly, Risk Tolerance is associated with more successful innovation, but less so for subjects who chose Cost Information.

This finding reflects an interesting non-linearity in the role of risk preferences: risk tolerance leads to more successful innovation, but too much risk tolerance is a liability because it does not temper the subject's propensity to explore.

3.3.3 Additional Findings

Non-Pecuniary Benefits of Entrepreneurship Hamilton (2000) finds that the median entrepreneur could have made more money if he had chosen to go into paid employment (instead of self-employment) and attributes over-entry into self-employment as suggestive of the non-pecuniary benefits of entrepreneurship. Similarly, Moskowitz and Vissing-Jorgensen (2002) find that the returns that entrepreneurs earn are not enough to account for the significant amount of risk and that non-pecuniary benefits might account for the discrepancy.

Our experiment permits a very straightforward test of these observations. When a subject chooses entrepreneurship we know his counter-factual earnings, that is, what he would earn if he entered Industry D. Existing suggest that increased Openness is associated with non-pecuniary returns to entrepreneurship. In particular, Hamilton et al. (2014) find that Openness is associated with a preference for entrepreneurship, but that Openness was also a liability.

In Table 3.13 we estimate the effect of individual traits on whether an individual foregoes Industry D and opts to invest in another Industry when he would have made more if he entered Industry D. We add an additional control, a dummy indicating whether the subject has entered Industry D in a previous round (otherwise, we include the same controls as in Table 3.5 and Table 3.6). We estimate a probit regression where the omitted category is the dummy for subjects who choose to receive Investment Information.

The most striking finding is the positive and significant coefficient on Openness for the Choice Treatment. Our finding corroborates the finding in Hamilton et al. (2014): increased Openness is associated with choosing entrepreneurship even when there is a better paying alternative, i.e., paid employment. A similar conclusion can be drawn for subjects with an internal locus of control. This is intuitive, since an internal locus is associated with belief that one has control over outcomes and is associated with a preference for autonomy and need for high achievement (McClelland, 1965), which is one of the main non-pecuniary benefits of entrepreneurship (Åstebro et al., 2014; Hurst and Pugsley, 2011).

3.4 Conclusion

This paper presents results from a laboratory experiment in which we study the effect of information, and how it interacts with personality, on innovative behavior. We depart from the majority of studies on entrepreneurship and study innovative behavior in a laboratory setting, thereby avoiding problems associated with survivor bias.

We find that different information results in two types of entrepreneurs: “Jacks of All Trades” and “Specialists”. “Jacks of All Trades” accumulate a wider variety of knowledge by engaging in more exploration, while “Specialists” exploit their ideas more and are more successful. We also find that Extroversion and Risk Tolerance are assets for “Jacks of All Trades” while Introversion and Risk-Aversion are assets for “Specialists”.

Further, when subjects are allowed to chose the type of information they prefer to receive; they select the information that appears most compatible for their personality.

3.5 Tables and Figures

TABLE 3.1: SUMMARY STATISTICS

	Mean (sd)
Openness	46.89 (9.05)
Extroversion	50.13 (8.09)
Neuroticism	48.50 (7.50)
Conscientiousness	49.84 (8.39)
Agreeableness	49.16 (7.68)
Locus of Control	11.62 (3.69)
CRRA coefficient	.89 (.93)
Raven Score, Cognitive Ability	7.03 (2.47)
Female	.51 (.50)
Age	22.95 (4.22)
Observations	117

TABLE 3.2: EXPLORATION, TREATMENT EFFECTS

	Control (1)	Investment Info (2)	Cost Info (3)	Diff. (1)-(2)	Diff. (1)-(3)	Diff. (2)-(3)
Exploration, variance in industry-specific investment strategies						
Mean, rounds 1-10	15.40	10.22	13.53	5.18**	1.87	-3.31*
Mean, all rounds	13.35	8.73	12.86	4.62**	.49	-4.13***
Exploration, industry changes						
Total industries explored	2.73	2.32	2.85	.41**	-.12	-.53***
Mean, 1-10	.34	.18	.46	.15***	-.11*	-.27***
Mean, all rounds	.27	.17	.32	.11**	-.05	-.16***
Exploration, Exploration index						
Mean, 1-10	.39	.29	.41	.10**	-.01	-.11***
Mean, all rounds	.24	.18	.25	.06**	-.002	-.06***
Observations	22	22	27			

Two-tailed t test of significance; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

EXPLORATION, TREATMENT EFFECTS

	Investment variance		Industry changes			Exploration
	Rounds 1-10	All rounds	Industries explored	Rounds 1-10	All rounds	Index
Investment Info	-5.18**	-4.62**	-0.41*	-0.16***	-0.11**	-0.06**
	(2.45)	(1.96)	(0.23)	(0.05)	(0.05)	(0.03)
Cost Info	-1.87	-0.49	0.12	0.11*	0.05	0.002
	(2.51)	(2.04)	(0.16)	(0.06)	(0.05)	(0.02)
Constant	15.40***	13.35***	2.73***	0.34***	0.27***	0.24***
	(2.17)	(1.73)	(0.13)	(0.05)	(0.04)	(0.02)
Observations	71	71	71	71	71	71
R^2	0.07	0.1	0.11	0.27	0.14	0.12

TABLE 3.3: SUCCESSFUL INNOVATION, TREATMENT EFFECTS

	Control (1)	Investment Info (2)	Cost Info (3)	Diff. (1)-(2)	Diff. (1)-(3)	Diff. (2)-(3)
Distance from Optimal Investment Levels						
Mean, rounds 1-10	24.74	17.94	25.66	6.80**	-.92	-7.72***
Mean, all rounds	19.03	13.45	19.76	5.59**	-.73	16.93***
Operating in the Minimum Cost Industry						
Mean, 1-10	.24	.21	.26	.02	-.02	-.04
Mean, all rounds	.25	.23	.25	.03	0	-.02
Observations	22	22	27			

Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.4: TREATMENT EFFECT OF SUCCESSFUL INNOVATION (FINDING COMPLEMENTARITIES)

	DIST TO OPTIMUM		MIN COST INDUSTRY		DIST TO OPTIMUM	
	Mean rounds 1-10	Mean all rounds	Mean rounds 1-10	Mean all rounds	Rounds 1-10 1-10	All rounds
Investment Info	-6.80**	-5.59**	-0.02	-0.03	-6.31**	-5.32**
	(3.19)	(2.74)	(0.09)	(0.1)	(3.19)	(2.70)
Cost Info	0.92	0.73	0.02	-0.004	0.92	0.89
	(3.15)	(2.66)	(0.08)	(0.09)	(3.14)	(2.63)
Round	.	.	.	.	-0.69**	-1.03***
					(0.31)	(0.09)
Constant	24.74***	19.03***	0.24***	0.25***	28.31***	29.70***
	(2.61)	(2.23)	(0.05)	(0.06)	(2.89)	(2.49)
Observations	71	71	71	71	671	1365
R^2	0.11	0.1	0.003	0.001	0.04	0.14

Robust Standard Errors in parentheses, columns (3)-(5) clustered at the subject level, and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.5: PREFERENCE FOR ENTREPRENEURSHIP, PROPENSITY TO EXPLORE AND SUCCESSFUL INNOVATION

	Pref for Entrepreneurship Pr[$Industry \neq D$]	Propensity to Explore Exploration Index	Successful Innovation Dist. to Optimum
Industry D Payoff	-0.0002 (0.0003)	.	.
Average Previous Payments	.	-0.001*** (0.0003)	-0.1*** (0.02)
Extroversion	0.0004 (0.0007)	0.0006 (0.001)	0.17 (0.11)
Openness	0.001** (0.0004)	-0.002** (0.001)	-0.17** (0.08)
Internal Locus of Control	-0.001 (0.001)	-0.005** (0.002)	-0.18 (0.2)
Risk Tolerance	-0.0005 (0.003)	0.001 (0.01)	-0.33 (0.8)
Cognitive Ability	-0.001 (0.002)	0.001 (0.004)	-0.79** (0.34)
Cost Info	0.01 (0.008)	-0.009 (0.03)	-0.44 (2.23)
Investment Info	0.009 (0.009)	-0.06*** (0.02)	-2.73 (1.79)
Constant	.	0.56*** (0.16)	14.51 (14.00)
Observations	1080	1026	997
R^2	.	.	0.28
Pseudo R^2	0.1	.	.

Col (1) contains marginal effects from a probit regression; col (2) contains coefficients from a Heckman Selection Model; col (3)contains OLS coefficients. Additional controls include Gender, Agreeableness (Big 5), Conscientiousness (Big 5), Neuroticism (Big 5), Round of the Industry Game. Robust Standard Errors clustered at the subject-level in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.6: INFORMATION AND PERSONALITY INTERACTIONS: PROPENSITY TO INNOVATE AND SUCCESSFUL INNOVATION

	Propensity to Explore Exploration Index	Successful Innovation Dist. to Optimum
Extroversion	0.006 (0.004)	0.35 (0.26)
Openness	-0.006*** (0.002)	-0.53*** (0.17)
Internal Locus of Control	-0.02** (0.008)	-1.30** (0.55)
Risk Tolerance	0.01 (0.02)	-2.27 (2.48)
Cognitive Ability	-0.002 (0.01)	-0.57 (0.83)
Cost Info	1.56*** (0.53)	79.34** (37.95)
Investment Info	0.31 (0.35)	-18.08 (27.63)
Investment Info × Opennes	0.002 (0.003)	0.45** (0.22)
Cost Info × Opennes	-0.004 (0.003)	-0.16 (0.26)
Investment Info × Extroversion	-0.01** (0.005)	-0.3 (0.3)
Cost Info × Extroversion	-0.03*** (0.007)	-1.76*** (0.42)
Investment Info × Locus of Control	0.02** (0.008)	1.03* (0.6)
Cost Info × Locus of Control	0.01 (0.01)	1.43* (0.76)
Investment Info × Risk Tolerance	-0.03 (0.03)	5.52* (3.07)
Cost Info × Risk Tolerance	-0.006 (0.02)	0.85 (2.71)
Investment Info × Cognitive Ability	0.006 (0.01)	-0.16 (0.88)
Cost Info × Cognitive Ability	-0.007 (0.02)	-2.95* (1.59)
Constant	0.68*** (0.15)	34.43* (18.09)
Observations	997	997
R^2	0.31	0.32

Estimates are coefficients from OLS regressions. Additional controls include Gender, Agreeableness (Big 5), Conscientiousness (Big 5), Neuroticism (Big 5), Round of the Industry Game and their interactions with Information Treatments. Robust Standard Errors clustered at the subject-level in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.7: TESTING FOR SIGNIFICANCE, F-STATISTICS FOR COLUMN (3) TABLE 3.6

	Investment Information	Cost Information	Difference
Extroversion	.13	18.07***	16.31***
Openness	.36	12.14***	6.23**
Internal Locus	1.36	.06	.48
Risk Tolerance	3.21*	1.68	4.85**
Cognitive Ability	6.06**	6.73**	4.04**

*, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.8: DETERMINANTS OF INFORMATION CHOICE

	Pr[Choose Investment Info=1]
Risk Tolerance	-0.17**
	(0.08)
Neuroticism	-0.0005
	(0.01)
Conscientiousness	0.002
	(0.01)
Openness	0.004
	(0.009)
Agreeableness	-0.02
	(0.01)
Extraversion	-0.02*
	(0.01)
External Locus of Control	-0.03
	(0.02)
Cognitive Ability	0.006
	(0.03)
Female	-0.15
	(0.14)
Observations	57
χ^2 statistic	10.95

Probit marginal effects. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.9: EXPLORATION, TREATMENT EFFECTS

	Investment Info (2)	Cost Info (3)	Diff.
Exploration, variance in industry-specific investment strategies			
Mean, rounds 1-10	13.73	12.27	1.46
Mean, all rounds	11.29	10.63	.66
Exploration, industry changes			
Total industries explored	2.23	2.61	-.39*
Mean, 1-10	.21	.34	-.14**
Mean, all rounds	.21	.28	-.07
Exploration, innovation index			
Mean, 1-10	.32	.37	-.05
Mean, all rounds	.19	.21	-.01
Observations	39	21	

Two-tailed t test of significance; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.10: SUCCESSFUL INNOVATION, TREATMENT EFFECTS

	Investment Info	Cost Info	Diff.
Distance from Optimal Investment Levels			
Mean, rounds 1-10	21.67	24.66	-3.00
Mean, all rounds	16.55	20.74	-4.19
Operating in the Minimum Cost Industry			
Mean, 1-10	.25	.39	-.14
Mean, all rounds	.25	.29	-.14
Observations	39	21	

Two-tailed t test of significance; *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.11: PREFERENCE FOR ENTREPRENEURSHIP, PROPENSITY TO EXPLORE AND SUCCESSFUL INNOVATION, INFORMATION CHOICE TREATMENT ONLY

	Pref for Entrepreneurship Pr$[Industry \neq D]$	Propensity to Explore Exploration Index	Successful Innovation Dist. to Optimum
Industry D Payoff	-0.0005 (0.0009)	.	.
Average Previous Payments	.	-0.001*** (0.0002)	-0.17*** (0.02)
Extroversion	0.001 (0.002)	-0.0007 (0.001)	-0.1 (0.12)
Openness	-0.002 (0.001)	-0.0002 (0.001)	-0.03 (0.1)
Internal Locus of Control	-0.0004 (0.003)	0.003 (0.003)	0.11 (0.27)
Risk Tolerance	-0.002 (0.008)	-0.0007 (0.009)	-0.84 (0.74)
Cognitive Ability	-0.004 (0.005)	-0.001 (0.003)	-0.13 (0.25)
Cost Info	-0.05 (0.04)	0.03* (0.02)	4.47*** (1.67)
Constant	.	0.35** (0.17)	36.36*** (12.66)
Observations	1140	1083	1016
R^2	.	.	0.33
Pseudo R^2	0.06	.	.

Col (1) contains marginal effects from a probit regression; col (2) contains coefficients from a Heckman Selection Model; col (3)contains OLS coefficients. Additional controls include Gender, Agreeableness (Big 5), Conscientiousness (Big 5), Neuroticism (Big 5), Round of the Industry Game. Robust Standard Errors clustered at the subject-level in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 3.12: INFORMATION AND PERSONALITY INTERACTIONS: PROPENSITY TO EXPLORE AND SUCCESSFUL INNOVATION

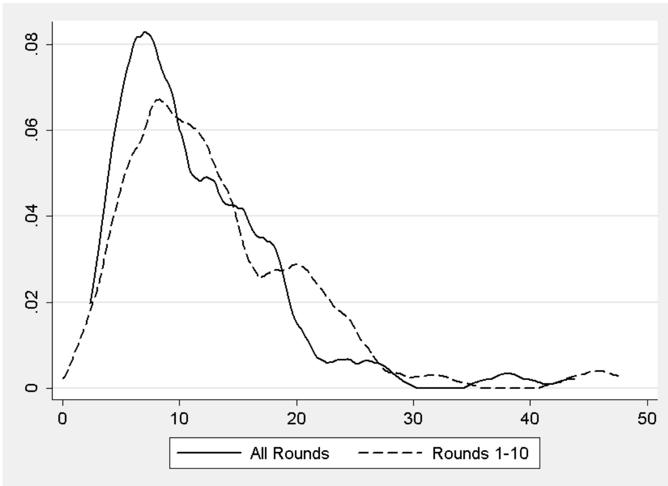
	Propensity to Innovate Innovation Index	Successful Innovation Dist. to Optimum
Extroversion	-0.002 (0.002)	-0.13 (0.12)
Openness	-0.0005 (0.001)	-0.08 (0.1)
Internal Locus of Control	0.005 (0.004)	0.36 (0.29)
Risk Tolerance	-0.01** (0.007)	-2.29*** (0.74)
Cognitive Ability	-0.003 (0.004)	-0.22 (0.31)
Cost Info	-0.11 (0.25)	1.90 (28.39)
Cost Info × Opennes	0.003 (0.003)	-0.05 (0.21)
Cost Info × Extroversion	0.003 (0.003)	0.3 (0.22)
Cost Info × Locus of Control	-0.007 (0.008)	0.48 (0.54)
Cost Info × Risk Tolerance	0.04** (0.02)	3.50* (1.97)
Cost Info × Cognitive Ability	0.02 (0.01)	0.19 (0.99)
Constant	0.46*** (0.17)	33.91** (15.23)
Observations	1016	1016
R^2	0.28	0.36

Estimates are coefficients from OLS regressions. Additional controls include Gender, Agreeableness (Big 5), Conscientiousness (Big 5), Neuroticism (Big 5), Round of the Industry Game and their interactions with Information Treatments. Robust Standard Errors clustered at the subject-level in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

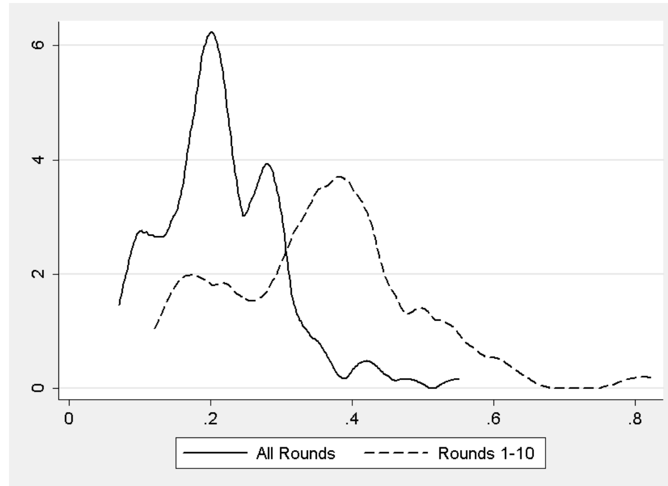
TABLE 3.13: NON-PECUNIARY UTILITY OF ENTREPRENEURSHIP

	Pr[Not Choosing Industry D | Earn more in Industry D = 1]
Average Previous Payments	-0.003***
	(0.0006)
Industry D PayOff Known	-0.03
	(0.05)
Extroversion	-0.005
	(0.004)
Openness	0.008**
	(0.003)
Risk Tolerance	-0.002
	(0.03)
Internal Locus of Control	0.02**
	(0.008)
Cognitive Ability	-0.006
	(0.009)
Female	0.01
	(0.06)
Cost Info	0.03
	(0.07)
Round	-0.01***
	(0.003)
Observations	1083
Pseudo R^2	0.23

Probit marginal effects. Robust Standard Errors in parentheses clustered at the subject-level and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

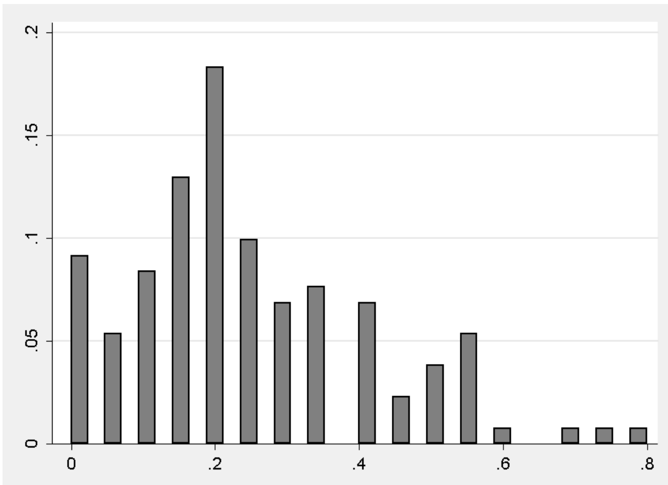


(a)

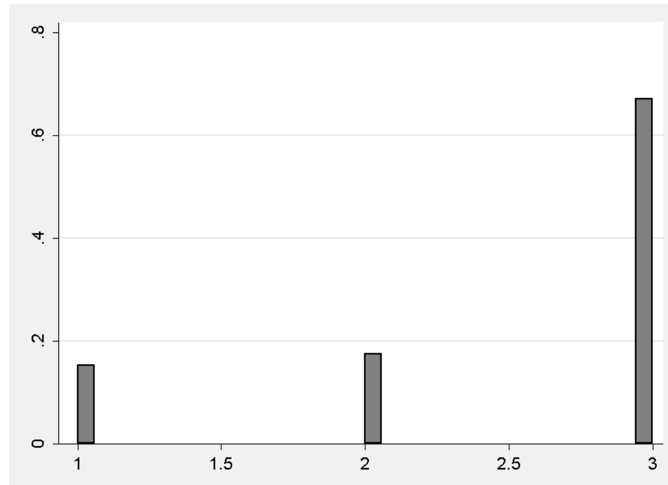


(b)

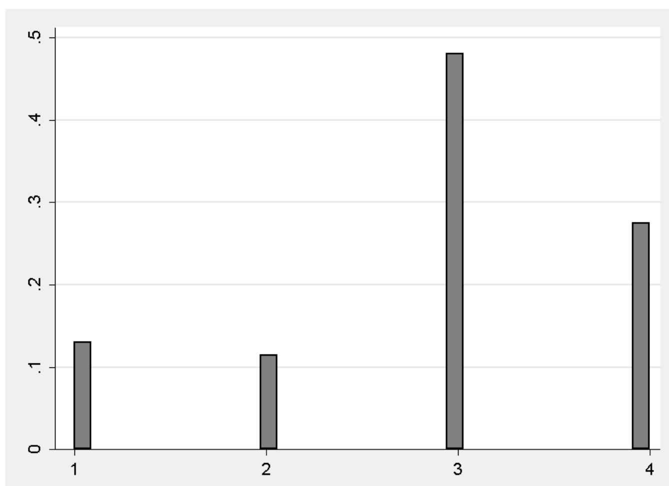
FIGURE 3.1: INVESTMENT EXPLORATION, ALL TREATMENTS POOLED Figure 1(a) DISTRIBUTION OF AVERAGE STANDARD DEVIATION IN INVESTMENT STRATEGIES. Figure 1(b) DISTRIBUTION OF AVERAGE EXPLORATION INDEX.



(a)

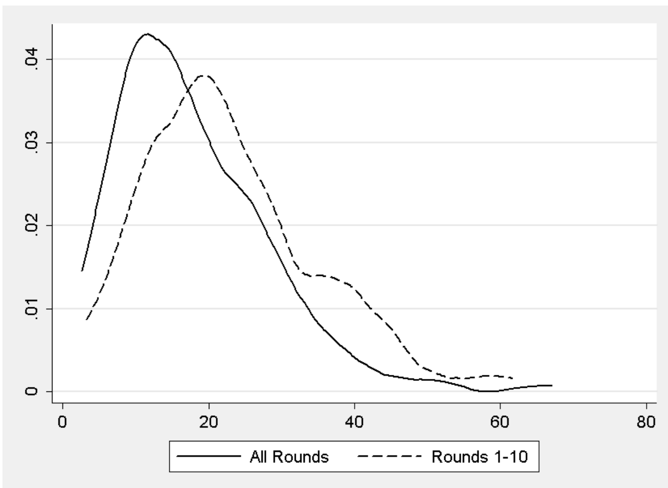


(b)

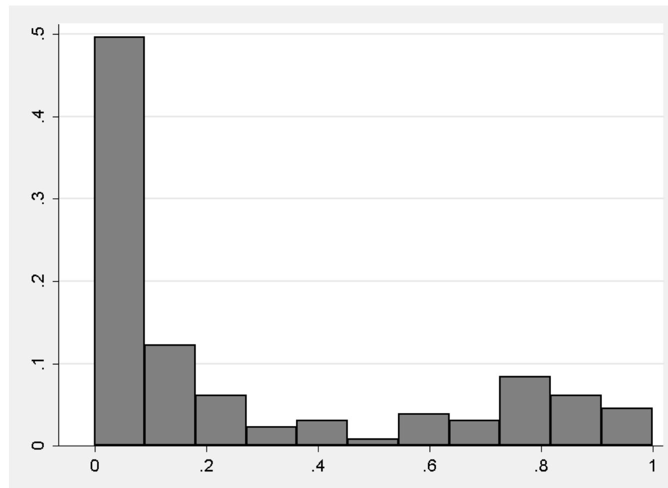


(c)

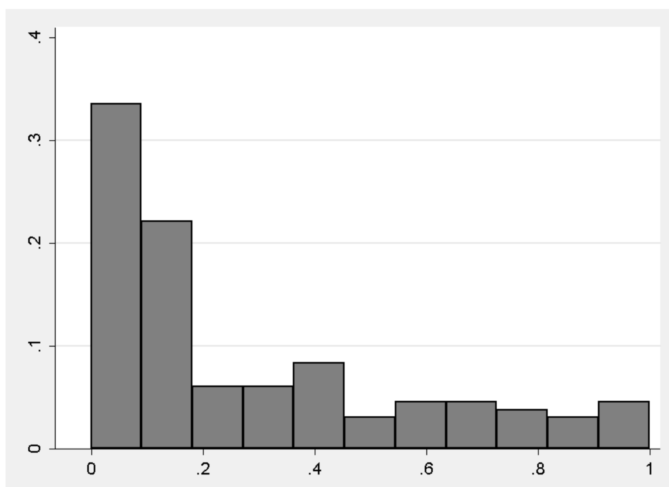
FIGURE 3.2: INDUSTRY EXPLORATION, ALL TREATMENTS POOLED Figure 2(a) PERCENTAGE OF ROUNDS WITH AN INDUSTRY SWITCH. Figure 2(b) TOTAL INDUSTRIES EXPLORED, EXCLUDING INDUSTRY D. Figure 2(c) TOTAL INDUSTRIES EXPLORED.



(a)



(b)



(c)

FIGURE 3.3: SUCCESSFUL INNOVATION, ALL TREATMENTS POOLED Figure 3(a) AVERAGE DISTANCE FROM OPTIMAL INVESTMENT STRATEGY. Figure 3(b) FREQUENCY OF OPERATING IN MINIMUM COST INDUSTRY. Figure 3(c) FREQUENCY OF OPERATING IN MINIMUM COST INDUSTRY, ROUNDS 1-10.

3.6 Appendix C

3.6.1 Profit Functions

TABLE C.1: INVESTMENT PRODUCT BLISS POINTS

Industry A	$x_A^* = 2 \times y_A^*$, $z_A^* = 60$
Industry B	$x_B^* = 50$, $y_B^* = z_B^*$
Industry C	$2 \times x_C^* = z_C^*$, $y_C^* = 20$

In particular, subject $i's$ total earnings in Industry I for round j are given by

$$Earnings_{i,j} = 2 \times [Investment_{i,j} - |x_{i,j} - x_I^*| - |y_{i,j} - y_I^*| - |z_{i,j} - z_I^*|] - f_{i,I} + Savings_{i,j}$$

Industry D differs from the other three Industries in that there are no investment decisions to be made and subject i always earns

$$Earnings_{i,j} = 100 - f_{i,D}$$

3.6.2 Signals

Investment Information Signal Let subject i's investment strategy in Industry I in round j be given by $(x_{I,i,j}, y_{I,i,j}, z_{I,i,j})$ where the optimal investment strategy in Industry I is given by (x_I^*, y_I^*, z_I^*). The subject only receives a signal about one of the investment products and each product has $\frac{1}{3}$ chance of being chosen for a signal. If product x is randomly chosen for subject i in round j, then the subject receives a signal

$$\text{signal}_{I,i,j} = \begin{cases} \text{Increase } x_I & \text{if } x_{I,i,j} < x_I^* \\ \text{Decrease } x_I & \text{if } x_{I,i,j} > x_I^* \\ \text{Do not change } x_I & \text{if } x_{I,i,j} = x_I^* \end{cases}$$

Cost Information Signal Suppose subject i is operating in Industry I during round j. After round j he receives a signal about $f_{i,I}$ that is determined in the following way. Let $Z \sim U[50, 100]$, where realizations are given by z. Then

$$\text{signal}_{I,i,j} = \begin{cases} \text{Your fixed cost is below } z & \text{if } f_{i,I} < z \\ \text{Your fixed cost is above } z & \text{if } f_{i,I} > z \\ \text{Your fixed cost is } z & \text{if } f_{i,I} = z \end{cases}$$

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