The Innovative Personality*

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Abstract: We study how selection shapes innovative 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.

Keywords: selection, innovation, traits, information,

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1 Introduction

The role of the individual 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). Yet most of what we know about the determinants of innovation are at the firm or industry level (see Hall and Rosenberg (2010) and the articles within, including Arora and Gambardella (2010); Fagerberg et al. (2010); Teece (2010)).

A primary difficulty in studying the individual determinants of innovative behaviour can be attributed to selection, rendering inconclusive and even contradictory answers. For example, recent literature in entrepreneurship (i.e., one category of innovation) finds contradictory results on the link between entrepreneurship and personality. 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 no association between entrepreneurship and personality.

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 activities, including innovative activities. 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 and innovation in the laboratory and thus can examine the fundamental problem of selection that arises when asking the question "who are the (successful) innovators?" 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 innovative endeavors. We examine innovation in the laboratory because the laboratory allows for us to control the information acquisition process. We thus join a small, but notable literature examining innovation and creativity in the laboratory Charness and Grieco (2018); Ederer and Manso (2013); Herz et al. (2014); Meloso et al. (2009). Of these studies, only Herz et al. (2014) relates individual traits to innovative behavior and find that optimism is related to increased innovative behavior, while overconfidence is related to less innovation.[1]

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) and 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). While exploration-exploitation trade-offs do not embody every aspect of innovation, various literatures acknowledge its importance in understanding a wide range of behaviours linked to innovation, including the paradoxical thinking from psychology (Amabile, 1983; Smith and Tushman, 2005), organizational and managerial ambidexterity in management and strategy (Tushman et al., 1996), competing cognitive processes in neuroscience (Aston-Jones and Cohen, 2005; Daw et al., 2006). We thus follow an impressive line of research that uses March (1991)'s concept of exploration versus exploitation to model and measure innovation (Manso, 2011).

Subjects in the Industry Game 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 to an information sector (i.e., No Choice treatments),[2] 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

[1] Hirshleifer et al. (2012) and Galasso and Simcoe (2011) also study the relationship between overconfidence and innovative behaviour, but do so using observational data rather than experimental data.

[2] 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.

and McCrae, 1985),[3] locus of control Rotter (1971),[4] 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.[5] We 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.[6] 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.

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

[3]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).

[4]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).

[5]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.

[6]Fréchette et al. (2017) also finds evidence that personality predicts information demand.

screenshots.

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).[7] While there are small changes in the structure of the game, the main elements remain the same.

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 fixed cost.[8] 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

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

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

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, 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.[9]

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.

Rounds 1-10 are an information accumulation phase. Investment Information and Cost Information are quite different forms of feedback in the Industry Game and thus, upon reaching Round 11, subjects assigned to the Investment Information Treatment have accumulated significantly different types of knowledge than subjects in the Cost Information Treatment. Investment Information provides highly specific feedback with explicit advice about how to increase profits. The individual simply needs to follow the advice to increase or decrease an investment in a product and their profits will increase. On the other hand, Cost Information is sparser and does not contain explicit advice. Instead, individuals must make additional inferences to effectively use Cost Information. For example, Cost information tells individuals whether their cost is above or below a randomly drawn number from the same distribution. Based on this information, the individual must decide whether to stay or leave the Industry. The updated belief that an individual has about his expected fixed cost in an industry will vary with respect to the expected value of the fixed cost and the expected variance. As we show in Section 3, the variation in expected variance plays an important role on the type of individuals who are able to more successfully use Cost 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

[9] S2 formally describes the signals.

switched the order for the other half. We conduct all four treatments of the Industry Game with both task orders.

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.[10] 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.

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.

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.

[10]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.

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

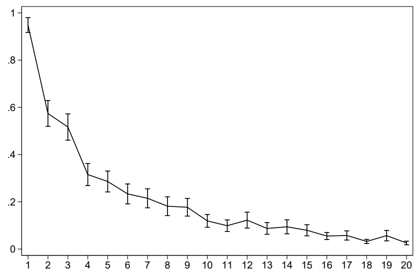
We were unable to estimate risk preferences for 8 subjects. See Table S1 for more detail on sample sizes.

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.[11] 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.

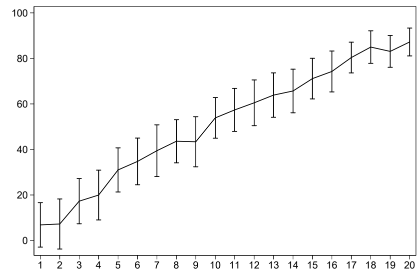
We obtain the Exploration Index for subject i in period j in the following way. Define $I_{i,j} \in \{A, B, C, D\}$ be the industry chosen by subject i in period j. Let $(x_{i,j}, y_{i,j}, z_{,i,j})$ be a vector of subject i's investment strategy in period j. Define the Exploration Index of subject i in period j

[11] 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).

Figure 1: Outcomes: Exploration Index and Earnings



(a) Exploration Index



(b) Earnings ($)

as follows

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

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

[12]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 $\frac{200}{1} \times \kappa = 1$.

2.4 Effects 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.[13] 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.[14] 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 innovators emerge: Cost Information generates innovators that look like "Jack of All Trades" while Investment Information results in innovators 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.

As mentioned in Section 2.1, the differences in the type of information provided by the Investment information and the Cost Information treatments are significant. Investment information provides specific and explicit advice about how to increase profits, while Cost Information does not and instead requires subjects to make their own inferences about how to use the information to increase profits. Given these differences, it is not surprising that individuals may have preferences over information type. For example, and as we will see in Section 3, individuals who are more activity- and excitement-oriented (i.e., more extraverted) over-explore and subsequently achieve significantly lower earnings when they are assigned to Investment Information, but earn significantly more when assigned to Cost Information.

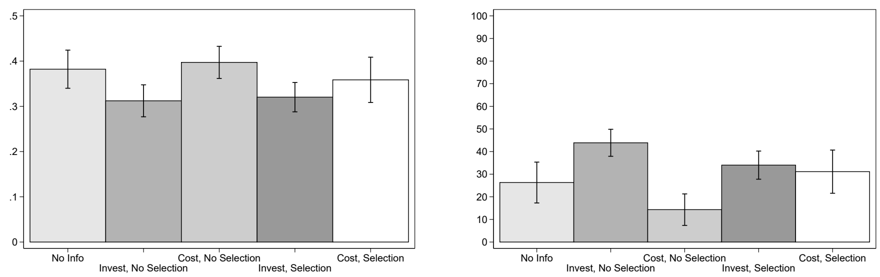
2.5 The Role of Traits

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

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

[14]In Table S5 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.

Figure 2: Average Treatment Effects



(a) Exploration

(b) Earnings

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 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*

Table 2: No Selection Treatments: The Role 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.

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.

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

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 when assigned Investment Information but an asset when assigned Cost Information. For example, a standard deviation increase in Extraversion leads to an average 12 dollar loss in earnings in Investment Information, but a 16 dollar gain in Cost

Information. By contrast, Locus of Control, Neuroticism, and Agreeableness play similar roles in the exploration and earnings for both types of information.[15]

Why do more extraverted and more risk-tolerant individuals respond differently to Investment Information versus Cost Information? An underlying facet of the Extraversion trait is tendency towards activity and excitement-seeking (**?**). Thus, we may expect that the Investment Information treatment is too restrictive and does not allow for the type of self-directed activity favored by extraverts. In fact, this is exactly what the data shows—when receiving Investment Information, extraverts are equally likely to follow the advice given, but they *also* engage in additional exploration. For example, in the No Selection treatments, when extraverts receive a signal to "Increase your investment in x", they are equally likely to increase their investment in x, but individuals scoring high on extraversion are significantly more likely to also change their investments in products y and z and change industries (see Table S3). Importantly, this heterogeneity in the responsiveness to signals disappears in the Selection treatments.

Individuals who are more risk-tolerant explore significantly less and significantly earn more when they receive Cost Information. Similar to the Extraverts' differential response to Investment information, we find that increasing risk-tolerance is associated with a differential response to Cost Information signals. Conceptually, when a subject receives Cost Information, he updates his belief about the expected value of the fixed cost in the current Industry as well as the expected variance and decides whether to change industries or remain in his current industry given his updated belief. We find that when Cost Information is assigned (i.e., No Selection treatments), subjects with greater risk-tolerance are less responsive (i.e., less likely to change industries) to changes in expected variance of the expected fixed cost, holding constant the expectation of the fixed cost (see Table S4). This decrease in responsiveness allows more risk-tolerant subjects to focus on their investment strategy within an Industry and increase their earnings. Again, this heterogeneity disappears when subjects self-select into Cost Information.

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.[16] 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.[17]

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

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

[17]By contrast, Supplementary Material B.2 shows the effect of traits on innovation and earnings in the Information

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

	No Information		Investment Info Only		Cost Info Only	
	Exploration	Earnings	Exploration	Earnings	Exploration	Earnings
Extraversion	0.0000113	-0.01	0.004**	-1.32***	-0.0007	1.63**
	(0.002)	(0.65)	(0.002)	(0.48)	(0.002)	(0.66)
Openness	0.001	-1.59*	-0.0003	0.08	-0.0009	-0.78**
	(0.002)	(0.94)	(0.0008)	(0.33)	(0.001)	(0.38)
Neuroticism	0.0006	-0.77	0.003**	-1.69***	0.004***	-1.26***
	(0.002)	(0.81)	(0.001)	(0.52)	(0.002)	(0.47)
Agreeableness	0.001	-0.25	-0.002**	0.39	-0.006***	4.32***
	(0.002)	(0.68)	(0.0009)	(0.52)	(0.002)	(0.45)
Conscientiousness	-0.001	0.15	-0.0000669	-1.17*	0.002	-0.53
	(0.002)	(0.8)	(0.001)	(0.61)	(0.002)	(0.41)
Risk Tolerance	0.009	21.37**	0.03	-24.92***	-0.02**	18.03***
	(0.03)	(10.57)	(0.02)	(7.05)	(0.008)	(2.21)
Internal Locus of Control	-0.002	-0.79	0.0002	-0.06	-0.001	0.91
	(0.006)	(1.81)	(0.002)	(0.59)	(0.003)	(0.74)
Female	0.08***	-39.50***	0.03	-7.12	-0.02	24.27***
	(0.03)	(11.14)	(0.02)	(8.78)	(0.03)	(8.69)
Constant	0.28	254.51***	0.24	356.09***	0.64**	-315.68***
	(0.23)	(86.48)	(0.16)	(78.38)	(0.27)	(87.78)
Observations	682	682	769	769	623	623
R^2	0.35	0.26	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	Y	Y
Round FE	Y	Y	Y	Y	Y	Y
Round 1 Pay-Off	Y	Y	Y	Y		
Age & Year in School	Y	Y	Y	Y	Y	Y
Order FE	Y	Y	Y	Y	Y	Y

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.*

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.

Selection treatment if we *ignore* their role in information demand.

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

	Pr[Cost Info=1]		
Risk Tolerance	0.14* (0.07)	0.13* (0.08)	0.16** (0.08)
Neuroticism	0.01 (0.01)	0.01 (0.01)	0.02 (0.01)
Conscientiousness	0.002 (0.008)	0.003 (0.008)	0.008 (0.009)
Openness	-0.007 (0.007)	-0.008 (0.007)	-0.006 (0.008)
Agreeableness	0.01 (0.009)	0.01 (0.009)	0.01 (0.009)
Extraversion	0.02** (0.01)	0.02** (0.01)	0.02* (0.01)
Internal Locus of Control	-0.002 (0.02)	-0.01 (0.02)	-0.002 (0.02)
Cognitive Ability	-0.002 (0.02)	-0.01 (0.02)	.
Female	0.1 (0.14)	0.05 (0.14)	0.02 (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** (6.90)	19.97* (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 literature in fields from economics and management to psychology and neuroscience.

In this paper, we step back from the traditional approach of studying innovation and go into the laboratory. By doing so, we are able to directly study the interaction of individual traits and selection of information, 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.

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