The Innovative Personality*

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Abstract: We study how selection shapes innovative and entrepreneurial behavior. Using a laboratory experiment, we decompose Roy's (1951) theory of selection and study the effect of traits on innovative behavior when experience is assigned versus when it is endogenously accumulated. Consistent with theory, when experience is assigned, we find that (1) there are distinct behavioral patterns leading to earnings' disparities and (2) the returns to personality traits are ambiguous, and significantly depend on the type of experience assigned. By contrast, when individuals self-select experience we show that they leverage their trait-based advantage and subsequently earnings' disparities disappear.

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1 Introduction

The role of the individual entrepreneur in fostering innovation and economic growth has obtained nearly folkloric stature. Knight (1921)'s sentiment that a society's economic fortune rests upon its supply of "entrepreneur qualities" is echoed by Schumpeter (1947), who notes that producing "caviar from sawdust" is the result of "only one man or a few men who see the new possibility". These early scholars ignited a large literature in economics and business, as well as psychology and neuroscience, that attempts to characterize the preferences, personality and even the biological underpinnings of innovative behavior (see Åstebro et al. (2014) for a current review).

The recent literature in economics has taken on the question of who becomes a successful entrepreneur from two distinct perspectives. The primary difficulty in answering this question can be attributed to selection, rendering inconclusive and even contradictory answers. For example, one strand of literature has sought to characterize the traits and preference parameters of individuals who become entrepreneurs. Knight (1921) emphasized the role of risk tolerance as a defining characteristic of the entrepreneur, a notion later formalized by Kihlstrom and Laffont (1979). However, there is no solid empirical evidence that entrepreneurs are less risk-averse than non-entrepreneurs (Elston et al., 2006). More recently, research has turned to link personality traits and entrepreneurship (Brandstätter, 1997; Caliendo et al., 2011; Evans and Leighton, 1989; Fairlie and Holleran, 2012; Hamilton et al., 2014). Using the Big Five Personality construct (Costa and McCrae, 1985), Caliendo et al. (2011) find a positive relationship between Extraversion, Openness, Neuroticism and Agreeableness and self-employment, Hamilton et al. (2014) find that increased Openness, Conscientiousness, and Agreeableness are a liability among the self-employed and increased Extraversion is an asset, and Fairlie and Holleran (2012) find little association between entrepreneurship and personality.

While a second strand of literature seeks to characterize the types of experiences, knowledge and skill-sets that are predictive of successful entrepreneurship. Lazear (2004)'s "Jack of All Trades" theory of entrepreneurship and Gompers et al. (2005)'s theory of small firms argue that individuals who accumulate a general skill set or a wider breadth of knowledge are most likely to become entrepreneurs.[1] While Wagner (2003) finds support in favor of the Jack of All Trades theory of entrepreneurship,Silva (2007) and Åstebro and Thompson (2011) do not. Further, Elfenbein et al. (2010) provide evidence in support of both preference-based sorting and human capital accumulation: small firms may foster entrepreneurial-relevant human capital, and individuals who have a strong preference for autonomy have a preference for working for a smaller firms and are likely to become entrepreneurs.

Roy (1951)'s model of occupation choice provides a framework for understanding the implications of selection bias that can occur when individuals self-select into occupations or sectors, including the entrepreneurial sector.Roy models have been used in a variety of contexts to better understand how the interaction of self-selection and individual characteristics drive different earnings' patterns, including immigration (Borjas, 1987), college attendance (Willis and Rosen, 1979), and labor force participation (Gronau, 1974; Heckman, 1974). The underlying difficulty in these questions is that the researcher only observes behavior and earnings conditional on self-selection, rather than for the entire population.

This paper purposefully circumvents this problem by studying selection in the laboratory and thus can examine the fundamental problem of selection that arises when asking the question "who are the (successful) entrepreneurs?" We are not interested in studying which specific traits lead to more successful innovation, but instead, we conjecture and show that individual traits play a significant role in the selection of information (i.e., experience) in entrepreneurial endeavors. We examine innovation in the laboratory because

[1] We note that 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., 2015).

the laboratory allows for us to control the information acquisition process.[2] The main task in our experiment, the Industry Game, is adapted from Ederer and Manso (2013) and Herz et al. (2014) and embodies the trade-off between exploration and exploitation (March, 1991). Subjects take on the role of a manager in which they must decide which Industry to enter and how to invest their money across the Industry's products. The objective in each of the 20 rounds of the Industry Game is to maximize earnings. In each Industry, there is an unknown optimal product mix that maximizes the subject's investment in the Industry and an unknown Industry-specific fixed cost. Thus, to maximize earnings subjects must decide when to explore new Industries or investment strategies and when to exploit (or fine-tune) their current strategy.

We employ a between-subject design where our main treatment manipulation is information in the Industry Game. Subjects are randomly assigned to one of four treatments: No Information, Investment Information, Cost Information or Information Choice (i.e., subjects choose the type of information they prefer to receive). The No Information treatment provides subjects only with earnings feedback after each round. By contrast, in the Investment Information and Cost Information treatments, we randomly assign subjects to receive either Investment Information *or* Cost Information, in addition to the earnings feedback. Investment Information consists of an unbiased signal about the optimal industry-specific investment level relative to their current investment strategy (this is equivalent to the feedback in Ederer and Manso (2013) and Herz et al. (2014)), whereas Cost Information consists of an unbiased signal about the subject's industry-specific fixed cost. In the fourth treatment, the Information Choice treatment, subjects *choose* the type of information that want to receive: no information (Control), Investment Information, or Cost Information. Importantly, the first three treatments *assigns* subjects

[2] Notable exceptions include Charness and Grieco (2018); Ederer and Manso (2013); Herz et al. (2014); Meloso et al. (2009). Of these studies, only Herz et al. (2014) relate individual traits to innovative behavior and find that optimism is related to increased exploratory behavior, while overconfidence is related to less exploration. Charness and Grieco (2018) and Ederer and Manso (2013) focus on the effects of incentive schemes on creativity and innovation.

to an information sector (i.e., No Choice treatments),[3] while the fourth treatment allows subjects to *self-select* into their preferred information sector. In addition to the Industry Game, we elicit Big Five personality traits (Costa and McCrae, 1985),[4] locus of control Rotter (1971),[5] risk preferences and cognitive ability Raven and Court (1998), thus also contributing to a growing literature of non-cognitive skills on economic outcomes (see Almlund et al. (2011) for an overview of this literature).

Our pattern of findings closely mirrors the predictions put forth by Roy (1951). In particular, there are significant innovation and earnings' disparities when information is randomly assigned, but these disappear when subjects are able to leverage their comparative advantage and self-select into their preferred information sector (Heckman and Honore, 1990). For example, subjects randomly *assigned* to Cost Information explore more, innovate less successfully and earn significantly less than subjects randomly *assigned* to Investment Information, but we find no significant differences in the Information Choice treatment when subjects *self-select* either Investment or Cost Information. Roy's prediction stems from the idea that when selection occurs, individuals are able to leverage their comparative advantage. This is exactly what we find: subjects leverage their trait-based comparative advantage, rather than a single set of traits or information sector being universally advantageous.[6] We

[3]To our knowledge, Fairlie et al. (2015) and **?** are the only other studies that look at the effect of information on innovative behavior. Both papers report results from a large-scale field experiments in which aspiring entrepreneurs are randomly assigned to training programs, while the control treatment receives no training.

[4]Recent literature links the Big Five to a host of factors that may affect labor market outcomes (Barrick and Mount, 1991; Caliendo et al., 2011; Fletcher, 2013; Hamilton et al., 2014; Cubel et al., 2016).

[5]Rotter's External-Internal Locus of Control is designed to determine the extent to which an individual views his life as under his control. Individuals with an internal locus of control view 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).

[6]Similarly, Lundberg (2013) finds that personality traits interact with socioeconomic status such that Conscientiousness was associated with better educational outcomes for advantaged males, whereas Openness was associated with better outcomes for disadvantaged males.

find that extraversion and risk tolerance are assets for subjects *assigned* to Cost Information, but liabilities for subjects *assigned* to Investment Information. In the Information Choice treatment, subjects who are more extroverted and risk tolerant are significantly more likely to select Cost Information than Investment Information.[7] Finally, we show that subjects select optimally–on average, subjects who choose Cost (Investment) Information earn more using Cost (Investment) Information than they would have had they chosen Investment (Cost) Information.

Our findings suggest that differentiating between types of entrepreneurship may be fruitful for identifying the "innovative personality". For example, the individual who starts a high-tech company out of his garage using highly-specialized knowledge is very different from a restauranteur who manages a large staff of employees and diverse business relationships.

2 Experimental Design & Data

The experiments were run at the University of Sydney in May and October 2014. Our sample consists of 208 subjects recruited through ORSEE (Greiner, 2015) and the experiment was programmed using Z-Tree (Fischbacher, 2007). Sessions lasted approximately 90 minutes and the average earnings were approximately 33 AUD. During the experiment, subjects could earn money during an Industry Game (20 Rounds), a lottery task (45 lottery choices) and a cognitive test (answer up to 12 questions, earn $5 per correct question). This means, there were 66 items (20+45+1) for which the subject could earn money. At the end of the experiment, we randomly choose one of these decisions for payment. Additionally, subjects completed unincentivized personality and locus of control assessments. See Supplementary Material D for the experimental instructions and screenshots.

[7] Fréchette et al. (2011) also finds evidence that personality predicts information demand.

2.1 The Industry Game

The Industry Game used in our experiment is a version of the Lemonade Stand Task in Ederer and Manso (2013) and the Ice Cream Stand Task in Herz et al. (2014).[8] While there are small changes in the structure of the game, the main elements remain the same. The Industry Game captures the idea that innovative activity involves finding new ways to combine existing resources that exploit complementarities to generate a profit (Schumpeter, 1947; Meloso et al., 2009). 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". This notion of experimental innovation highlights the importance of learning and experience for innovation.

In the Industry game, subjects take on the role of a manager who must decide how to invest resources for 20 rounds. At the beginning of each round, each subject i is endowed with 100 Australian dollars (AUD) and must make two choices: first, the subject chooses which of four industries to operate (Industry A, Industry B, Industry C, or Industry D); second, the subject decides how to invest in his chosen industry. Each subject 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, $f_{i,I} \sim U\,[50, 100]\ \ \forall I \in \{A, B, C, D\}$. The subject knows that if he enters Industry A, B, and C he will have to make a positive investment by allocating his endowment across three investment products, x, y and z. The subject does not have to invest the entire endowment; any endowment that is not invested is considered savings for that round, although subjects are informed that savings do not carry over between rounds. The profit function is defined so that within each Industry, there is a unique, profit-maximizing investment strategy, $(x^*_I, y^*_I, z^*_I)\ \forall I \in \{A, B, C\}$. 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 this bliss point, and their industry-specific

[8]The authors thank Florian Ederer and Holger Herz for generously sharing their Z-Tree programs.

fixed cost.[9] 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. Subjects are also told that the maximum they can earn is 150 AUD (i.e., invest the entire endowment at the bliss point, which earns the subject 200 AUD and have the minimum possible fixed cost, 50 AUD) and that there is limited liability so any negative profits result in a payoff of 0 AUD.

There are four treatments: the Control treatment, the Investment Information treatment, the Cost Information treatment, and the Information Selection treatment. In the Control treatment, subjects play the Industry Game, as described above, and receive profit feedback after every round. The other three treatments provide profit feedback in every round as well as an additional piece of information, to be described, after each of the first 10 rounds.

Investment Information Treatment In the Investment Information treatment, subjects receive an unbiased signal about their investment strategy. The computer randomly determines whether to give information about one of the three products and then provides feedback about whether the subject should increase, decrease or not change the investment level in that product. 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. (2014).

Cost Information Treatment In the Cost Information treatment, in addition to profit feedback, subjects also receive an unbiased signal about their industry-specific fixed cost. The information is relevant to the Industry in which they are operating. Thus, if the subject is operating in Industry A,

[9] Appendix Supplementary Material C.1 shows the Industry-specific bliss points and profit functions.

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.[10]

Information Selection Treatment In the Information Selection treatment, subjects choose whether they prefer to receive Cost Information, Investment Information or No Information during the first 10 rounds. Before the game begins, subjects are shown each type of information and then asked to choose a single type of information to receive throughout the first 10 rounds. 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.

In rounds 1-10, subjects are in an information accumulation phase. 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.

2.2 Risk preferences, cognitive and non-cognitive skills

After subjects completed the Industry Game, we elicited risk preferences, cognitive ability, and personality traits. During the experiment, the elicitation of personality was always the final task. During approximately half of our sessions, we elicited risk preferences before cognitive ability and switched the order for the other half. We conduct all four treatments of the Industry Game with both task orders.

[10] S2 formally describes the signals.

Risk preferences We elicit risk preferences following Hey and Orme (1994). Subjects faced a series of 45 lottery pairs and were asked to choose which lottery in the pair they preferred. We then follow Andersen et al. (2014) and estimate risk preferences at the individual-level, assuming CRRA utility, via maximum likelihood.

Cognitive Skills 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 diagrams 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.

Personality Traits We use the Big Five Personality inventory to assess personality.[11] We measured the Big 5 using the 120 item short form developed by Johnson (2014).

We use Rotter's External-Internal Locus of Control test to measure locus of control (Rotter, 1971). 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.

[11] The Big 5 include Extraversion, Openness, Conscientiousness, Agreeableness and Neuroticism. Extraversion is associated with high energy, assertiveness, and positive affect. Openness reflects the degree of intellectual curiosity, creativity and is associated with 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.

2.3 Data

Table 1 presents summary statistics of our sample. Note that the sample size is 194, rather than 208, 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.

TABLE 1: SUMMARY STATISTICS

	All	Control	Investment	Cost	Selection
Openness	46.03	43.41	46.91	45.88	46.80
	(9.01)	(9.07)	(9.52)	(9.50)	(8.40)
Extraversion	49.09	49.80	47.43	51.54	50.32
	(8.04)	(9.87)	(7.48)	(8.01)	(7.29)
Neuroticism	48.96	48.22	48.80	52.54	48.26
	(7.61)	(7.91)	(8.30)	(7.91)	(6.80)
Conscientiousness	49.36	49.76	49.80	45.89	50.47
	(8.77)	(9.92)	(7.45)	(8.49)	(8.80)
Agreeableness	48.18	47.97	49.48	45.40	48.79
	(8.44)	(9.92)	(6.98)	(8.60)	(8.26)
Locus of Control	11.49	11.97	11.43	11.31	11.37
	(3.95)	(3.74)	(4.44)	(4.48)	(3.55)
CRRA coefficient	.81	.85	.59	.87	.89
	(.78)	(.53)	(.51)	(.97)	(.89)
Raven Score, Cognitive Ability	7.20	7.19	7.20	7.20	7.19
	(2.36)	(2.19)	(2.87)	(1.81)	(2.39)
Female	.55	.60	.43	.60	.60
	(.50)	(.49)	(.50)	(.50)	(.50)
Age	22.74	22.33	22.61	22.57	23.06
	(3.85)	(3.68)	(3.47)	(2.66)	(4.54)
Observations	194	36	44	35	79

We were unable to estimate risk preferences for 8 subjects. See Table S1 for more detail on sample sizes.

The Industry Game is designed to measure degrees of exploration, but can also distinguish between exploration and "successful innovation". Throughout our analysis, our main outcome variables are (1) exploration, and (2) earnings.

Exploration Ederer and Manso (2013) and Herz et al. (2014) measure 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 the industry is perhaps the biggest exploration since it requires an entirely new and unknown investment strategy and, in our setting, an unknown fixed cost. Our measure of exploration, the Exploration Index, captures the degree of change in investment strategies and industry switches into a single measure.[12] 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 its similarity to the most similar strategy previously used. This allows us to identify when a subject returns to a previously tried idea (even when that choice happened several rounds before). 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 j in the following way. Define $I_{i,j} \in \{A, B, C, D\}$ be the industry chosen by subject i in period j. Let $(x_{i,j}, y_{i,j}, z_{i,j})$ be a vector of subject i's investment strategy in period j. Define the Exploration Index of subject i in period j as follows

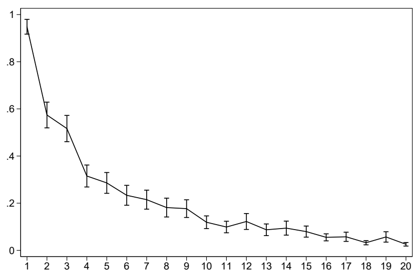
$$EI_{i,j} = \begin{cases} 0 & \text{if } I_{i,j} = D \\ 1 & \text{if } \forall\ j' < j\ I_{i,j'} \neq I_{i,j} \\ \kappa \times \min_{j' | I_{i,j'} = I_{i,j}} \mid x_{i,j} - x_{i,j'} \mid + \mid y_{i,j} - y_{i,j'} \mid + \mid z_{i,j} - z_{i,j'} \mid & \text{otherwise.} \end{cases} \tag{1}$$

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.[13] The average Exploration Index with 95% confidence intervals for

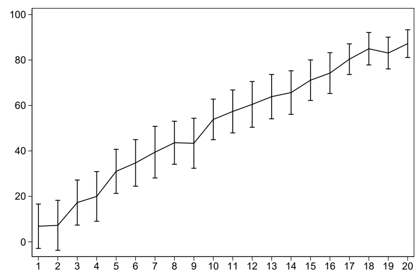
[12] In the Supplementary Material, we show that we obtain qualitatively equivalent results using the measure of exploration proposed in Ederer and Manso (2013) and Herz et al. (2014).

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

Figure 1: Outcomes: Exploration Index and Earnings



(a) Exploration Index



(b) Earnings ($)

each of the 20 periods is shown in Figure 1a with 95% confidence bands.

Successful Innovation We also measure the degree to which subjects successfully innovate, which we measure in terms of money earned (see Figure 1b). Figure 1b shows the average earnings in each period. The trend shows that subjects perform better as the game unfolds.

Additional Control Variables In addition the control variables of interest (i.e., to personality and risk),we also include a set of control variables throughout our analysis. First, we exclude data from the first round of play since subjects make round 1 choices without any information and thus this choice is as good as random and only introduces noise. However, we do control for the pay-off the subject receives in round 1, since a "lucky" choice in round 1, and thus a lucky high pay-off, might influence how the subject plays the industry game. Second, we include fixed effects for cognitive ability (i.e., the number of correctly answered questions from the Raven's test), round of play in the industry game (2-20), age, year in school, and order of play (i.e., some sessions completed the Raven's test before the risk and other sessions performed the tasks in the opposite order).

2.4 Effect of Information

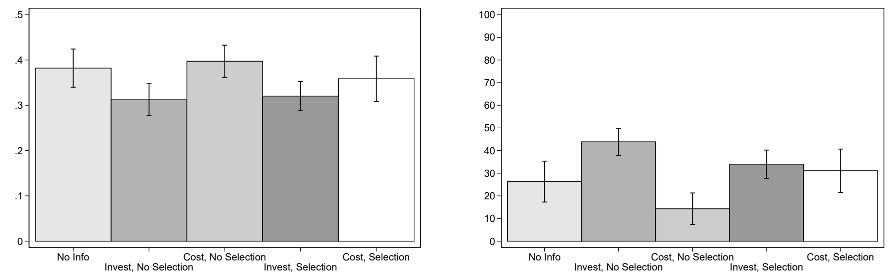
Prior to exploring the role of traits, we first examine whether our main treatment manipulation (i.e., information types) results in differential outcomes for innovation and earnings.[14] Figure 2 shows the average outcomes for exploration and earnings during the first 10 rounds by treatment (i.e., (1) No Information; (2) Investment Information; (3) Cost Information; (4) Information Selection-split by selection). We make three important observations. First, subjects assigned to the Cost Information treatment explore significantly more during the first 10 rounds than subjects assigned to the Investment Information treatment. This means, that at the conclusion of the first 10 rounds subjects assigned to receive Cost Information have experienced a wider breadth of investment strategies and industry choice combinations due to their greater propensity for exploration than subjects assigned to receive Investment Information.[15] Due to their lower propensity to explore, subjects assigned to the Investment Information treatment have more finely-tuned and specialized knowledge. We conclude that to two types of entrepreneurs emerge: Cost Information generates entrepreneurs that look like "Jack of All Trades" while Investment Information results in entrepreneurs that behave like "Specialists".

Second, the fine-tuning strategy of the subjects assigned to Investment Information appears to be advantageous; random assignment to Investment Information, compared to Cost Information, leads to significantly more earnings. However, our third observation rules out the idea that Investment information is necessarily a superior form of information. Third, as predicted by Roy (1951), the innovation and earnings disparities *disappear* when subjects have the opportunity to select their preferred type of information.

[14] In Table S2, we present evidence that shows that subjects effectively use the information they receive by changing industries or adjusting their investment strategy.

[15] In Table S3 we follow the measurement of exploration in Ederer and Manso (2013) and Herz et al. (2014) and show the average standard deviation in investment strategies is significantly greater for subjects in the No Selection Cost Treatment than in the No Selection Investment Treatment. We also show that subjects in the No Selection Cost Treatment explore significantly more industries on average than subjects in the No Selection Investment Treatment.

Figure 2: Average Treatment Effects



(a) Exploration

(b) Earnings

2.5 Effect of Traits

We now examine the role of traits on innovative behavior. To do so, we regress our two outcome measures–Exploration Index and Earnings–on a vector of individual traits and treatment dummies using data from the No Selection Treatments only (i.e., when information sector is exogenously assigned). In sum, we find that the Big Five personality traits are not jointly predictive of exploration or earnings and that there is no specific trait that plays a significant role.

2.6 Hypotheses

In Sections 2.4 and 2.5, we established two findings: (1) innovation and earnings' disparities emerge when information is randomly assigned, but disappear when information is chosen; and (2) traits do not unambiguously drive innovative behavior. These two findings suggest that traits and information interact and that we may expect to find a pattern of predictable pattern of selection. To preview, our hypotheses and results are structured by decomposing a selection model (Roy, 1951). We hypothesize and show that (1) first, the returns to traits are information-dependent; (2) second, individuals' demand for information is trait-based; and (3) third, individuals' trait-based demand for information is optimal. Alternatively, in Supplementary Material B.1 we estimate a structural selection model and come to similar conclusions. We prefer

Table 2: No Selection Treatments: Effect of Individual Traits

	Exploration	Earnings
Investment Info	-0.06***	17.27**
	(0.02)	(8.14)
Cost Info	-0.004	-9.47
	(0.02)	(9.14)
Extraversion	0.0005	-0.37
	(0.001)	(0.48)
Openness	0.0007	-0.52
	(0.001)	(0.41)
Neuroticism	0.001	-0.13
	(0.001)	(0.59)
Agreeableness	-0.001	0.64
	(0.001)	(0.45)
Conscientiousness	-0.0006	0.04
	(0.001)	(0.48)
Risk Tolerance	-0.008	7.09*
	(0.009)	(4.04)
Internal Locus of Control	-0.004**	2.30***
	(0.002)	(0.69)
Female	0.02	-14.30*
	(0.02)	(7.54)
Constant	0.55***	64.77
	(0.16)	(63.32)
Observations	2074	2074
R^2	0.3	0.23
F-test		
Cost Info=Invest Info	9.19***	11.38**
Big Five traits	.65	.88
Controls		
Cognitive Skill FE	Y	Y
Round FE	Y	Y
Round 1 Pay-Off	Y	Y
Age & Year in School FE	Y	Y
Order FE	Y	Y

Table 3: OLS estimates. Robust Standard Errors clustered at the subject-level in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

the approach here because it more clearly shows the nature of selection and how it relates to the question of understanding the "innovative personality".

Hypothesis 1. *Information interacts with individual traits to drive innovation. The return to traits and information are interdependent.*

Our first hypothesis posits an interaction effect between traits and information. To test this hypothesis, we estimate equation 2 for subjects assigned to Investment Information and Cost Information, separately.

$$Y_{i,j} = \beta_0 + \beta_{\text{Traits}} \times \mathbf{X}_i + \beta_{\text{Controls}} \times \mathrm{Z}_i + \eta_{i,j} \tag{2}$$

If the interaction effects between traits and information are sufficiently strong, then, following Roy (1951), we expect that (1) information demand will be trait-based and (2) individuals optimally demand information. We turn to these hypotheses now.

Hypothesis 2. *Individuals will demand information that leverages their trait-based advantage. In particular, if a trait is an asset when assigned Investment Information, but a liability when assigned Cost Information, then an individual with this trait will be more likely to choose Investment Information.*

We test this information demand hypothesis using data from the Information Selection treatment and estimating the following probit regression

$$Pr[\text{Cost Information} = 1] = P_0 + \mathbf{P}_{\text{Traits}} \times \mathbf{X}_i + \varepsilon_i, \tag{3}$$

where the outcome variable takes a value of 1 if subject i chooses Cost Information and a value of 0 if the subject chooses Investment Information.

Our third hypothesis pushes the trait-based advantage further to better understand the nature of the selection problem. We hypothesize that individuals not only leverage their trait-based advantage through information demand but that they do so optimally; that is, on average, individuals could not have done better had they chosen a different type of information in the Information Selection treatment.

Hypothesis 3. *Individuals who chose Investment (Cost) Information could not have made more money choosing Cost (Investment) Information.*

To construct the counterfactual estimates of earnings and successful for subjects in the Information Selection Treatment, we use the estimates obtained from estimating equation 2 to predict the counterfactual outcomes. For subjects who chose Investment (Cost) Information, we use the estimated effects of individual traits from the average individual assigned to Cost (Investment) Information to predict what these subjects would have made if they had chosen the other type of information. We then construct four residual terms and test whether the residuals are consistent with subjects choosing optimally.

$$
\begin{array}{lcc}
E[\text{Dist To Optimum}_1|\text{Invest Info=1}] - E[\text{Dist To Optimum}_2|\text{Invest Info=1}] & < & 0 \\
E[\text{Earnings}_1|\text{Invest Info=1}] - E[\text{Earnings}_2|\text{Invest Info=1}] & > & 0 \\
E[\text{Dist To Optimum}_2|\text{Cost Info=1}] - E[\text{Dist To Optimum}_1|\text{Cost Info=1}] & < & 0 \\
E[\text{Earnings}_2|\text{Cost Info=1}] - E[\text{Earnings}_1|\text{Cost Info=1}] & > & 0
\end{array} \tag{4}
$$

We estimate equation 4 by regressing (via OLS) the difference in the outcome variable in the chosen information sector with the predicted outcome variable in the alternative information section on a vector of individual traits and a constant. Thus, the constant represents the average difference in the residual, controlling for individual traits. A positive (negative) constant in the Earnings (Distance to Optimum) indicate that, on average, individuals perform better in their chosen information sector than they would have in the alternative.

3 Main Findings

In this section, we test each of the hypotheses described in the previous section. We begin with a statement of the result, followed by a brief discussion.

Result 1. *Individual traits interact with information to drive innovation. In* *particular, Extraversion and risk tolerance are assets when using to Cost Information, but liabilities when using Investment Information.*

In Table 4, we present the estimates from equation 2 to test Hypothesis 1. We find that increased Extraversion and risk tolerance is a liability for “Specialists” but an asset for “Jacks of All Trades”. For example, a standard deviation increase in Extraversion leads to an average 12 dollar loss in earnings for Specialists, but a 16 dollar gain for Jacks of All Trade. By contrast, Locus of Control, Neuroticism, and Agreeableness play similar roles in the exploration, successful innovation and earnings for both types of innovators.[16]

Result 2. *Individuals leverage their trait-based advantage when demanding Information. Increased Extraversion and risk tolerance is associated with a significantly increased likelihood of choosing Cost Information.*

Next, we turn to the Information Selection Treatment, where subjects self-select into receiving Cost Information or Investment Information after they have had a chance to learn about each type of information.[17] Of the 79 subjects assigned to the Information Selection treatment, 52 chose Investment Information and 27 chose Cost Information. In Table 5, we present estimates from equation 3 and find that an increase in one standard deviation in Extraversion and Risk Tolerance is associated with 20 percentage point and 12 percentage point increase, respectively, in the likelihood of choosing Cost Information.[18]

Result 3. *Individuals optimally choose Information type; that is, individuals who choose Investment (Cost) Information earn more than they would have if they had chosen Cost (Investment) Information.*

[16] There are traits that play a significant role for one type of entrepreneur and an insignificant role for the other type of entrepreneur. We focus on those traits that have significant and opposite effects.

[17] They also had the choice to choose No Information (i.e., the Control Treatment), but no subject made this choice.

[18] By contrast, Supplementary Material B.2 shows the effect of traits on innovation and earnings in the Information Selection treatment if we *ignore* their role in information demand.

Table 4: No Selection Treatments: Effect of Individual Traits on Outcomes, by treatment

	Investment Info Only		Cost Info Only	
	Exploration	Earnings	Exploration	Earnings
Extraversion	0.004**	-1.32***	-0.0007	1.63**
	(0.002)	(0.48)	(0.002)	(0.66)
Openness	-0.0003	0.08	-0.0009	-0.78**
	(0.0008)	(0.33)	(0.001)	(0.38)
Neuroticism	0.003**	-1.69***	0.004***	-1.26***
	(0.001)	(0.52)	(0.002)	(0.47)
Agreeableness	-0.002**	0.39	-0.006***	4.32***
	(0.0009)	(0.52)	(0.002)	(0.45)
Conscientiousness	-0.0000669	-1.17*	0.002	-0.53
	(0.001)	(0.61)	(0.002)	(0.41)
Risk Tolerance	0.03	-24.92***	-0.02**	18.03***
	(0.02)	(7.05)	(0.008)	(2.21)
Internal Locus of Control	0.0002	-0.06	-0.001	0.91
	(0.002)	(0.59)	(0.003)	(0.74)
Female	0.03	-7.12	-0.02	24.27***
	(0.02)	(8.78)	(0.03)	(8.69)
Constant	0.24	356.09***	0.64**	-315.68***
	(0.16)	(78.38)	(0.27)	(87.78)
Observations	769	769	623	623
R^2	0.22	0.34	0.5	0.42
F-test				
Big Five traits	2.77**	3.70***	5.05***	34.22***
Controls				
Cognitive Skill FE	Y	Y	Y	Y
Round FE	Y	Y	Y	Y
Round 1 Pay-Off	Y	Y	Y	Y
Age & Year in School FE	Y	Y	Y	Y
Order FE	Y	Y	Y	Y

Table 6 presents estimates from equation 4 to test whether individuals earn more in their chosen information sector than they would have if they had chosen the alternative information sector. We report the estimated mean residual calculated at the average of the covariates of personality, risk, locus of control and cognitive ability. Overall, subjects have higher earnings in the information regime they selected into than they would have in the alternate information regime.

Table 5: Selection Treatment: Effect of Individual Traits on Information Demand

	Pr[Cost Info=1]		
Risk Tolerance	0.14*	0.13*	0.16**
	(0.07)	(0.08)	(0.08)
Neuroticism	0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)
Conscientiousness	0.002	0.003	0.008
	(0.008)	(0.008)	(0.009)
Openness	-0.007	-0.008	-0.006
	(0.007)	(0.007)	(0.008)
Agreeableness	0.01	0.01	0.01
	(0.009)	(0.009)	(0.009)
Extraversion	0.02**	0.02**	0.02*
	(0.01)	(0.01)	(0.01)
Internal Locus of Control	-0.002	-0.01	-0.002
	(0.02)	(0.02)	(0.02)
Cognitive Ability	-0.002	-0.01	.
	(0.02)	(0.02)	
Female	0.1	0.05	0.02
	(0.14)	(0.14)	(0.16)
Observations	76	76	73
Pseudo R^2	.	.	.
Controls			
Age, Year	No	Yes	Yes
Cognitive Ability FE	No	No	Yes
Task Order FE	No	Yes	Yes

Marginal effects from a probit regression. Robust Standard Errors in parentheses and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6: Counterfactuals: Test of Residuals

	Investment Info Only Earnings	Cost Info Only Earnings
Constant	15.77**	19.97*
	(6.90)	(10.53)
Observations	980	540

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

4 Conclusion

Understanding the innovative personality has been a fascination among scholars dating back at least to Knight (1921), spurring two kinds of literature in economics that have approached this question from different angles. One literature studies the role of individual traits on the decision to become self-employed and the success in self-employment. The other literature focuses on the role of past experiences in shaping entrepreneurship. Both kinds of literature have been inconclusive and even contradictory.

In this paper, we step back from the traditional approach of studying entrepreneurship and innovation and go into the laboratory. By doing so, we are able to directly study the interaction of individual traits and selection, in the form of information acquisition, that drives innovative behavior. We find that there is no individual trait that unambiguously drives exploration or successful innovation, but rather that traits drive information demand and jointly determine innovative behavior. We find that individuals leverage their trait-based advantage and, when given the opportunity, optimally demand information.

Our findings suggest a variety of ways forward in studying the role of the individual in entrepreneurship and innovation. First, acknowledging and differentiating between types of entrepreneurship may be fruitful for identifying whether individual traits are assets or liabilities. Surely, the individual who starts a high-tech company out of his garage using highly specialized knowledge is very different from a restauranteur who manages a large staff of employees and diverse business relationships. Second, the paths taken by the high-tech specialist versus the restauranteur, such as previous employment or investment decisions, are also likely to be shaped by individual traits and preferences. Thus, it may be just as necessary to study the path to entrepreneurship as it is the decision to enter entrepreneurship.

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