Attention Allocation in Venture Capital Investment Selection

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Abstract

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This dissertation uses verbal interactions between investment-seeking entrepreneurs and VC investors to uncover how variation in attention allocation by VC investors during venture screening influences venture funding decisions. Chapter 1 focuses on gender and investigates if VC investors evaluate male entrepreneurs differently from female entrepreneurs. The results show that female VCs appear to pay up to 23% more attention to entrepreneur / team criteria when evaluating female entrepreneurs than male VCs screening male entrepreneurs. This effect is explained by product gender orientation where female investors appear to favor female entrepreneurs whose ventures offer female-oriented products. Chapter 2 focuses on ethnicity and investigates if shared ethnicity between a VC investor and an entrepreneur influences the investor's assessment of the investment potential of the venture. The results provide evidence that co-ethnicity increases the likelihood of promotion-focused feedback from investors by up to 74%. However, rather than being systematically widespread among investors, this effect is limited to ethnic minority investors and entrepreneurs, who are severely under-represented in US VC and high-growth entrepreneurship. Chapter 3 focuses on personality factors and investigates the relationship between the Five Factor Model (FFM) personality traits verbally promoted by an entrepreneur and subsequent venture financing outcomes. The results suggest that entrepreneurs who communicate higher levels of *extraversion* via language are 13.5% more likely to receive venture funding, provided their ventures meet certain baseline quality standards. The results also provide evidence that investors perceive *extraversion* as a desirable entrepreneurial trait while *neuroticism* is perceived negatively.

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List of Abbreviations

Abbreviation	Full Description
CEO	Chief Executive Officer
FE	Fixed Effect
FFM	Five-Factor Model
IDF	Inverse Document Frequency
IT	Information Technology
JD	Juris Doctor
LIWC	Linguistic Inquiry and Word Count
LPM	Linear Probability Model
MBA	Master of Business Administration
MD	Doctor of Medicine
MIT	Massachusetts Institute of Technology
NLP	Natural Language Processing
RFT	Regulatory Focus Theory
TF	Term Frequency
URL	Uniform Resource Locator
US	United States (of America)
VC	Venture Capital

Introduction

Over the last fifty years, Venture Capital (VC) has proven to be essential for innovation and economic growth. However, VC investments are extremely risky (Ewens & Rhodes-Kropf, 2015), with only a small fraction of investments accounting for the majority of returns. For instance, Sahlman (2010) reports that only 10% of VC investments account for 85% of returns. Therefore, investment selection is a critical activity for VC investors.

Investment selection is challenging for two reasons. First, there exists severe pre-investment information asymmetry between entrepreneurs and investors. Particularly in the early stages, entrepreneurs often know a lot more about the viability of their ventures than investors. Furthermore, these resource-constrained entrepreneurs have an incentive to deliberately misrepresent their ventures to attract critical resources. Secondly, investors are exposed to post-investment agency conflicts with entrepreneurs; entrepreneurs may make decisions that are not in the best interest of the venture or investment.

Investors therefore pay attention to information that can lead them to conclude whether or not a venture has return-maximizing potential (Huang et al., 2020; Jin et al., 2017; Maxwell & Lévesque, 2014). This information falls into two broad categories: venture viability data and signals of quality (Kanze et al., 2018). Venture viability data represent quantitative performance metrics such as revenue, market share etc. that can be objectively analyzed to directly assess the potential profitability of a venture(Huang & Pearce, 2015). Signals of quality refer to qualitative factors that are subjectively evaluated and function as heuristics (Tversky, A., & Kahneman, 1974) in assessing venture quality. Examples include the degree of passion and preparedness of entrepreneurs(Cardon et al., 2009; Chen et al., 2009), their ethnic backgrounds (Bengtsson & Hsu, 2015; Hegde & Tumlinson, 2014) and education (Franke et al., 2006). Extant research suggests that while there is heterogeneity among VC investors in how these factors are combined and ranked (Gompers et al., 2019), both categories of information are considered to make investment decisions.

However, attention is a scarce cognitive resource (Kahneman, 1973). Giving attention to one task necessarily requires a substitution of cognitive resources away from others(Peng & Xiong, 2006)**.** Given the attention constraints VC investors face coupled with the multiple sources of uncertainty inherent in new ventures, they are forced to allocate attention to factors that minimize this uncertainty and facilitate return-maximizing investment decisions. These attention allocation choices result in heterogeneity of investment decisions and ultimately, heterogeneity in the performance of VC investments and firms.

This dissertation aims to uncover how variation in attention allocation by VC investors during new venture screening, influences venture funding decisions. Observing real-world venture capital decision-making is notoriously challenging due to the confidential nature of the process. Thus, to overcome this challenge, the research setting of the studies in this dissertation is TechCrunch Disrupt, a premier technology startup competition, from which several of today's technology unicorn ventures (e.g., Dropbox, Yammer, etc.) launched. This setting has gained recent acceptance among VC and entrepreneurship scholars as it permits full observation of the pitch presentation, Q&A / feedback sessions by judges (comprising prominent VC investors) and subsequent decision outcomes. Using automated speech-to-text transcription of verbal exchanges between entrepreneurs and VC investors, coupled with novel Natural Language Processing (NLP) and Machine Learning techniques, three sources of variation in attention allocation by VC investors are examined in detail: 1) gender, 2) ethnicity, and 3) personality traits.

The first chapter, co-authored with Sampsa Samila, investigates if VC investors evaluate male entrepreneurs differently than female entrepreneurs and if this difference, (if it exists), varies based on the gender of the VC investor. We find that female VCs appear to focus up to 23% more on entrepreneur / team criteria when evaluating female entrepreneurs than male investors evaluating male entrepreneurs. They also pay significantly closer attention to the upsides of both product and entrepreneur / team dimensions when screening female entrepreneurs, suggesting that female VCs may view female entrepreneurs and their products more favorably. This effect is in part driven by product gender orientation, i.e., female entrepreneurs building female-focused products which female VCs consider attractive for investment. For male VCs, we do not observe a significant difference in the focus of screening criteria based on the gender of the entrepreneur. These results provide evidence that gender-driven differences in ex-ante information collection at the level of the individual investor have consequences for funding outcomes at the venture level.

The second chapter, also co-authored with Sampsa Samila, investigates if co-ethnicity between a VC investor and an entrepreneur influences the investor's assessment of the investment potential of the venture. Our results reveal that within minority ethnic groups, co-ethnicity between an entrepreneur and investor is associated with more positive evaluation of the entrepreneur's venture by the investor. Specifically, co-ethnicity between ethnic minority investors and entrepreneurs increases the likelihood of receiving promotion-focused questions / feedback by up to 74% above the baseline probability. This ethnic minority group comprises people of Black, American Indian / Alaskan Native, and Native Hawaiian / Pacific Islander ethnicities, who are severely under-represented in US VC and high-growth entrepreneurship. We do not observe similar effects among investors and entrepreneurs who are White or Asian. We argue that one explanation for this unique co-ethnicity effect among ethnic minorities is ethnic solidarity, born in response to the shared challenge of access to entrepreneurial financing in the current entrepreneurship landscape. Therefore, ethnic minority investors may pose more promotion-focused questions / feedback as a means of providing support to this under-represented / under-served group of co-ethnic entrepreneurs.

The third chapter investigates the relationship between the personality traits verbally promoted by an entrepreneur and subsequent venture financing outcomes. I measure the Five Factor Model (FFM) personality traits via the language used by entrepreneurs during pitch presentations to panels of VC investors. The results suggest that entrepreneurs who communicate higher levels of *extraversion* via language are evaluated more positively by investors and are 13.5% more likely to receive venture funding, provided their ventures meet certain baseline quality standards. The results also suggest that entrepreneurs who communicate with higher levels of *neuroticism* are evaluated more negatively by investors. I argue that the ability of an entrepreneur to communicate convincingly with employees, partners and investors is critical for venture survival. Thus, entrepreneurs who communicate *extraversion* i.e., enthusiasm and energy, in their pitches are likely better at persuading VC investors of a venture's investment potential. However, entrepreneurs who communicate higher levels of *neuroticism* are perceived by investors as less likely to be able to cope with the demanding work environment and personal responsibility of entrepreneurship. This essay highlights the ability of the language of an entrepreneurial pitch to promote personality traits and also the conditions under which such self-promotional behavior by entrepreneurs matters (more) to investors i.e., as a complement for venture quality.

This dissertation advances knowledge of the venture capital decision-making process. In doing so, it makes a number of empirical and methodological contributions. From an empirical standpoint, it provides evidence of how variations in attention allocation to subjectively-evaluated qualitative factors such as entrepreneur gender, ethnicity and personality traits may influence investment decisions and subsequent venture outcomes. From a methodological standpoint, it demonstrates novel applications of natural language processing techniques in uncovering subtle decision-making behaviors. The contributions foster a better understanding of the investor - entrepreneur dynamic and reveal important factors that should be accounted for in future VC and entrepreneurship research.

Chapter 1

Investor – Entrepreneur Gender Effects in New Venture Screening[1]

1.1 Introduction

Early-stage venture capital (VC) investments are essential for the survival and growth of new ventures which are often resource-constrained. However at this stage, VC investors face high risks due to ex-ante information asymmetries and ex-post agency conflicts with the entrepreneur (Davila & Guasch, 2020). Financial contracting theory identifies several mechanisms to mitigate these risks: ex-ante information collection, contract designs (e.g., pay-for-performance), and ex-post monitoring (Kaplan & Strömberg, 2001). We focus on ex-ante information collection.

Prior research identifies that investors primarily demand information about 4 aspects of a venture: (1) product/service attractiveness, (2) market/competitive conditions, (3) entrepreneur/team capabilities, and (4) financial returns if the venture is successful (Hall & Hofer, 1993; Macmillan et al., 1985, 1987; Tyebjee & Bruno, 1984; Zacharakis & Meyer, 1998). Of these 4 categories, information about the entrepreneur / team and the venture's financial returns are especially important for investors to assess the viability of the venture (Gompers et al., 2019; Huang & Pearce, 2015).

However, evidence indicates that the investment decision process is not completely objective i.e. based solely on formal analysis of venture viability data(Huang & Pearce, 2015). Investors recognize that the available venture viability information may be biased by the entrepreneurs' incentives to present a favorable representation of the venture (Armstrong et al., 2007). Therefore, they additionally rely on subjective evaluation of informal information including intuition about an entrepreneur (Huang & Pearce, 2015),

[1] Co-authored with Sampsa Samila

gender (Kanze et al., 2018), ethnicity (Bengtsson & Hsu, 2015) and education(Franke et al., 2006). In this study, we focus on role of the gender on the sides of both investors and entrepreneurs.

Prior research on the role of gender in VC investing has focused primarily on uncovering the reasons why female entrepreneurs receive significantly less equity funding than their male counterparts. Important findings from this research include: i. taste-based discrimination by male investors against female entrepreneurs (Ewens & Townsend, 2019), ii. gender homophily between investors and entrepreneurs who are both predominantly male (Solal, 2019); iii. weaker growth orientation signaling from female-led startups (Guzman & Kacperczyk, 2019); and iv. underrepresentation and underperformance of female VC investors (Gompers et al., 2014; Gompers & Wang, 2017a).

Yet, there is still limited research on whether male and female VC investors elicit, process and utilize ex-ante information differently in decision-making. Kanze *et al.* (2018) highlights that in VC investing, male entrepreneurs receive and answer questions with a promotion focus, i.e., the presence of positives or rewards, while female entrepreneurs receive and answer questions with a prevention focus i.e., the presence or avoidance of negatives or risks. Yet the question of whether or not the gender of the VC plays a role in this information collection process remains unanswered. We argue that answering this question holds important insights that improve our understanding of the VC investment decision-making process. This knowledge has practical implications for scholars, entrepreneurs and policy-makers. For scholars, it highlights new sources of variation in venture-level funding outcomes. While the magnitude of this variation is context-sensitive, it nevertheless warrants further research attention. For entrepreneurs, understanding these differences allows them to tailor their pitches to better suit their investment targets and improve their chances of securing critical resources. For policy-makers, this knowledge is useful in designing venture screening processes and policies that could create vibrant entrepreneurial ecosystems that address peculiar socio-economic requirements.

Thus, our research questions are: *Do VCs screen male entrepreneurs differently than female entrepreneurs? Does this difference, if it exists, vary based on the gender of the VC?* Our approach examines two aspects of the venture screening process: i. the *screening criteria* used by VCs (i.e. product characteristics, market conditions, entrepreneur / team profile, and financial position), as identified in previous VC literature (Hall & Hofer, 1993; Macmillan et al., 1985, 1987; Tyebjee & Bruno, 1984; Zacharakis & Meyer, 1998); ii. the *polarity* of the criteria i.e. risk (negative) versus reward (positive) focus, of screener's questions which have been demonstrated to affect venture funding outcomes (Crowe & Higgins, 1997; Kanze et al., 2018). In addition, we examine the impact of the screening process on subsequent venture funding outcomes.

We address our research question using data from TechCrunch Disrupt, one of the most prestigious competitions in the world for technology startups seeking venture capital. Our analysis covers competition events across 4 locations – New York, San Francisco, London and Berlin – from 2010 to 2017. Our final sample comprises 390 startups. Using transcribed textual data of the questions asked by VC judges during Q&A sessions that follow each startup's pitch, first, we investigate the effect of the interaction between the gender of the VC and the gender of the entrepreneur on the likelihood of the topical focus and polarity of the question asked. In addition, we investigate how the topical focus of questions asked affects likelihood that a startup advances through the competition. Finally, we test the effect of competition outcomes on subsequent venture performance with respect to post-competition survival.

Our key findings suggest that the existence of gendered differences in the venture screening process used by investors is limited to the screening of female entrepreneurs by female VCs. We find that female investors are up to 23% more interested in entrepreneur / team criteria when evaluating female entrepreneurs than male investors evaluating male entrepreneurs. In addition, they are also 34.7% more likely to focus on product upsides and 67% more likely to pay attention to entrepreneur / team upsides. These findings imply that female investors may view female entrepreneurs and their products more favorably. We argue that one mechanism through which this occurs is via product gender orientation -- female entrepreneurs who focus on female-oriented products are favored more by female VCs who appreciate these products and / or their market potential better than their male counterparts. A similar argument is proposed by Brooks *et al.* (2014). Our findings reveal that female investors are up to 4.8 times more likely to focus on the upsides of the entrepreneur / team when screening female entrepreneurs whose products are highly oriented toward female customers.

With respect to how the focus of screening criteria affects venture outcomes, we find that for each additional entrepreneur / team-related question, male entrepreneurs are 7.9% less likely to advance through the 1st stage of the competition while female entrepreneurs are 29.3% more likely to advance. In addition, we observe similar results for the number of finance related questions on likelihood of winning. While the effect is positive for male entrepreneurs (i.e., each additional finance question increases the likelihood of winning by 13.4%), it is negative for female entrepreneurs (with each additional finance question reducing the likelihood of winning by 28.2%). Taken together, these results provide evidence that gender-driven differences in ex-ante information collection by VC investors are likely to have an impact on venture outcomes.

Our study contributes to the conceptual understanding of how gender at the individual investor level influences funding outcomes at the venture level. By inspecting the screening dimensions where these effects materialize, we uncover that gender-driven differences in ex-ante information collection by VCs are context-specific, i.e., rather than being broadly generalizable, they occur only during the screening of specific types of ventures. More broadly however, we highlight that the impact of gender in VC investing, often highlighted to be detrimental to female entrepreneurs (Ewens & Townsend, 2019; Gompers et al., 2014; Guzman & Kacperczyk, 2019; Kanze et al., 2018), may also be beneficial. In doing so, we extend the knowledge of interventions that could help to close the gender gap in new venture funding (Kanze et al., 2018).

The rest of the study proceeds as follows. Section 1.2 explains our empirical setting. Section 1.3 describes the data. Section 1.4 discusses the empirical strategy and main results. Section 1.5 concludes.

1.2 TechCrunch Disrupt

Startup competitions are critical opportunities for entrepreneurs to articulate their venture's business propositions not only to competition screeners but also to other potential investors. If the screeners / investors form negative impressions of the entrepreneur or venture during these presentations, the entrepreneur is highly unlikely to obtain funding (Lounsbury & Glynn, 2001; Martens et al., 2007a).

“TechCrunch Disrupt is widely regarded as the most prestigious setting in which high-tech startups can launch”(Kanze et al., 2018). Since its inception in 2007, the 763 startups that presented at the competition have raised a total of $8.8 billion in funding, with 109 having been acquired or gone public. Notable TechCrunch Disrupt alumni include Yammer, Dropbox and Qwiki.

The competition takes place across a number of locations, once a year each. These locations include San Francisco, New York, London and Berlin. Online applications to each competition open three months before the actual event. TechCrunch reviews applicants and selects contestants based on their team, product and market potential. Selection is highly competitive and acceptance rates range between 3% to 6%. Typically, the number of accepted startups in each competition ranges between 15 and 30. These startups get the opportunity to pitch to panels of 4 - 6 judges (screeners) in a style similar to an investment pitch meeting. These screeners are prominent Silicon Valley VCs and technologists and include figures like Marissa Mayer – former CEO of Yahoo, Roelof Botha – a partner at Sequioa Capital, a prominent VC firm - etc.

The competition takes place over the course of 3 days across 2 stages – a semi-final and final round. Competing startups are allocated 6 minutes for their pitch presentation followed by a question-and-answer session with the panel of screeners. Each team is scored by each screener and the scores are collated by TechCrunch. The highest scoring startups, typically 4 – 6 in number, proceed to the final round. In the final round, the startup entrepreneurs repeat the presentation to a new independent set of screeners, participate in a question-and-answer session and are scored by individual screeners. After the scores are collated by TechCrunch, the highest scoring team from the final round wins the competition and the $100,000 prize.

Our sample comprises the data set of startups that participated in TechCrunch Disrupt from 2010 – 2017 across 4 locations: New York, San Francisco, London and Berlin. During this period, a total of 390 participating startup entrepreneurs were asked a total of 4081 questions. Tables 2, 3 and 4 provide an overview of the descriptive statistics.

Our list of participating startups was gathered manually from the TechCrunch Disrupt website. The records of conversations between entrepreneurs and screeners were obtained by transcribing publicly available video footage of each pitch session to text via YouTube's automated speech-to-text feature. Supporting information on the profile of the participating startups was obtained manually from Crunchbase, a publicly available database maintained by TechCrunch.

Using TechCrunch Disrupt as our research setting provides a number of important benefits. First, it permits full observation of the pitch presentation and Q&A sessions based on complete and publicly available video footage hosted on YouTube. This has the added benefit of allowing speaker identification and automated speech-to-text transcription of verbal exchanges between entrepreneurs and screening panels. Furthermore, the enforced time limits for both presentation and Q&A sessions across all events minimizes the variability of the conditions across which competing startups are evaluated and allows for robust comparison of screening processes and outcomes across various competitions. Yet another benefit of this research setting is that TechCrunch maintains a database, Crunchbase, which makes background information on the participating startups publicly available. This information includes the names of entrepreneurs, founding date, business category, operating status and company description. Finally, participation is open only to companies that demonstrate a need for venture capital. Thus, we are able to eliminate variability regarding the entrepreneurs' intentions and reject the demand-side question, "Are women asking for less money because they simply found companies with lower capital needs?" (Kanze et al., 2018).

1.3 Data

We describe our key variables, data sources, sample restrictions and summary statistics. A complete list of variables and their descriptions is provided in Table 1.1.

1.3.1 Question Topic / Focus

As described in Section 1.2, VC investors interact with competing startups primarily by asking questions to entrepreneurs at the end of timed startup pitch presentations. According to financial contracting theory, when investors are faced with severe information asymmetry, they can collect information ex-ante to allow them screen out bad ventures and screen in good ones(Kaplan & Strömberg, 2001). Thus, questions from investors are pivotal in the venture screening process.

We focus on identifying the topic of each question using the "bag-of-words" approach (Harris, 1954) which allows the mapping of keywords to specific venture screening criteria. In this approach, a piece of text is regarded as a multi-set (i.e., a bag) of words and the word order / syntactic relations appearing in the original text is ignored. Even though the bag-of-words representation is naive and does not always convey the meaning of the original text, reasonable accuracy is possible because each word occurring in the text is highly relevant to the predefined "topics" to be identified(Kudo & Matsumoto, 2004).

We focus our analysis on 4 topics (criteria) - product, market, entrepreneur / team and financial. These criteria are chosen based on results of previous research which show that the information critical to VC's investment decisions appear to fit into 4 categories: (1) product/service attractiveness, (2) market/competitive conditions, (3) entrepreneur/team capabilities, and (4) financial returns if the venture is successful (Hall & Hofer, 1993; Macmillan et al., 1985, 1987; Tyebjee & Bruno, 1984; Zacharakis & Meyer, 1998).

For each criterion, we assign identifying keywords based on the categorization of Zacharakis and Meyer (1998), who identify specific sub-topics that map onto these 4 previously highlighted topical areas (see Appendix Table A1). We identify the topic of a question as the criterion with the largest proportion of matching keywords. Where there is a tie in the proportion of matching keywords on a number of criteria, we assign the topic of the question to multiple criteria. For each question, we use dummy variables to indicate which of the 4 screening criteria they map onto. We exclude from our analysis questions where there is no match between the words in the question and criterion-specific keywords.

Table 1.1: *Description of main variables*

Variable	Description
finance_wds	Dummy variable equal to 1 if the topic of a question is financial
finance_risk	Dummy variable equal to 1 if the focus of a question is financial risk
finance_reward	Dummy variable equal to 1 if the focus of a question is financial reward
market_wds	Dummy variable equal to 1 if the topic of a question is the market
market_risk	Dummy variable equal to 1 if the focus of a question is market risk
market_reward	Dummy variable equal to 1 if the focus of a question is market reward
product_wds	Dummy variable equal to 1 if the topic of a question is the product
product_risk	Dummy variable equal to 1 if the focus of a question is product risk
product_reward	Dummy variable equal to 1 if the focus of a question is product reward
team_wds	Dummy variable equal to 1 if the topic of a question is the team / entrepreneur
team_risk	Dummy variable equal to 1 if the focus of a question is team risk
team_reward	Dummy variable equal to 1 if the focus of a question is team reward
entrepreneur_female	Dummy variable equal to 1 if the entrepreneur is female, 0 for male
investor_female	Dummy variable equal to 1 if the investor is female, 0 for male
entrepreneur_prev_ent_exp	Dummy variable equal to 1 if the entrepreneur has previous entrepreneurial experience
entrepreneur_adv_deg	Dummy variable equal to 1 if the entrepreneur has an advanced degree e.g., Masters, MD, JD, PhD etc.
entrepreneur_ivy_plus	Dummy variable equal to 1 if the entrepreneur has a graduate or undergraduate degree from Brown, Caltech, Univ. of Chicago, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, Univ. of Pennsylvania, Princeton, Yale, Stanford, Cambridge, Oxford, Ecole Polytechnique, and Ecole Normale Superieur (Bengtsson & Hsu, 2015).
entrepreneur_tech	Dummy variable equal to 1 if the entrepreneur has previous experience working at the major big tech companies i.e., Facebook, Apple, Amazon, Netflix, Microsoft or Google.
female_dominated_panel	Dummy variable equal to 1 if there are more female investors than male investors on a panel
male_dominated_panel	Dummy variable equal to 1 if there are more male investors than female investors on a panel
male_investor_questions	Count variable of the number of questions asked by male investors
female_investor_questions	Count variable of the number of questions asked by male investors
winner_stage_1	Dummy variable equal to 1 if a startup advances through the 1st stage of the competition.
winner_stage_2	Dummy variable equal to 1 if a startup advances through the 1st stage of the competition.
survived	Dummy variable equal to 1 if a startup survives for up to 3 years after the competition.
gender_score	Continuous variable that measures the relative appeal of a product to either men, women or both genders. Higher (positive) values indicate that the product likely appeals more to women, lower (negative) values indicate appeal to men and 0 indicates the products are gender-neutral

Similarly, we also examine the polarity i.e. risk versus reward focus, of screener's questions based on findings from Regulatory Focus Theory (RFT) literature (Crowe & Higgins, 1997; Kanze et al., 2018). These findings suggest that in the context of venture screening, questions and answers with a promotion focus, i.e., the presence of positives or rewards, lead to more favorable funding outcomes than those with a prevention focus i.e., the presence or avoidance of negatives or risks. Thus, we determine the polarity of the question based on the proportion of question words which match keywords that indicate risk or reward (see Appendix Table A2). We interact the risk-reward scores with the topic dummy variables to generate composite topic-polarity dummy variables. For instance, a question identified as relating to product, with a score of 0.3 for risk and 0.5 for reward will have 3 dummy variables – *product_words, product _risk, product_reward* - each with value 1, while all other topic / topic-polarity dummy variables are set to 0.

1.3.2 Gender

We identify the genders of the investors and entrepreneurs in our sample based on video footage and profile information from Crunchbase and LinkedIn. We set the gender of the investor, *investor_female* to 1 if the investor is female and 0 otherwise. Similarly, we set the gender of the entrepreneur, *entrepreneur_female* to 1 if the entrepreneur is female and 0 otherwise.

It is important to note that while we observe gender at the entrepreneur level, the outcomes we examine are at the startup level. Therefore, it is necessary to assign a gender to a startup. Since the pitch presentation is conducted by a single entrepreneur, we use the gender of the presenting entrepreneur to represent the gender categorization of the startup.

1.3.3 Non-gender entrepreneur characteristics

Crunchbase typically provides profile information about entrepreneurs including links to personal social media pages such as Facebook, Twitter and LinkedIn. Using this information, we identify educational information, previous work experience and previous entrepreneurial experience of the entrepreneurs. Based on this information we construct 4 dummy variables which are equal to 1 if the entrepreneur has an advanced degree e.g. Masters, PhD, MD etc., attended an Ivy League Plus school – undergraduate or graduate degree from Brown, Caltech, University of Chicago, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, University of Pennsylvania, Princeton, Yale, Stanford, Cambridge, Oxford, Ecole Polytechnique, and Ecole Normale Superieur (Bengtsson & Hsu, 2012), worked for any of the top-performing big technology companies – Facebook, Apple, Amazon, Netflix, Google and Microsoft, and has previously been the founder or co-founder of a company.

1.3.4 Product Gender Orientation

In order to determine if a startup's product offerings are more likely to appeal to either men, women or both genders equally, we construct a measure of the product gender orientation. This measure is identical to the product gender orientation measure developed by Cao, Koning and Nanda (2020).

To construct the measure, the individual words of the entrepreneur's pitch are transformed into numeric vectors through a process called word embedding. These vector representations capture important information about words such as their context and their similarity / distance in relation to other words. This step is implemented using *fasttext*[2], a natural language processing library developed by Facebook and trained on the entire Wikipedia text corpus. Using each word's vector representation, we calculate the distance / similarity of each word to keywords that are closely associated with men and women, using the formula developed by Cao, Koning and Nanda (2020):

$$F_{\{f,m\}}(\boldsymbol{w}) = \frac{Cos(\boldsymbol{w}-\boldsymbol{v}_m, \boldsymbol{v}_f-\boldsymbol{v}_m) \, . \, |\, \boldsymbol{v}_f-\boldsymbol{v}_m|}{|\, \boldsymbol{v}_f-\boldsymbol{v}_m|} - 0.5 \tag{1.1}$$

where $\boldsymbol{w}$ represents the vector representation of a word, $\boldsymbol{v}_f$ represents a female keyword such as "woman", $\boldsymbol{v}_m$ represents a male keyword such as "man". Thus, for any pair of female – male keywords, $\{f, m\}$, $F_{\{f,m\}}(\boldsymbol{w})$ measures the relative closeness of word $\boldsymbol{w}$ to f. $F_{\{f,m\}}(\boldsymbol{w})$ increases the relative closeness of word $\boldsymbol{w}$ to f and a value of 0 indicates the word is likely to be gender-neutral (Cao, Koning and Nanda, 2020).

To measure gender orientation at the startup level, we aggregate the gender measure over the entire text of each entrepreneur's pitch. This aggregate measure is the weighted sum of each word's gender score, using each word's term-frequency-inverse-document-frequency

2 Available at https://fasttext.cc/

(TF-IDF) as weights. We compute TF-IDF scores for each word across the entire text of startup pitches using Python's *sklearn* library.

To ensure the robustness of final measure, we calculate multiple gender focus measures based on different combinations of male-female keywords i.e. "he"-"she", "male" - "female" and "man"-"woman" . The final measure, *gender_score,* is a continuous variable equal to the first principal component of the intermediate measures, normalized to have mean 0 and variance equal to 1. Higher (positive) scores indicate more female-oriented products while lower (negative) scores indicate less female-oriented products.

1.3.5 Startup Outcomes

We focus on 2 aspects of startup outcomes: competition outcomes and post-competition performance. With respect to competition outcomes, we focus on two measures. The first, *winner_stage_1*, is an indicator equal to 1 if a startup advances through the 1st stage of the competition and into the 2nd (final) stage. Typically, there are 4 - 6 startups in this category per competition event.   The 2nd measure of startup outcomes, *winner_stage_2,* is an indicator equal to 1 if a startup emerges as the sole winner of the 2nd stage, and by implication, the competition.

With respect to post-competition performance, we focus on *survival,* an indicator variable equal to 1 if a startup survives for *x* or more years after the competition. We examine both 3- and 5-year post competition survival outcomes. These time choices are motivated by previous empirical findings (e.g. Laitinen, 1992) showing that about 50% of new firms fail within the first 5 years.

1.3.6 Summary Statistics

We begin in Table 1.2 by examining the composition of questions used by VC investors as part of the venture screening process. In our data, we observe that questions from male investors account for more than 70% of the total questions asked to pitching entrepreneurs. Furthermore, across both male and female investors, the distribution of questions by topics remains roughly consistent with market-related questions being the most prevalent and accounting for a little over 40% of the questions asked. Product-related questions account for a little more than 20% while team and finance related questions combined account for less than 10% of screening questions. Across rounds of the competition, the distribution of questions across male and female investors also remains consistent with about 80% of questions asked in the 1st round and about 20% asked to the startups that advance to the 2nd (final) round. These results provide evidence of consistent screening criteria used by both male and female investors in their assessment of ventures.

In Panel B, we observe that the average number of questions asked per screener as well as the word counts per question. The behavior of both male and female screeners is fairly consistent with each screener asking 1 question per startup per round, usually in a round-robin manner. The word counts per question are highly variable across both male and female screeners.

In Table 1.3, we examine startup and competition level statistics. Panel A shows that across the 19 competition events, a total of 390 startups have participated with an average of 20.5 firms pitching at each competition event. Across these events, on average, about 5 startups advance through the 1st stage of the competition and into the 2nd (final) stage where 1 winner per competition event emerges.

In addition, we observe post-competition startup outcomes for startups that have been in existence long enough. For startups that are 3 or more years old, we find that about 84% companies survive for up to 3 years post-competition. For startups that are 5 or more years old, the number drops to about 53% when we observe survival over a 5-year post competition period. This is fairly consistent with empirical findings from previous research (e.g. Laitinen, 1992) showing that about 50% of new firms fail within the first 5 years.

In Panel B, we present competition level statistics, focusing on the structure of the screening panels. We find a total of 355 unique screening panels with an average size of about 5 investors, typically comprising 4 males and 1 female. Across both stages of the competition, the total number male investors is roughly twice the number of female investors. Unsurprisingly, as described above, the distribution of questions by the gender of the investor approximates this pattern. This serves as evidence that the participation of investors in screening is unaffected by gender dominance on screening panels. In other words, even though investors of one gender may outnumber those of the opposite gender, it does not affect the level of screening participation across investors measured in terms of the number of questions asked.

In Table 1.4, we examine entrepreneur level characteristics. Of the total number of 390 startups, 325 are male-led while 65 are female-led, representing a split of 83.33% to 16.67% respectively across our sample. Across education and experience, our results show that a larger proportion of female entrepreneurs have MBAs - 15.38% vs 12.92% for male entrepreneurs, advanced degrees, attended Ivy-plus universities and have work experience within at least one large major technology company. On the other hand, a larger proportion of male entrepreneurs have previous entrepreneurial experience - 84.3 % versus 76.92% for female entrepreneurs.

Table 1.2: *Question-level statistics*

The table reports the question-level summary statistics from 19 TechCrunch Disrupt startup competition events between 2010 and 2017. % values marked with $^{\mu}$ represent the percentage of total observations in the sample. Other % values represent percentage of group totals in the sample.

Panel A: *Question count by gender (totals)*

	Male Investor Questions		Female Investor Questions	
	Obs	%	Obs	%
	2878	70.52 $^{\mu}$	1203	29.48 $^{\mu}$
By Topic				
Product	607	21.09	266	22.11
Market	1217	42.29	497	41.31
Team	131	4.55	55	4.57
Finance	85	2.95	38	3.16
By Round				
1st	2204	76.58	969	80.55
2nd	674	23.42	234	19.45

Panel B: *Question details by gender (averages)*

	Mean	Std. Dev.	Min	Max
1st stage				
Questions (count) per female investor	0.98	0.18	0	3
Questions (word count) per female investor	45.71	33.47	4	268
Questions (count) per male investor	0.99	0.08	0	4
Questions (word count) per male investor	49.28	40.73	2	364
2nd stage				
Questions (count) per female investor	0.98	0.21	0	2
Questions (word count) per female investor	47.55	37.08	5	243
Questions (count) per male investor	0.99	0.08	0	4
Questions (word count) per male investor	48.93	44.29	2	323

Table 1.3: *Startup- and competition-level statistics*

The table reports the startup-level summary statistics from 19 TechCrunch Disrupt startup competition events between 2010 and 2017.

Panel A: *Startup statistics per competition*

	Obs	Mean	Std.Dev.	Min	Max
Startups	390	20.53	5.32	10	28
1st-stage winners	94	4.95	1.35	3	7
2nd-stage winners	19	1	0	1	1
Survived (>=3 yrs)	331	17.42	5.24	9	25
Survived (>= 5 yrs)	208	10.94	7.16	2	22

Panel B: *Competition level statistics*

	Obs	Mean	Std.Dev.	Min	Max
Screening Panels	355				
1st stage					
Investors	345	4.72	1.03	2	7
Male investors	231	3.31	1.12	1	6
Female investors	114	1.42	0.86	0	4
2nd stage					
Investors	162	5.32	1.06	4	8
Male investors	107	4.00	1.20	2	6
Female investors	55	1.32	0.75	0	3

Table 1.4: *Entrepreneur characteristics*

The table reports the entrepreneur-level summary statistics from 19 TechCrunch Disrupt startup competition events between 2010 and 2017. % values marked with µ represent the percentage of total observations in the sample. Other % values represent percentage of group totals in the sample.

	Male Entrepreneurs		Female Entrepreneurs	
	Obs	%	Obs	%
	325	83.33µ	65	16.67 µ
By Education / Experience				
MBA	42	12.92	10	15.38
Other Advanced Degree	253	77.85	59	90.77
Ivy-plus Alma Mater	108	33.23	30	46.15
Previous *Big Tech* Experience	39	12.00	9	13.85
Previous Entrepreneurial Experience	274	84.31	50	76.92

1.4 Empirical Strategy and Results

To answer our research questions, first we examine how the focus of screening questions changes based on the gender of the entrepreneur, the gender of the VC investor and the interaction of both genders. To understand if our findings have any significant effects on the ventures themselves, we investigate their influence on competition outcomes. Finally, to highlight the generalizability and policy implications of our findings, we examine the influence of competition outcomes on subsequent venture performance as measured by post-competition venture survival rates.

We conduct our analysis primarily using the linear probability model (LPM). This choice is motivated by the advantages the LPM possesses over non-linear models like logit with respect to the interpretation of the magnitude of interaction effects (Ai & Norton, 2003) and the coefficients of dummy variables(Caudill, 1988), both of which we heavily rely on in our analysis. Unlike in linear models, the magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term(Ai & Norton, 2003). Furthermore, it has been demonstrated that the coefficient of observation-specific dummy variables cannot be estimated in either logit or probit models(Caudill, 1988). Our choice of the LPM allows us to overcome these challenges and correctly interpret the significance and magnitude of our results.

1.4.1 Identification Strategy

We exploit the random assignment of VCs to startup screening panels as our primary identification strategy. In essence, there is no systematic assignment of VC investor screeners to startups on the basis of previous affiliation, product / service category expertise or other factors that may bias the screening process. This allows us to eliminate any endogenous link between startup characteristics and the profiles of the investors.

1.4.2 Investor gender, entrepreneur gender and the topic / focus of screening questions

We now explore in a regression framework how the topic / risk-reward focus of screening questions is correlated with the interaction between the gender of the investor and the gender of the entrepreneur. Specifically, we estimate equations of the form:

$$\Pr(y_{nit}) = \alpha + \beta_1 \text{female\_entrepreneur}_i + \beta_2 \text{female\_investor}_{ni} + \beta_3 \text{female\_entrepreneur}_i * \text{female\_investor}_{ni} + \delta' \mathbf{X}_i + \varepsilon_{ni}, \quad (1.2)$$

where y represents a question, n indexes ordinality, i indexes startups, t indexes the topic / focus of the question, female_entrepreneur is an indicator variable equal to 1 if the pitching entrepreneur is female, female_investor is an indicator variable equal to 1 if the investor asking the question is female, $\mathbf{X}$ represents a vector of startup and entrepreneur-level controls and ε is the error term.

We begin in Table 1.5 by estimating the likelihood that a question asked by an investor is product / technology-related. In column (1) we regress the gender of the investor, the gender of the entrepreneur and the interaction term of both variables on the likelihood that a question is product-related. We find no evidence of an effect of entrepreneur or investor gender dynamics on product question likelihood. In column (2) we include entrepreneur and startup controls. In the full model in column (3), we include entrepreneur and investor fixed effects but still find no evidence of investor-entrepreneur gender dynamics as a significant predictor of the likelihood of product-related questions.

We perform similar analyses in Tables 1.6, 1.7a and 1.8 in which the topical focus of questions are the market, entrepreneur / team and financials respectively. In Table 1.7a, in column (1), while the main effects of the gender of the entrepreneur and the gender of the investor are non-significant, the interaction between female investors and female entrepreneurs is positive and significant. Adding entrepreneur and startup controls (in column (2)) and investor and entrepreneur fixed effects to the model (in column (3)), the significance and magnitude of the coefficient of the interaction term remain fairly similar. We present the magnitudes of the investor - entrepreneur gender interaction terms of the model (in column (2)) in Table 1.7b. The magnitude of the female investor – female entrepreneur interaction term with respect to other investor – entrepreneur gender interaction terms, implies that female investors are about 22.9% more likely to focus on entrepreneur / team criteria when evaluating female entrepreneurs than male investors evaluating male entrepreneurs.

Table 1.5: *Entrepreneur gender, investor gender and question topic (product)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment is the product / technology of the startup. The unit of observation is the question / comment from an investor to a startup which participated in the competition. "Event FE" are event (competition) fixed effects that account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) product_wds	(2) product_wds	(3) product_wds
entrepreneur_female	-0.003	-0.004	-
	(0.025)	(0.026)	
investor_female	-0.020	-0.017	-
	(0.023)	(0.023)	
investor_female#entrepreneur_female	0.059	0.052	0.072
	(0.054)	(0.053)	(0.052)
entrepreneur_prev_ent_exp		-0.057**	-
		(0.023)	
entrepreneur_adv_deg		0.026	-
		(0.021)	
entrepreneur_ivy_plus		0.003	-
		(0.017)	
entrepreneur_tech		-0.011	-
		(0.026)	
company_age		-0.043**	-
		(0.021)	
Constant	0.372***	0.418***	0.412***
	(0.014)	(0.031)	(0.015)
Observations	4,081	4,081	4,045
R-squared	0.010	0.013	0.224
Event FE	YES	YES	YES
Investor FE	NO	NO	YES
Entrepreneur FE	NO	NO	YES
N_clust	360	360	324

Table 1.6: *Entrepreneur gender, investor gender and question topic (market)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment is the market the startup operates in. The unit of observation is the question / comment from an investor to a startup which participated in the competition. "Event FE" are event (competition) fixed effects that account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) market_wds	(2) market_wds	(3) market_wds
entrepreneur_female	-0.024	-0.018	-
	(0.033)	(0.033)	
investor_female	-0.010	-0.009	-
	(0.021)	(0.021)	
investor_female#entrepreneur_female	0.006	0.005	0.010
	(0.049)	(0.048)	(0.055)
entrepreneur_prev_ent_exp		-0.001	-
		(0.025)	
entrepreneur_adv_deg		-0.006	-
		(0.024)	
entrepreneur_ivy_plus		-0.021	-
		(0.019)	
entrepreneur_tech		0.037	-
		(0.027)	
company_age		-0.020	-
		(0.023)	
Constant	0.468***	0.485***	0.461***
	(0.013)	(0.031)	(0.021)
Observations	4,081	4,081	4,045
R-squared	0.007	0.009	0.217
Event FE	YES	YES	YES
Investor FE	NO	NO	YES
Entrepreneur FE	NO	NO	YES
N_clust	360	360	324

In Table 1.9, we further examine the risk focus of screening questions along various topical dimensions. Columns (1) – (4) show the full fixed effects models along product risk, market risk, entrepreneurial / team risk and financial risk dimensions respectively. We find no evidence of gender dynamics between investors and entrepreneurs as predictors of the risk focus of screening questions. These results may indicate that while there may be gender differences in the screening focus of venture investors, the threats of risks are assessed in the same (negative) way.

Table 1.7a: *Entrepreneur gender, investor gender and question topic (team)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment relates to the skills / expertise of a startup's founder(s) / team. The unit of observation is the question / comment from an investor to a startup which participated in the competition. "Event FE" are event (competition) fixed effects that account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)
VARIABLES	team_wds	team_wds	team_wds
entrepreneur_female	-0.020	-0.023	-
	(0.022)	(0.022)	
investor_female	-0.005	-0.004	-
	(0.014)	(0.014)	
investor_female#entrepreneur_female	0.062*	0.061*	0.065*
	(0.034)	(0.034)	(0.034)
entrepreneur_prev_ent_exp		-0.010	-
		(0.021)	
entrepreneur_adv_deg		0.020	-
		(0.018)	
entrepreneur_ivy_plus		0.011	-
		(0.016)	
entrepreneur_tech		-0.048**	-
		(0.019)	
company_age		-0.037*	-
		(0.019)	
Constant	0.131***	0.148***	0.129***
	(0.009)	(0.027)	(0.011)
Observations	4,081	4,081	4,045
R-squared	0.011	0.015	0.234
Event FE	YES	YES	YES
Investor FE	NO	NO	YES
Entrepreneur FE	NO	NO	YES
N_clust	360	360	324

Table 1.7b: *Entrepreneur gender, investor gender and question topic (team)*

Notes: This table reports the magnitude of coefficients of the interaction terms of model 2 of Table 1.7a.

Entrepreneur

Investor	Female	Male
Female	**0.182**	0.144
Male	0.125	0.148

Table 1.8: *Entrepreneur gender, investor gender and question topic (finance)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment relates to the startup's financials. The unit of observation is the question / comment from an investor to a startup which participated in the competition. "Event FE" are event (competition) fixed effects that account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) finance_wds	(2) finance_wds	(3) finance_wds
entrepreneur_female	-0.010	-0.009	-
	(0.012)	(0.013)	
investor_female	-0.011	-0.011	-
	(0.012)	(0.012)	
investor_female#entrepreneur_female	0.024	0.022	0.026
	(0.024)	(0.025)	(0.029)
entrepreneur_prev_ent_exp		-0.010	-
		(0.016)	
entrepreneur_adv_deg		-0.002	-
		(0.012)	
entrepreneur_ivy_plus		-0.001	-
		(0.010)	
entrepreneur_tech		0.012	-
		(0.014)	
company_age		-0.002	-
		(0.010)	
Constant	0.094***	0.098***	0.072***
	(0.006)	(0.017)	(0.011)
Observations	4,081	4,081	4,045
R-squared	0.007	0.008	0.189
Event FE	YES	YES	YES
Investor FE	NO	NO	YES
Entrepreneur FE	NO	NO	YES
N_clust	360	360	324

We perform similar analyses on the reward focus of screening questions in Table 1.10. Columns (1) – (4) show the full fixed effects models along product reward, market reward, entrepreneurial / team reward and financial reward dimensions respectively. Our results indicate that while the main effects of the gender of the entrepreneur and the gender of the investor are non-significant, the interaction between female investors and female entrepreneurs is positive and significant on dimensions of product reward and entrepreneur / team reward. The coefficients of the interaction terms indicate that female investors are about 34.7% more likely to focus on product upsides and about 63% more likely to focus on entrepreneur / team upsides in their questions than male investors screening male entrepreneurs. These findings suggest that female investors may view female entrepreneurs and their products more favorably.

Table 1.9: *Entrepreneur gender, investor gender and question focus (risk)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment relates to the risk factors of startup along product, market, team and financial dimensions. The unit of observation is the question / comment from an investor to a startup which participated in the competition. Column (1) tests product risk. Column (2) tests market risk. Column (3) tests team risk. Column (4) tests financial risk. "Entrepreneur Controls" control for entrepreneur characteristics e.g., previous entrepreneurial experience, previous work experience in major technology companies etc. "Startup Controls" control for startup's age. "Event FE" are event (competition) fixed effects that account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

VARIABLES	(1) product_risk	(2) market_risk	(3) team_risk	(4) finance_risk
entrepreneur_female	-	-	-	-
investor_female	-	-	-	-
investor_female#entrepreneur_female	-0.004	-0.010	0.019	0.003
	(0.019)	(0.021)	(0.013)	(0.009)
Entrepreneur Controls	YES	YES	YES	YES
Startup Controls	YES	YES	YES	YES
Constant	0.062***	0.065***	0.028***	0.011***
	(0.007)	(0.008)	(0.005)	(0.004)
Observations	4,045	4,045	4,045	4,045
R-squared	0.194	0.186	0.189	0.217
Event FE	YES	YES	YES	YES
Investor FE	YES	YES	YES	YES
Entrepreneur FE	YES	YES	YES	YES
N_clust	324	324	324	324

There are a number of potential reasons why we may expect these results specifically on product and entrepreneur / team. One possibility is that female entrepreneurs focus on female-oriented products which female investors are appreciate more than their male counterparts. For instance, Chiara Bell, founder of Careticker, a San Francisco 2012 competition participant, pitched a fertility tracking app. Since this app is exclusively targeted to female users, it is possible that female investors will have more positive evaluations of the upside of this app and the entrepreneur who created it. Another possibility may be explained by female homophily between the investors and entrepreneurs.

However, this is less likely since it would explain the focus on the upside of the entrepreneur (who is female) but not necessarily the upside of the product.

Table 1.10: *Entrepreneur gender, investor gender and question focus (reward)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment relates to the reward factors of startup along product, market, team and financial dimensions. The unit of observation is the question / comment from an investor to a startup which participated in the competition. Column (1) tests product reward. Column (2) tests market reward. Column (3) tests team reward. Column (4) tests financial reward. “Entrepreneur Controls” control for entrepreneur characteristics e.g., previous entrepreneurial experience, previous work experience in major technology companies etc. “Startup Controls” control for startup’s age. “Event FE” are event (competition) fixed effects that account for both the year and location of the competition. “Investor FE” are investor fixed effects. “Entrepreneur FE” are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) product_reward	(2) market_reward	(3) team_reward	(4) finance_reward
entrepreneur_female	-	-	-	-
investor_female	-	-	-	-
investor_female#entrepreneur_female	0.067*	0.042	0.046*	0.028
	(0.035)	(0.041)	(0.024)	(0.021)
Entrepreneur Controls	YES	YES	YES	YES
Startup Controls	YES	YES	YES	YES
Constant	0.193***	0.200***	0.073***	0.032***
	(0.012)	(0.016)	(0.008)	(0.007)
Observations	4,045	4,045	4,045	4,045
R-squared	0.217	0.213	0.210	0.187
Event FE	YES	YES	YES	YES
Investor FE	YES	YES	YES	YES
Entrepreneur FE	YES	YES	YES	YES
N_clust	324	324	324	324

1.4.3 Product gender orientation, investor gender, entrepreneur gender and the topic / focus of screening questions

In order to determine if more favorable evaluation of female entrepreneurs and their products by female investors is driven (at least in part) by product gender orientation, we estimate equations of the form:

$$\Pr(y_{nit}) = \alpha + \beta_1 \text{female\_entrepreneur}_i + \beta_2 \text{female\_investor}_{ni} + \beta_3 \text{female\_entrepreneur}_i * \text{female\_investor}_{ni} + \delta' \mathbf{X}_i + \varepsilon_{ni} \quad (1.3)$$

where y represents a question, n indexes ordinality, i indexes startups, t indexes the topic / focus of the question, female_entrepreneur is an indicator variable equal to 1 if the pitching entrepreneur is female, female_investor is an indicator variable equal to 1 if the investor asking the question is female, **X** represents a vector of startup and entrepreneur-level controls and ε is the error term.

We perform our analysis by comparing the magnitude and significance of the effect of the female investor – female entrepreneur interaction terms across samples of ventures at various *gender_score* thresholds. Our analysis is in Table 1.11.

First, we select ventures whose products are identified by our scoring system as being non-feminine. These ventures have products with gender scores below -1. These ventures offer products such as ride-hailing services, enterprise management software etc. which are not specifically targeted toward female customers. This reduces our sample size to 92. Using the likelihood of receiving entrepreneur / team, entrepreneur / team reward and product reward questions / feedback as dependent variables, we find that the coefficient of the female investor – female entrepreneur interaction is not significant for entrepreneur / team and product reward questions / feedback. However, while it is significant for entrepreneur / team questions / feedback, the coefficient is negative contradicting our previous positive results.

For the 2nd sample, we adjust our *gender_score* threshold to include ventures whose products are identified as more female-oriented (i.e., *gender_score* > 1). These ventures offer products such as female fertility & health services, beauty & makeup, female fashion and infant & childcare. This reduces the size of our sample to 77. When we repeat our regressions with (the likelihood of) entrepreneur / team, entrepreneur / team reward and product reward questions as dependent variables, we find that the coefficient of the female investor – female entrepreneur interaction term becomes positive and significant in predicting the likelihood of receiving entrepreneur / team-related questions. The magnitude of the interaction coefficient suggests that female investors are twice as likely to ask entrepreneur / team-focused questions when screening female entrepreneurs whose products are female-oriented. However, the interaction term is still not a significant predictor of the likelihood of receiving entrepreneur / team reward and product reward questions.

To ensure that our scoring system only includes the products that are strictly female-oriented, we further increase the *gender_score* threshold to include only the products whose gender scores are above the 90th percentile (above 1.7). At this threshold value, only ventures whose products are highly female-oriented remain in the sample. This reduces our sample size to 38. At this threshold, the female investor – female entrepreneur terms become even more significant in predicting the likelihood of receiving entrepreneur / team-related questions and the likelihood that those questions focus on the upsides / rewards of the entrepreneur / team. Our results suggest that female investors are 3.3 times more likely to ask entrepreneur / team-focused questions and 4.8 times more likely to focus on the upsides of entrepreneur / team when screening female entrepreneurs whose products are highly female-oriented. This finding presents strong evidence that female investors' interest in female entrepreneurs and their investment potential is influenced (at least in part) by the product offerings of their ventures.

Taken together, our analysis provides evidence that female investors favor female entrepreneurs because their products (and by extension the entrepreneurs themselves) cater to female-specific needs which the investors identify as important and potentially lucrative.

1.4.3 Entrepreneur gender, topic / focus of screening questions and competition outcomes

In order to determine if the differences in screening topic / focus affect competition outcomes we estimate equations of the form:

$$\Pr(y_{ir}) = \alpha + \beta_1 \text{female\_entrepreneur}_i + \beta_2 \text{product\_questions\_count}_{ir} + \beta_3 \text{market\_questions\_count}_{ir} + \beta_4 \text{team\_questions\_count}_{ir\,+} + \beta_5 \text{finance\_questions\_count}_{ir} + \beta_5 \text{female\_entrepreneur}_i * \text{product\_questions\_count}_{ir} + \beta_6 \text{female\_entrepreneur}_i * \text{market\_questions\_count}_{ir} + \beta_7 \text{female\_entrepreneur}_i * \text{team\_questions\_count}_{ir} + \beta_8 \text{female\_entrepreneur}_i * \text{finance\_questions\_count}_{ir} + \delta' \mathbf{X}_i + \delta'' \mathbf{X'}_i + \varepsilon_{ir}, \quad (1.4)$$

where y represents the startup outcome of winning, i indexes startups, r indexes the stage / round of the competition, $\text{female\_entrepreneur}$ is an indicator variable equal to 1 if the pitching entrepreneur is female, $\text{product\_questions\_count}$ is the number of product-related questions asked, $\text{market\_questions\_count}$ is the number of market-related questions, $\text{team\_questions\_count}$ is the number of entrepreneur / team-related questions, $\text{finance\_questions\_count}$ is the number of finance-related questions, **X** represents a vector of startup and entrepreneur-level controls, **X'** represents a vector of screening panel-level controls.

In Table 1.12, in column (1) we regress our primary variables (with no interactions or controls) on the likelihood of winning the first round / stage of the competition. We find significant effects of the number of product-, market- and finance-related questions a startup receives.

However, when we control for the size of the screening panel (i.e., the number of investors) and include interaction terms of the numbers of questions with the gender of the entrepreneur, we observe the following results. First, the number of market-related questions a startup receives has a positive and significant effect on the likelihood of winning the first stage of the competition for both male and female entrepreneurs. However, while the number of entrepreneur / team-related questions a team receives reduces the chances of winning the 1st stage of the competition for startups with male founders, the interaction term indicates that the reverse is the case for female entrepreneurs, increasing their chances of winning. Specifically, for each additional entrepreneur / team-related question, male entrepreneurs are 7.9% less likely to advance through the 1^{st} stage of the competition while female entrepreneurs are 29.3% more likely to advance. In addition, we observe similar results for the number of finance related questions on likelihood of winning. While the effect is positive for male entrepreneurs (i.e., each additional finance question increases the likelihood of winning by 13.4%), it is negative for female entrepreneurs (with each additional finance question reducing the likelihood of winning by 28.2%). Taken together, these results provide evidence that the focus of venture screening is likely to have an impact on venture outcomes at the 1st stage of the competition.

We perform similar analyses for the 2nd (final) stage of the competition. However, we find no evidence of the influence of the focus of venture screening questions on venture outcomes. A possible explanation is that the variance in quality of the competing startups is higher in the 1st stage of the competition. However, advancing to the 2nd (final) stage of the competition reduces this variance, serving as a certification of the venture quality.

1.4.4 Venture competition outcomes and subsequent venture performance

Our findings suggest that the influence of the investor – entrepreneur gender effects on venture outcomes features in the early stages of venture screening. However, to understand if these effects predict subsequent (post-competition) venture performance, we estimate equations of the form:

$$\Pr(y_{it}) = \alpha + \beta_1 \text{female\_entrepreneur} + \beta_2 \text{winner\_stage\_1}_i + \beta_3 \text{female\_entrepreneur}_i * \text{winner\_stage\_1}_i + \delta' \mathbf{X}_i + \varepsilon_i, \quad (1.5)$$

$$\Pr(y_{it}) = \alpha + \beta_1 \text{female\_entrepreneur} + \beta_2 \text{winner\_stage\_2}_i + \beta_3 \text{female\_entrepreneur}_i * \text{winner\_stage\_2}_i + \delta' \mathbf{X}_i + \varepsilon_i, \quad (1.6)$$

where y represents the startup outcome of survival, i indexes startups, t is a continuous variable representing the number of years after the competition, female_entrepreneur is an indicator variable equal to 1 if the pitching entrepreneur is female, winner_stage_1 is an indicator variable equal to 1 if the startup advances through the 1st stage of the competition, winner_stage_2 is an indicator variable equal to 1 if the startup advances through the 2nd (final) stage of the competition and $\mathbf{X}$ represents a vector of startup and entrepreneur-level controls.

The results for the 1st stage of the competition are presented in Table 1.13 while the results for the 2nd (final) stage of the competition are presented in Table 1.14. In Table 1.13, columns (1) – (3), we test the likelihood of that the startup survives 3 years after the startup competition while in columns (4) – (6), we test the likelihood of survival 5-years after the competition. We restrict our analysis to the subset of startups that were founded 3 or more and 5 or more years prior to the current date.

Table 1.11: *Entrepreneur gender, investor gender and question focus (Product Gender Scores)*

Notes: This table reports the linear probability model where the dependent variable is 1 if the topic of the question / comment relates to the entrepreneur / team and reward factors of startup along product / technology and entrepreneur / team dimensions. The unit of observation is the question / comment from an investor to a startup which participated in the competition. For products whose gender scores are below -1 (i.e., non-feminine products), column (1) tests the entrepreneur / team focus, column (2) tests product reward and column (6) tests entrepreneur / team reward. For products whose gender scores are above 1 (i.e., feminine products), column (4) tests the entrepreneur / team focus, column (5) tests product reward and column (6) tests entrepreneur / team reward. For products whose gender scores are above the 90th percentile (i.e., highly feminine products), column (7) tests the entrepreneur / team focus, column (8) tests product reward and column (9) tests entrepreneur / team reward. "Entrepreneur Controls" control for entrepreneur characteristics e.g., previous entrepreneurial experience, previous work experience in major technology companies etc. "Startup Controls" control for startup's age. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

	Scores below -1 *(non-feminine products)*			**Scores above 1** *(feminine products)*			**Scores above 90th percentile** *(highly feminine products)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	team_wds	product_ reward	team_ reward	team_wds	product_ reward	team_ reward	team_wds	product_ reward	team_ reward
investor_ female	-	-	-	-	-	-	-	-	-
entrepreneur_ female	-	-	-	-	-	-	-	-	-
investor_ female# entrepreneur_ female	-0.184**	0.058	0.016	0.124*	-0.032	0.062	0.312**	-0.077	0.243**
	(0.087)	(0.137)	(0.093)	(0.071)	(0.090)	(0.046)	(0.121)	(0.200)	(0.120)
Entrepreneur Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Startup Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.110***	0.206***	0.041**	0.122***	0.239***	0.077***	0.096**	0.301***	0.051
	(0.032)	(0.033)	(0.017)	(0.025)	(0.034)	(0.019)	(0.047)	(0.062)	(0.046)
Observations	794	794	794	777	777	777	357	357	357
R-squared	0.422	0.371	0.394	0.303	0.374	0.328	0.351	0.416	0.392
Event FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Judge FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Founder FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N_clust	92	92	92	77	77	77	38	38	38

Our results suggest that advancing through the 1st round of the competition has a significant positive effect on the likelihood of survival. This effect persists with the addition of entrepreneur and startup controls. On average, 1st round competition winners are 9.4% more likely to survive for up to 3 years after the competition and 15.9% more likely to survive for up to 5 years after. However, when we perform the same analyses on 2nd round winners, our results reveal no evidence that winning the 2nd stage of the competition is correlated with 3 or 5-year post competition survival. This finding provides further evidence of higher variance in quality among startups that participate in the 1st round of the competition. Therefore, the 1st round of the competition performs two functions. First, it is effective in selecting high quality startups and perhaps more importantly, it certifies the quality of startups, sending positive signals to potential investors.

1.5 Concluding Discussion

In this study, we investigate whether VCs screen male founders differently than female founders. Further, we explore whether the screening focus of VCs vary based on the gender of the VC. We find that female investors are up to 23% more interested in entrepreneur / team criteria when evaluating female entrepreneurs than male investors evaluating male entrepreneurs. In addition, they are also 34.7% more likely to focus on product upsides and 67% more likely to pay attention to entrepreneur / team upsides. These findings imply that female investors may view female entrepreneurs and their products more favorably.

With respect to competition outcomes, we also find that this female investor – female entrepreneur interaction is positively correlated with winning the 1st round of the competition, but not the 2nd (final) round. We do not observe this effect with any other combination of investor gender – entrepreneur gender interaction.

One explanation for our results that female investors are more focused on female entrepreneurs and the upsides of the entrepreneurs and their products is product-gender orientation. Specifically, female-founded technology ventures with products that target primarily female customers e.g., fertility tracking and childcare apps etc. appeal especially to female VCs. This may be the case for two reasons.

Table 1.12: *Entrepreneur gender, question content and 1st stage competition outcomes*

Notes: This table reports the linear probability model where the dependent variable is 1 if the startup wins the first (semi-final) stage of the competition. The unit of observation is a startup which participated in the competition. "Entrepreneur Controls" control for entrepreneur characteristics e.g., previous entrepreneurial experience, previous work experience in major technology companies etc. "Startup Controls" control for startup's age. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) winner_stage_1	(2) winner_stage_1	(3) winner_stage_1
entrepreneur_female	-0.002	0.012	-0.147
	(0.060)	(0.061)	(0.146)
prod_que_count	0.039**	0.018	0.011
	(0.016)	(0.016)	(0.017)
mkt_que_count	0.051***	0.032***	0.027**
	(0.012)	(0.012)	(0.013)
team_que_count	0.029	0.008	-0.053*
	(0.031)	(0.029)	(0.027)
finance_que_count	0.084*	0.059	0.090**
	(0.043)	(0.043)	(0.045)
entrepreneur_female#prod_que_count			0.027
			(0.040)
entrepreneur_female#mkt_que_count			0.012
			(0.024)
entrepreneur_female#team_que_count			0.212***
			(0.070)
entrepreneur_female#finance_que_count			-0.164*
			(0.097)
female_investor_count		0.088*	0.092**
		(0.045)	(0.045)
male_investor_count		0.175***	0.176***
		(0.031)	(0.031)
Entrepreneur Controls	NO	YES	YES
Startup Controls	NO	YES	YES
Constant	-0.034	-0.688***	-0.671***
	(0.060)	(0.132)	(0.135)
Observations	390	390	390
R-squared	0.090	0.183	0.210
Event FE	YES	YES	YES
N_clust	390	390	390

First, it may be the case that female VCs simply admire female founders who tackle the often untapped / underserved market for female-oriented technology-enabled products. These investors may recognize certain traits about these entrepreneurs that they consider as having strong investment potential. It may also be the case that female investors are better able to recognize the market potential of these products and by extension, the ventures, especially if they imagine themselves as potential customers. This would be a lot more challenging for male investors since they may not find any of the female-focused aspects of the products directly relatable. While we cannot be certain which combination of the reasons drives this affinity, our analysis provides evidence that such ventures and their (female) founders garner favorable interest / evaluation from female VCs. Female VCs are up to 4.8 times more likely to focus on the upsides of the entrepreneur / team when screening female entrepreneurs whose products are oriented toward female customers.

Table 1.13: *First stage competition winners and post-competition performance (survival)*

Notes: This table reports the linear probability model where the dependent variable is 1 if a startup which won the first (semi-final) stage of the of the startup competition survived for a number of years post competition. The unit of observation is the startup which participated in the competition. Column (1) – (3) test 3-year post competition survival while Column (4) – (6) test 5-year post competition survival. “Event FE” are event (competition) fixed effects that take account for both the year and location of the competition. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

	3-year post-competition survival			**5-year post-competition survival**		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
winner_stage_1	0.081***	0.082***	0.083***	0.125***	0.125***	0.125**
	(0.023)	(0.023)	(0.027)	(0.043)	(0.043)	(0.048)
entrepreneur_female		-0.026	-0.028		-0.004	-0.004
		(0.037)	(0.049)		(0.060)	(0.073)
entrepreneur_female#			-0.016			-0.047
winner_stage_1			(0.050)			(0.094)
entrepreneur_prev_ent_exp			-0.009			0.008
			(0.029)			(0.051)
entrepreneur_adv_deg			0.025			0.048
			(0.037)			(0.062)
entrepreneur_ivy_plus			0.005			-0.044
			(0.032)			(0.053)
entrepreneur_tech			0.006			-0.005
			(0.041)			(0.060)
company_age			0.018			0.046
			(0.036)			(0.063)
Constant	0.909***	0.913***	0.887***	0.845***	0.846***	0.785***
	(0.017)	(0.017)	(0.046)	(0.026)	(0.027)	(0.087)
Observations	356	356	356	238	238	238
R-squared	0.105	0.106	0.109	0.165	0.165	0.174
Event FE	YES	YES	YES	YES	YES	YES
N_clust	356	356	356	238	238	238

Turning to the results for male VCs, we do not find that they exhibit any gender screening differences with respect to entrepreneurs or product orientation. We find very limited evidence of gender-oriented products by male-founded ventures. Therefore, we do not expect more interest / focus with respect to entrepreneur and / or product upsides, on the basis of product-gender appeal.

Table 1.14: *Second stage competition winners and post-competition performance (survival)*

Notes: This table reports the linear probability model where the dependent variable is 1 if a startup which won the second (final) stage of the of the startup competition survived for a number of years post competition. The unit of observation is the startup which participated in the competition. Column (1) – (3) test 3-year post competition survival while Column (4) – (6) test 5-year post competition survival. “Event FE” are event (competition) fixed effects that take account for both the year and location of the competition. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

	3-year post-competition survival			5-year post-competition survival		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
winner_stage_2	0.020	0.021	0.014	0.102	0.104	0.088
	(0.026)	(0.026)	(0.031)	(0.073)	(0.075)	(0.073)
entrepreneur_female		-0.001	-0.001		0.016	-0.104
		(0.003)	(0.009)		(0.014)	(0.062)
entrepreneur_female# winner_stage_2			0.009			-
			(0.039)			
entrepreneur_prev_ent_exp			0.005			-0.033
			(0.009)			(0.058)
entrepreneur_adv_deg			-0.006			0.218
			(0.014)			(0.210)
entrepreneur_ivy_plus			-0.004			-0.139
			(0.011)			(0.088)
entrepreneur_tech			0.032			0.194
			(0.045)			(0.116)
company_age			0.033			0.023
			(0.039)			(0.116)
Constant	0.985***	0.985***	0.963***	0.901***	0.899***	0.801***
	(0.014)	(0.014)	(0.035)	(0.041)	(0.043)	(0.214)
Observations	87	87	87	52	52	52
R-squared	0.246	0.246	0.269	0.364	0.364	0.496
Event FE	YES	YES	YES	YES	YES	YES
N_clust	87	87	87	52	52	52

These results have 2 important implications. First, by inspecting the screening dimensions used by VCs, we uncover that gender-driven differences in ex-ante information collection are context-specific, i.e., rather than being broadly generalizable, they occur only during the screening of specific types of ventures. This finding provides a potentially fruitful avenue for further research that focuses on fully describing which contexts these differences manifest as well as their context-specific effects on venture-level funding outcomes. This line of research also has practical relevance for VC investors, entrepreneurs and policy-makers. For investors, it identifies a key determinant of investment performance outcomes. The gender dynamics of the venture screening process directly influence investment selection choices and ultimately impact the performance of VC firms. For entrepreneurs, it allows them to tailor their pitches to better suit their investment targets and improve their chances of securing critical resources. For policy-makers, this knowledge is useful in designing venture screening processes and policies that could potentially stimulate more vibrant entrepreneurial ecosystems.

Second, our results provide support that supply-side adjustments i.e., increasing the representation of women in venture capital investing, has positive effects on funding outcomes for female entrepreneurs. A number of previous studies (e.g. (Brush et al., 2001)) have recommended this as a potential solution to the gender gap in entrepreneurial funding but do not provide empirical evidence of its efficacy.

Our study of VC screening of new venture investment opportunities is carried out within the narrow context of startup competitions, which represents one of several entrepreneurial investment avenues. In addition, within this context, an averaged decision process(Holloman & Hendrick, 1972) is used. Therefore, we are cautious regarding generalizing our results beyond this specific empirical setting. Upcoming research on the effect of decision-making structure on the outcomes of VC investment decisions will be essential to determine the generalizability of our findings.

Chapter 2

Co-Ethnicity Effects in New Venture Screening[3]

2.1 Introduction

There is a glaring lack of ethnic diversity in US high-growth entrepreneurship among both entrepreneurs and investors. For entrepreneurs, 79.6% are White, 15.8% are Asian, 3.8% are Hispanic and only 0.4% are Black. Within the venture capital community, an even higher percentage are White (86.3%), with Asian, Hispanic and Black investors accounting for 10.6%, 2.5% and 0.3% respectively (Gompers & Wang, 2017b). This distribution persists despite the growing proportions of ethnic minorities who possess the requisite backgrounds to participate in these sectors. Studying the influence of ethnicity in entrepreneurship and venture capital is therefore of critical importance.

Previous studies have examined the influence of co-ethnicity in facilitating business partnerships between venture capital investors and resource-seeking entrepreneurs(Bengtsson & Hsu, 2015; Hegde & Tumlinson, 2014; Zhang et al., 2016). These studies consistently argue that investors are more likely to invest in ventures with founders / entrepreneurs with whom they share ethnic ties. This is due to the anticipation of lower investment costs through reduced pre-investment information asymmetry and increased post-investment coordination and monitoring efficiency. They also claim that this ethnicity-driven behavior in investors persists despite observable heterogeneity in the overall quality of the ventures.

However, while these studies argue that co-ethnicity may override observable venture quality considerations, they are unable to directly observe how these quality signals are interpreted by investors. Our study closes this gap by directly analyzing questions / feedback from VC investors to entrepreneurs communicated during face-to-face screening of new ventures. According to financial contracting theory, when investors are faced with

[3] Co-authored with Sampsa Samila

severe information asymmetry, they can collect information ex-ante to allow them screen out bad ventures and screen in good ones(Kaplan & Strömberg, 2001). Questions / feedback from investors are therefore pivotal in the venture screening process.

Thus, we aim to answer the question of whether or not co-ethnicity between a VC investor and an entrepreneur influences the investor's assessment of the investment potential of the venture. We examine this question from the perspective of Regulatory Focus Theory (RFT) which highlights two distinct motivations that guide goal-oriented behavior: a *promotion* focus which is concerned with rewards and growth or a *prevention* focus which is concerned with minimizing risks and losses(Higgins, 1997, 1998). Regulatory focus has been shown to impact outcomes in a number of settings including in venture capital funding where promotion-focused exchanges between investors and entrepreneurs are associated with increased likelihood of funding and higher funding amounts, while prevention-focused exchanges result in lower likelihood of funding and lower funding amounts(Kanze et al., 2018).

We address our research question using data from TechCrunch Disrupt, one of the most prestigious competitions in the world for technology startups seeking venture capital. Our analysis covers competition events across 4 locations – New York, San Francisco, London and Berlin – from 2010 to 2017. Our final sample comprises 353 startups. Using transcribed textual data of the questions / feedback from VC judges to entrepreneurs following pitch presentations, we investigate whether or not co-ethnicity between an investor / judge and an entrepreneur: a. increases the likelihood of receiving promotion-focused feedback from the investor / judge; and / or b. reduces the likelihood of receiving prevention-focused feedback from the investor / judge.

Our results provide evidence that co-ethnicity increases the likelihood of promotion-focused questions/feedback from investors by up to 74%. However, rather than being systematically widespread among investors, this effect is limited to ethnic minority investors and entrepreneurs. This ethnic minority group comprises people of Black, American Indian / Alaskan Native, and Native Hawaiian / Pacific Islander ethnicities, who are severely under-represented in US VC and high-growth entrepreneurship. We do not observe similar effects among investors and entrepreneurs who are White or Asian. We argue that one explanation for this unique co-ethnicity effect among ethnic minorities is ethnic solidarity, born in response to the shared challenge of access to entrepreneurial financing in the current entrepreneurship landscape. Therefore, ethnic minority investors may pose more promotion-focused questions / feedback as a means of providing support to this under-represented / under-served group of co-ethnic entrepreneurs.

Our study contributes to the conceptual understanding of ethnicity-driven behavior of venture capital investors. While co-ethnicity fosters the formation of business relationships between an investor and an entrepreneur (Bengtsson & Hsu, 2015; Hegde & Tumlinson, 2014; Zhang et al., 2016), it may also bias the ability of certain investors to objectively assess the quality of the entrepreneur's venture. Therefore, ethnic diversity in VC investment decision-making can improve the quality of investment decisions.

The rest of the study proceeds as follows. In Section 2.2 we develop our hypotheses. Section 2.3 describes the empirical setting. Section 2.4 describes the data. Section 2.5 discusses the empirical strategy and main results. Section 2.6 presents the results of additional analyses. Section 2.7 concludes.

2.2 Theory & Hypothesis

2.2.1 Co-ethnicity in VC investing

We examine co-ethnicity from two related but distinct perspectives: social networks and social identity. The social network perspective posits that individual behavior, social relations and economic transactions are governed by shared cultural heritage(Aldrich & Waldinger, 1990; Levie, 2007). On the other hand, the central theme of the social identity theory is that in-group identification is causally related to intergroup discrimination(Brown, 2000).

In the context of venture capital, a social network of co-ethnic investors and resource-seeking entrepreneurs, facilitates investment via two mechanisms (Zhang et al., 2016). First, the social network minimizes information asymmetry and deters entrepreneurial opportunism. Resource-constrained entrepreneurs often know more about the underlying technology of their innovation-based new ventures than investors (Shane, 2000). This information asymmetry makes it challenging for investors to accurately assess the viability of the ventures and increases the risk of ex-ante and ex-post opportunism by entrepreneurs, (Gompers, 1995). For investors, social networks provide two benefits. First, they serve as a channel for critical information used by investors to screen ventures (Shane & Cable, 2002), thereby minimizing information asymmetry and the risk of ex-ante opportunism (i.e., misrepresentation) by entrepreneurs (Venkataraman, 1997). In addition, these social networks facilitate the rapid dissemination of information about opportunistic behaviors of entrepreneurs, leading to swift punitive responses (Zhang et al., 2016). Thus, they deter ex-post entrepreneurial misconduct and improve post-investment monitoring and coordination. Ethnic social networks therefore offer a number of advantages to VC investors and thus increase the likelihood of investment in a venture(Shane & Cable, 2002).

The second mechanism through which ethnic social networks facilitate venture capital investment is ethnic solidarity (Portes and Sensenbrenner, 1993), which may stem from homophily -- the principle that personal similarity breeds social connections (Mcpherson et al., 2001) -- or as a reaction to shared adversity – which leads to observance of norms of mutual support by in-group members. Thus, the affinity of investors for interaction with entrepreneurs with whom they share personal or situational similarities, also implies that co-ethnicity will increase the likelihood of investment in a venture.

There is compelling empirical support for the positive relationship between co-ethnicity of VC investors and entrepreneurs and likelihood of entrepreneurial financing. Hegde and Tumlinson (2014) find that VC investors are systematically more likely to invest in a venture when the investor and the venture have top-level personnel of the same ethnicity. They argue that VCs read the signals from co-ethnic companies more precisely, and anticipate co-ethnicity to yield adequate post-investment benefits despite, lower quality signals from co-ethnic ventures (Hegde & Tumlinson, 2014). Bengtsson and Hsu (2015) find similar results and also highlight that conditional on investment, investors are more involved in a venture when they share the ethnicity of the entrepreneur.

The social identity perspective of co-ethnicity in venture capital investing is put forth by Zhang, Wong and Ho (2016). Drawing on the arguments of Ndofor and Priem (2011) that immigrant communities are often perceived as having lower levels of status than their indigenous (mainstream) counterparts, they theorize that ethnic minority VC investors incur premiums in investing in mainstream entrepreneurs. This premium is driven by the status differential between (lower status) minority ethnicities and (higher status) mainstream ethnicities. This premium is asymmetric and consequently is not incurred by mainstream VCs when they invest with ethnic minority entrepreneurs. However, since mainstreams desire to keep their perceived higher social status (Tajfel, 1978), mainstream VCs may be reluctant to invest in ethnic minority entrepreneurs. Consequently, co-ethnicity-driven VC investment would be more likely between co-ethnic ethnic-minority investors and entrepreneurs. Their empirical analysis supports the theory and provides additional evidence for the structural social network perspective of co-ethnicity in VC investing.

2.2.2 Regulatory Focus in VC Investing

Regulatory focus theory (RFT) (Higgins, 1997, 1998) focuses on the motivational and strategic tendencies people draw on in the process of trying to attain their goals (Brockner et al., 2004). Thus, our use of RFT as a framework for explaining the VC investment process emphasizes the motivations and strategies used by VC investors to achieve investment success.

The highest priority of a VC investor is finding investments with large potential payoffs(Bygrave & Timmons, 1992). Therefore, they demonstrate a preference for investing in ventures that signal high-growth prospects (Guzman & Stern, 2015). This high-growth preference from an RFT perspective implies an orientation of investors toward promotion concerns and away from prevention concerns of the venture. In other words, ventures that signal promotion -- emphasizing rewards, upsides and advancement -- are more attractive to investors than those that signal prevention– which emphasizes non-losses and risks(Kanze et al., 2018). Given investors' aforementioned preference for rewards and growth over risk and non-losses, they are predominantly promotion-focused in screening-in new ventures that appear attractive enough for investment consideration. On the other hand, investors are more prevention-focused in screening-out new ventures which they consider less suitable for investment. Kanze et al., (2018) provide evidence that promotion-focused interactions between VC investors and entrepreneurs are associated with better funding outcomes than prevention-oriented interactions.

The anticipation of co-ethnicity's positive influence on venture outcomes facilitates the selection of co-ethnic entrepreneurs by investors and may also result in discrimination against opportunities outside their co-ethnic social networks (Hegde & Tumlinson, 2014). Thus, we anticipate the interactions between investors and entrepreneurs of shared ethnicity to be more promotion-focused than prevention-focused. Conversely, we anticipate that interactions between non-co-ethnic investors and entrepreneurs to be more prevention-focused than promotion focused. Therefore, we predict:

Hypothesis 1a. Ceteris paribus, co-ethnicity between a VC investor and an entrepreneur increases the likelihood of promotion-oriented feedback / questions from the investor to the entrepreneur.

Hypothesis 1b. Ceteris paribus, co-ethnicity between a VC investor and an entrepreneur reduces the likelihood of prevention-oriented feedback /questions from the investor to the entrepreneur.

2.3 Setting

Startup competitions are critical opportunities for entrepreneurs to articulate their ventures' business propositions not only to competition judges but also to other potential investors. If the judges / investors form negative impressions of the entrepreneur or venture during these presentations, the entrepreneur is highly unlikely to obtain funding (Lounsbury & Glynn, 2001; Martens et al., 2007a).

"TechCrunch Disrupt is widely regarded as the most prestigious setting in which high-tech startups can launch"(Kanze et al., 2018). Since its inception in 2007, the 763 startups that presented at the competition have raised a total of $8.8 billion in funding, with 109 having been acquired or gone public. Notable TechCrunch Disrupt alumni include Yammer, Dropbox and Qwiki.

The competition takes place across a number of locations, once a year each. These locations include San Francisco, New York, London and Berlin. Online applications to each competition open three months before the actual event. TechCrunch reviews applicants and selects contestants based on their team, product and market potential. Selection is highly competitive and acceptance rates range between 3% to 6%. Typically, the number of accepted startups in each competition ranges between 15 and 30. These startups get the opportunity to pitch to panels of 4 - 6 judges (judges) in a style similar to an investment pitch meeting. These judges are prominent Silicon Valley VCs and technologists and include figures like Marissa Mayer – former CEO of Yahoo, Roelof Botha – a partner at Sequioa Capital, a prominent VC firm - etc.

The competition takes place over the course of 3 days across 2 stages – a semi-final and final round. Competing startups are allocated 6 minutes for their pitch presentation followed by a question-and-answer session with the panel of judges. Each team is scored by each judge and the scores are collated by TechCrunch. The highest scoring startups, typically 4 – 6 in number, proceed to the final round. In the final round, the startup entrepreneurs repeat the presentation to a new independent set of judges, participate in a question-and-answer session and are scored by individual judges. After the scores are collated by TechCrunch, the highest scoring team from the final round wins the competition and the $100,00 prize.

Our sample comprises the data set of startups that participated in TechCrunch Disrupt from 2010 – 2017 across 4 locations: New York, San Francisco, London and Berlin. During this period, a total of 353 participating startup entrepreneurs were asked a total of 3792 questions.

Our list of participating startups was gathered manually from the TechCrunch Disrupt website. The records of conversations between entrepreneurs and judges were obtained by transcribing publicly available video footage of each pitch session to text via YouTube's automated speech-to-text feature. Supporting information on the profiles of the participating startups was obtained manually from Crunchbase, a publicly available database maintained by TechCrunch.

Using TechCrunch Disrupt as our research setting provides a number of important benefits. First, it permits full observation of the pitch presentation and Q&A sessions based on complete and publicly available video footage hosted on YouTube. This has the added benefit of allowing speaker identification and automated speech-to-text transcription of verbal exchanges between entrepreneurs and screening panels. Furthermore, the enforced time limits for both presentation and Q&A sessions across all events minimizes the variability of the conditions across which competing startups are evaluated and allows for robust comparison of screening processes and outcomes across various competitions. Yet another benefit of this research setting is that TechCrunch maintains a database, Crunchbase, which makes background information on the participating startups publicly available. This information includes the names of founders, founding date, business category, operating status and company description. Finally, participation is open only to companies that demonstrate a need for venture capital. Thus, we are able to eliminate variability regarding the founders' intentions and funding needs (Kanze et al., 2018).

2.4 Data

We describe our key variables, data sources, sample restrictions and summary statistics. A complete list of variables and their descriptions is provided in Table 2.1.

2.4.1 Dependent Variables

As described in Section 2.2, VC investors interact with competing startups primarily by asking questions to entrepreneurs at the end of timed startup pitch presentations. According to financial contracting theory, when investors are faced with severe information asymmetry, they can collect information ex-ante to allow them screen out bad ventures and screen in good ones(Kaplan & Strömberg, 2001). Thus, questions from investors are pivotal in the venture screening process.

We examine the regulatory focus of investors' questions by calculating the proportion of promotion and prevention terms appearing in the transcribed text of each question / comment. These calculations are computed as continuous measures using the Linguistic Inquiry and Word Count (LIWC) software application (Chung & Pennebaker, 2013; Pennebaker et al., 2007). Following Kanze et al., (2018), we classify each question / comment as promotion-focused if the proportion of promotion terms is higher than the proportion of prevention terms. Similarly, a question / comment is prevention-focused if the proportion of prevention terms is higher (see Appendix Table A2). This yields 2 binary variables: *promotion* and *prevention*. *Promotion* takes on the value of 1 if a question /

comment is promotion-focused, 0 otherwise. Similarly, *prevention* is set to 1 for questions / comments that are prevention-focused, 0 otherwise.

2.4.2 Independent Variables

We categorize both entrepreneurs and investors by ethnicity. To identify ethnicity, we use a combination of photos and biographical information collected from a variety of sources, primarily LinkedIn and Crunchbase. Following the classification of the U.S. Census Bureau[4], individual entrepreneurs and judges / investors are classified into five non-overlapping ethnic groups: White, Black, American Indian / Alaskan Native, Asian, and Native Hawaiian / Pacific Islander. However, due to the severe under-representation of Black, American Indian / Alaskan Native and Native Hawaiian / Pacific Islander ethnicities in US venture capital and high-growth technology entrepreneurship (Gompers & Wang, 2017b), we group these 3 ethnic minority groups together for the purpose of our analysis. For entrepreneurs, this yields 3 eponymous dummy variables: *entrepreneur_white, entrepreneur_asian and entrepreneur_eth_minority*. For each entrepreneur ethnicity identified, the corresponding dummy variable is set to 1 while all others are set to 0. Similarly, for investors, this yields 3 eponymous dummy variables: *investor_white, investor_asian, investor_eth_minority*. For each investor ethnicity identified, the corresponding dummy variable is set to 1 with all others set to 0.

2.4.3 Control variables

We identify educational information, previous work experience and previous entrepreneurial experience of the entrepreneurs from profile information from Crunchbase and LinkedIn. Based on this information we construct 4 dummy variables which are equal to 1 if the entrepreneur has an advanced degree e.g. Masters, PhD, MD etc., attended an Ivy League Plus school – undergraduate or graduate degree from Brown, Caltech, University of Chicago, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, University of Pennsylvania, Princeton, Yale, Stanford, Cambridge, Oxford, Ecole Polytechnique, and Ecole Normale Superieur (Bengtsson & Hsu, 2012), worked for any of the top-performing big technology companies – Facebook, Apple, Amazon, Netflix, Google and Microsoft, and has previously

[4] https://www.census.gov/topics/population/race/about.html

been the founder or co-founder of a company. Similarly, we identify gender information for both entrepreneurs and investors and code them using dummy variables that take on values of either 1 (indicating female) or 0 (indicating male).

Table 2.1: *Description of main variables*

Variable	Description
promotion	Dummy variable equal to 1 if an investor's question / feedback is predominated by promotion-focused terms. 0 otherwise.
prevention	Dummy variable equal to 1 if an investor's question / feedback is predominated by prevention-focused terms. 0 otherwise.
entrepreneur_female	Dummy variable equal to 1 if the entrepreneur is female, 0 for male
entrepreneur_adv_deg	Dummy variable equal to 1 if the entrepreneur has an advanced degree e.g., Masters, MD, JD, PhD etc.
entrepreneur_ivy_plus	Dummy variable equal to 1 if the entrepreneur has a graduate or undergraduate degree from Brown, Caltech, Univ. of Chicago, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, Univ. of Pennsylvania, Princeton, Yale, Stanford, Cambridge, Oxford, Ecole Polytechnique, and Ecole Normale Superieur (Bengtsson & Hsu, 2015).
entrepreneur_mba	Dummy variable equal to 1 if the entrepreneur has an MBA
entrepreneur_prev_ent_exp	Dummy variable equal to 1 if the entrepreneur has previous entrepreneurial experience
entrepreneur_tech	Dummy variable equal to 1 if the entrepreneur has previous experience working at the major big tech companies i.e., Facebook, Apple, Amazon, Netflix, Microsoft or Google.
entrepreneur_asian	Dummy variable equal to 1 if the entrepreneur is Asian, 0 otherwise
entrepreneur_white	Dummy variable equal to 1 if the entrepreneur is White, 0 otherwise
entrepreneur_eth_minority	Dummy variable equal to 1 if the entrepreneur is Black, American Indian / Alaskan Native, or Native Hawaiian / Pacific Islander, 0 otherwise.
entrepreneur_non_white	Dummy variable equal to 0 if the entrepreneur is White, 1 otherwise.
investor_female	Dummy variable equal to 1 if the investor is female, 0 for male
investor_asian	Dummy variable equal to 1 if the investor is Asian, 0 otherwise
investor_white	Dummy variable equal to 1 if the investor is White, 0 otherwise
investor_eth_minority	Dummy variable equal to 1 if the investor is Black, American Indian / Alaskan Native, or Native Hawaiian / Pacific Islander, 0 otherwise.
investor_non_white	Dummy variable equal to 0 if the investor is White, 1 otherwise.

2.4.4 Summary Statistics

We begin in Table 2.2 by examining the composition of entrepreneurs and investors in our sample. In Panel A, out of a total of 353 entrepreneurs, we observe that male entrepreneurs make up 83.85% while female entrepreneurs account for 16.15%. For investors, the gender distribution is more balanced with about female investors accounting for almost a third of the sample, while male investors account for about 69% of the total of 320. With respect to the ethnicity, the distribution of entrepreneurs and investors is fairly similar. White ethnicities represent 73.1% of entrepreneurs and 79.4% of investors. Asian ethnicities represent 20.4% of entrepreneurs and 14.7% of investors. For both groups, minority ethnicities account for roughly 6% of the sample.

In Panel B, we examine entrepreneur-level attributes along ethnic categories. Entrepreneurs of ethnic minority appear the most educated with almost 87% of having at least one advanced degree. By comparison, the corresponding proportion of Asian and White entrepreneurs with advanced degrees is 76.3% and 80.2% respectively. Almost half of the entrepreneurs of Asian ethnicity received at least one degree from an *Ivy-League-plus* university. The corresponding proportion for White and ethnic minority entrepreneurs is 30.2% and 43.4% respectively. With respect to prior work experience, 26% of ethnic minority entrepreneurs, 15.3% of Asian entrepreneurs and 10.5% of White entrepreneurs have worked for at least one major US technology company. Finally, more than 82% of entrepreneurs of all ethnicities in our sample have prior entrepreneurial experience, either as a founder or co-founder.

In Table 2.3, we report question-level summary statistics. Out of a total of 3792 investor questions, 1273 are promotion-focused while 241 are prevention-focused. Across both question categories, the distribution of questions by entrepreneur ethnicity is fairly similar. Out of the total number of questions / feedbacks received by White entrepreneurs, 84% are promotion-focused while 16% are prevention-focused. For Asian entrepreneurs, the split is 83% promotion-focused and 17% prevention-focused. For ethnic minority entrepreneurs, the split is 86% promotion-focused and 14% prevention-focused. The distribution of questions posed by investors categorized by ethnicity is very similar. Questions / comments from White investors are 84% of promotion-focused and 16% prevention-focused. For Asian and ethnic minority investors, the promotion-prevention question / feedback splits are 83% - 17% and 87% - 13% respectively.

The pairwise distribution of investor-entrepreneur questions categorized by ethnicity is presented in Table 2.4. Of the total number of questions / feedback received by White entrepreneurs, 82.1% come from White investors, 14.5% from Asian investors and 3.4% from ethnic minority investors. The distribution is fairly similar for Asian entrepreneurs who receive 81% of their questions from White investors, 15.1 from Asian investors and 3.9% from ethnic minority investors. The distribution of questions / feedback for ethnic minority entrepreneurs is slightly different. Only 73.6% of their questions come from White investors. Compared to Asian and White entrepreneurs, they receive a higher proportion of questions / feedback from Asian investors (20.6%) and from co-ethnic investors (5.69%).

In Table 2.5, we examine startup and competition level statistics. Panel A shows that across the 19 competition events, a total of 353 startups have participated with an average of 20.5 firms pitching at each competition event. Across these events, on average, about 5 startups advance through the 1st stage of the competition and into the 2nd (final) stage where 1 winner per competition event emerges.

In Panel B, we present competition level statistics, focusing on the structure of the screening panels. We find a total of 355 unique screening panels with an average size of about 4 investors, typically comprising 3 of White ethnicities and 1 of Asian ethnicity.

Table 2.2: *Individual-level Statistics*

Notes: The table reports the summary statistics for the sample of entrepreneurs and investors by gender and ethnicity from 19 TechCrunch Disrupt startup competition events between 2010 and 2017. % values represent percentage of group totals in the sample.

Panel A

Entrepreneur			**Investor**		
Gender	Obs.	% of total	Gender	Obs.	% of total
Male	296	83.85	Male	222	69.38
Female	57	16.15	Female	98	30.62
Total	353	100	Total	320	100
Ethnicity	Obs.	% of total	Ethnicity	Obs.	% of total
White	258	73.09	White	254	79.38
Asian	72	20.40	Asian	47	14.69
Ethnic Minority	23	6.51	Ethnic Minority	19	5.93
Total	353	100	Total	320	100

Panel B

Entrepreneur Ethnicity	**Holds an MBA**	**Has other Advanced Degree(s)**	**Ivy-League-*plus* Educated**	**Previous Big Tech Experience**	**Previous Entrep. Experience**
White	10.85%	80.23%	30.23 %	10.47%	83.72%
Asian	16.67%	76.39%	48.61%	15.28%	84.72%
Ethnic Minority	26.09%	86.96%	43.48%	26.09%	82.61%

Table 2.3: *Question-level statistics*

Notes: The tables report the question-level summary statistics from 19 TechCrunch Disrupt startup competition events between 2010 and 2017. % values represent percentage of row totals in the sample. Panel A summarizes the distribution of questions / feedback by regulatory focus received by entrepreneurs of each ethnic category. Panel B summarizes the distribution of questions / feedback by regulatory focus issued by investors of each ethnic category.

Panel A: *Regulatory Focus by Ethnicity (Entrepreneur)*

	Prevention (Risk)		**Promotion (Reward)**	
	Obs	% of total	Obs	% of total
White	173	15.78%	923	84.22%
Asian	53	17.21%	255	82.79%
Ethnic Minority	15	13.64%	95	86.36%
Total	241		1273	

Panel B: *Regulatory Focus by Ethnicity (Investor)*

	Prevention (Risk)		**Promotion (Reward)**	
	Obs	% of total	Obs	% of total
White	196	15.79%	1038	84.21%
Asian	38	16.59%	188	83.41%
Ethnic Minority	7	12.96%	47	87.04%
Total	241		1273	

Table 2.4: *Question Distribution by Ethnicity (Entrepreneurs & Investors)*

Notes: The table summarizes the distribution of questions (count) across combinations of entrepreneur-investor pairs categorized by ethnicity. % values represent percentage of the row totals of questions asked / received by investors / entrepreneurs of each ethnic category.

		Investor Ethnicity			
Entrepreneur Ethnicity	Obs.	White	Asian	Ethnic Minority	Total
White	2774	82.16%	14.49%	3.35%	100%
Asian	673	80.98%	15.16%	3.86%	100%
Ethnic Minority	281	73.67%	20.64%	5.69%	100%
Total	3,728				

Table 2.5: *Startup- and competition-level statistics*

Notes: The table reports the startup-level summary statistics from 19 TechCrunch Disrupt startup competition events between 2010 and 2017.

Panel A: *Startup statistics per competition*

	Obs	**Mean**	**Std.Dev.**	**Min**	**Max**
Startups	353	18.36	6.39	7	28
1st-stage winners	94	4.95	1.35	3	7
2nd-stage winners	19	1	0	1	1

Panel B: *Competition-level statistics*

	Obs	**Mean**	**Std.Dev.**	**Min**	**Max**
Screening Panels	355				
1st stage					
Investors	270	4.12	0.96	2	7
White	218	3.30	1.00	1	6
Asian	36	0.65	0.69	0	3
Ethnic Minority	16	0.17	0.42	0	2
2nd stage					
Investors	156	4.72	1.04	2	8
White	123	3.83	1.12	2	6
Asian	24	0.73	0.80	0	3
Ethnic Minority	9	0.16	0.40	0	2

2.5 Empirical Strategy & Results

To answer our research questions, we examine if co-ethnicity between an investor and an entrepreneur positively influences the regulatory focus of the questions / feedback from the investor to the entrepreneur.

We exploit the random assignment of VCs to startup screening panels as our primary identification strategy. In essence, there is no systematic assignment of VC investor judges to startups on the basis of previous affiliation, product / service category expertise or other factors that may bias the screening process. This allows us to eliminate any endogenous link between startup characteristics and the profiles of the investors.

We conduct our analysis primarily using the linear probability model (LPM). This choice is motivated by the advantages the LPM possesses over non-linear models like logit with respect to the interpretation of the magnitude of interaction effects (Ai & Norton, 2003) and the coefficients of dummy variables(Caudill, 1988), both of which we heavily rely on in our analysis. Unlike in linear models, the magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term(Ai & Norton, 2003). Furthermore, it has been demonstrated that the coefficient of observation-specific dummy variables cannot be estimated in either logit or probit models(Caudill, 1988). Our choice of the LPM allows us to overcome these challenges and correctly interpret the significance and magnitude of our results.

2.5.1 Hypothesis Testing

To test Hypothesis 1a which predicts a positive relationship between co-ethnicity and the likelihood of promotion-focused feedback, we regress the *promotion* dummy variable against ethnicity co-variates for both investors and entrepreneurs. We model co-ethnicity as interaction terms between investors and entrepreneurs of the same ethnic grouping. Our results are presented in Table 2.6.

We present the results of 3 LPM specifications. In model (1), we include only main and interaction ethnicity co-variates with competition-level fixed effects. In model (2), we introduce entrepreneur-level and venture-level controls. Model (3) presents the full model specification, including control variables and fixed effects at the competition, venture, entrepreneur and investor levels. The coefficient of the co-ethnicity interaction term for ethnic minority investors and entrepreneurs becomes positive and significant in the full model specification. Specifically, co-ethnicity between ethnic minority investors and entrepreneurs increases the likelihood of receiving promotion-focused questions / feedback by up to 74% above the baseline probability (of receiving a promotion-focused question / feedback). We do not find evidence of this effect among White or Asian co-ethnic investors and entrepreneurs. Thus, we find partial support for Hypothesis 1a.

In Table 2.7, we perform similar analyses to test Hypothesis 1b which predicts a negative relationship between co-ethnicity and the likelihood of prevention-focused questions. We present the results of 3 LPM specifications, where the dependent variable is *prevention.* In model (1), we include only main and interaction ethnicity co-variates with competition-level fixed effects. In model (2), we introduce entrepreneur-level and venture-level controls. Model (3) presents the full model specification, including control variables and fixed effects at the competition, venture, entrepreneur and investor levels. Based on the coefficients of the co-ethnicity interaction terms, we find no evidence of the effect of co-ethnicity on the likelihood of prevention-focused feedback / questions for any of the ethnicity groupings identified. Thus, we find no support for Hypothesis 1b.

Together, our results suggest that within minority ethnic groups, co-ethnicity between an entrepreneur and investor may bias the investor toward positive evaluation of the venture, as evidenced by the higher likelihood of promotion-focused questions / feedback. To understand if this finding is unique to co-ethnic investors and entrepreneurs of minority ethnicities, we perform some additional analyses. First, we test if non-co-ethnic (i.e., White and Asian) investors are also more likely to positively evaluate ventures whose entrepreneurs are ethnic minorities. If this is the case, then the positive evaluation of ventures of ethnic minority entrepreneurs is not peculiar to ethnic minority investors. In addition, we test if ethnic minority investors are also more likely to positively evaluate ventures whose entrepreneurs are not co-ethnics (i.e., White and Asian). If this is the case, then the positive evaluation of ventures by ethnic minority investors is not peculiar to ethnic minority entrepreneurs.

In Table 2.8, we test the likelihood of ethnic minority entrepreneurs receiving more promotion-oriented and fewer prevention-oriented questions / feedback from White and Asian investors. In models (1) – (3), the dependent variable is *promotion*. Based on the magnitude of the coefficients of minority ethnicity entrepreneur interaction terms with both White and Asian investors, we find no evidence that minority ethnicity entrepreneurs receive more promotion-focused questions / feedback from non-co-ethnic investors. Similarly, in models (4) – (6), where the dependent variable is *prevention,* we also find no evidence that minority ethnicity entrepreneurs receive fewer prevention-focused questions / feedback from non-co-ethnic investors. Together, these results suggest that the ventures of minority ethnicity entrepreneurs do not receive more positive evaluation by non-co-ethnic investors.

In Table 2.9, we test the likelihood of ethnic minority investors asking / issuing more promotion-focused and fewer prevention-focused questions / feedback to White and Asian entrepreneurs. In models (1) – (3), the dependent variable is *promotion*. Based on the magnitude of the coefficients of minority ethnicity investor interaction terms with both White and Asian entrepreneurs, we find no evidence that minority ethnicity investors pose more promotion-focused questions / feedback to non-co-ethnic entrepreneurs. Similarly, in models (4) – (6), where the dependent variable is *prevention,* we also find no evidence that minority ethnicity investors pose fewer prevention-focused feedback / questions to non-co-ethnic entrepreneurs. Together, these results suggest that minority ethnicity investors do not evaluate ventures of non-co-ethnic entrepreneurs more positively.

From our additional analyses, we rule out alternative explanations for the co-ethnicity effect observed between ethnic minority investors and entrepreneurs. Thus, we conclude that within minority ethnic groups, co-ethnicity between an entrepreneur and investor is associated with more positive evaluation of the entrepreneur's venture.

Table 2.6: *Regulatory Focus (Promotion) and Co-ethnicity*

Notes: This table reports the linear probability model where the dependent variable measures the promotion focus of an investor's question / comment to an entrepreneur. The measure is expressed as a binary variable where 1 indicates that the question / comment is promotion-oriented and 0 otherwise. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

VARIABLES	(1) **Promotion**	(2) **Promotion**	(3) **Promotion**
investor_asian	0.010	0.016	-
	(0.060)	(0.061)	
investor_eth_minority	0.018	0.026	-
	(0.060)	(0.062)	
entrepreneur_asian	0.051	0.056	-
	(0.062)	(0.062)	
entrepreneur_eth_minority	0.012	0.022	-
	(0.063)	(0.063)	
investor_white#entrepreneur_white	0.011	0.021	-0.058
	(0.062)	(0.063)	(0.065)
investor_asian#entrepreneur_asian	-0.048	-0.048	-0.056
	(0.084)	(0.085)	(0.098)
investor_eth_minority#entrepreneur_eth_minority	-0.041	-0.047	0.279*
	(0.083)	(0.080)	(0.152)
entrepreneur_prev_ent_exp		-0.016	-
		(0.024)	
entrepreneur_adv_deg		-0.009	-
		(0.024)	
entrepreneur_ivy_plus		0.005	-
		(0.018)	
entrepreneur_tech		0.004	-
		(0.028)	
company_age		0.026	-
		(0.021)	
Constant	0.324***	0.327***	0.377***
	(0.061)	(0.069)	(0.038)
Observations	3,728	3,686	3,698
R-squared	0.011	0.012	0.208
Event FE	YES	YES	YES
Judge FE	NO	NO	YES
Founder FE	NO	NO	YES
N_clust	320	319	291

Table 2.7: *Regulatory Focus (Prevention) and Co-ethnicity*

Notes: This table reports the linear probability model where the dependent variable measures the prevention focus of an investor's question / comment to an entrepreneur. The measure is expressed as a binary variable where 1 indicates that the question / comment is prevention-oriented and 0 otherwise. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) **Prevention**	(2) **Prevention**	(3) **Prevention**
investor_asian	0.002	-	
	(0.027)	-	
investor_eth_minority	-0.023	-0.026	-
	(0.029)	(0.030)	
entrepreneur_asian	0.014	0.012	-
	(0.028)	(0.027)	
entrepreneur_eth_minority	-0.018	-0.021	-
	(0.025)	(0.024)	
investor_white#entrepreneur_white	-0.001	-0.003	0.017
	(0.029)	(0.030)	(0.043)
investor_asian#entrepreneur_asian	-0.011	-0.012	-0.009
	(0.038)	(0.037)	(0.052)
investor_eth_minority#entrepreneur_eth_minority	0.047	0.058	0.116
	(0.067)	(0.067)	(0.090)
entrepreneur_prev_ent_exp		0.003	
		(0.012)	
entrepreneur_adv_deg		-0.011	-
		(0.013)	
entrepreneur_ivy_plus		-0.008	-
		(0.008)	
entrepreneur_tech		0.011	-
		(0.013)	
company_age		-0.022**	-
		(0.011)	
Constant	0.065**	0.090***	0.054**
	(0.029)	(0.033)	(0.025)
Observations	3,728	3,686	3,698
R-squared	0.011	0.014	0.182
Event FE	YES	YES	YES
Judge FE	NO	NO	YES
Founder FE	NO	NO	YES
N_clust	320	319	291

2.6 Beyond Co-ethnicity: Additional Analyses

For a more complete understanding of the ethnicity-driven behavior of VC investors during new venture screening, we examine the likelihood of both promotion-oriented and prevention-oriented questions / feedback between all investor – entrepreneur ethnicity pairs. We present the results for promotion orientation in Table 2.10 and for prevention orientation in Table 2.11.

With respect to the likelihood of receiving promotion-oriented feedback / questions, in our full fixed effects model (column (3) of Table 2.10), we observe a significant negative effect of the *investor_ethnic_minority* and *entrepreneur_white* interaction term. The magnitude of the coefficient implies that ethnic minority investors evaluating White entrepreneurs are 20.6% less likely to ask / give promotion-oriented questions / feedback. One potential explanation is that ethnic minority investors scrutinize the ventures of White entrepreneurs more thoroughly prior to making investment decisions. However, testing if this is the case is beyond the scope of this paper. Nevertheless, it offers a potentially fruitful avenue for future research.

With respect to prevention-oriented feedback, we do not find any evidence of the influence of ethnicity-driven behavior by investors. While our full fixed effects model (column (3) of Table 2.11) explains only 18.3% of the variation in our sample, this result aligns with findings from our previous co-ethnicity analysis.

An issue that relates closely to ethnicity in venture capital investing is whether or not there is any apparent ethnicity-driven discrimination by White investors against non-White entrepreneurs. In our setting, this implies asking whether White investors are systematically more prevention-focused and less promotion-focused in evaluating ventures of entrepreneurs with whom they do not share ethnicity i.e., Asian and other ethnic minorities. We present results of our analyses predicting the likelihood of promotion-focused questions / feedback in Table 2.12 and prevention-focused questions / feedback in Table 2.13.

Our results provide no evidence of systematic discrimination by White investors against non-White entrepreneurs. It is not the case that if the investor is white, the likelihood of non-White entrepreneurs receiving promotion-focused questions / feedback experiences a significant decrease. Similarly, we do not find any evidence that if the investor is white, the likelihood of non-White entrepreneurs receiving prevention-focused feedback increases and is significant.

Table 2.8: *Regulatory Focus and minority ethnicity entrepreneurs*

Notes: This table reports the linear probability model where the dependent variable measures the regulatory focus of an investor's question / comment to an entrepreneur. In models (1) – (3), the dependent variable is *promotion*. In models (4)-(6), the dependent variable is *prevention*. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

		Promotion			**Prevention**	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
investor_asian	-0.016	-0.020	-	0.021	0.021	-
	(0.045)	(0.047)		(0.020)	(0.020)	
investor_white	-0.010	-0.011	-	0.021	0.023	-
	(0.042)	(0.044)		(0.017)	(0.017)	
entrepreneur_eth_minority	-0.040	-0.037	-	0.026	0.035	-
	(0.077)	(0.072)		(0.064)	(0.063)	
investor_white#entrepreneur_eth_minor.	0.037	0.035	-0.219	-0.049	-0.059	-0.133
	(0.080)	(0.075)	(0.153)	(0.067)	(0.067)	(0.086)
investor_asian#entrepreneur_eth_minor.	0.034	0.042	-0.303*	-0.033	-0.043	-0.108
	(0.092)	(0.090)	(0.159)	(0.068)	(0.067)	(0.084)
entrepreneur_prev_ent_exp		-0.015	-		0.003	-
		(0.023)			(0.012)	
entrepreneur_adv_deg		-0.012	-		-0.012	-
		(0.024)			(0.012)	
entrepreneur_ivy_plus		0.009	-		-0.006	-
		(0.018)			(0.008)	
entrepreneur_tech		0.004	-		0.012	-
		(0.028)			(0.013)	
company_age		0.027	-		-0.021*	-
		(0.021)			(0.011)	
Constant	0.353***	0.366***	0.358***	0.045***	0.068***	0.074***
	(0.040)	(0.048)	(0.011)	(0.015)	(0.022)	(0.006)
Observations	3,728	3,686	3,698	3,728	3,686	3,698
R-squared	0.010	0.011	0.207	0.011	0.013	0.182
Event FE	YES	YES	YES	YES	YES	YES
Judge FE	NO	NO	YES	NO	NO	YES
Founder FE	NO	NO	YES	NO	NO	YES
N_clust	320	319	291	320	319	291

Table 2.9: *Regulatory Focus and minority ethnicity investors*

Notes: This table reports the linear probability model where the dependent variable measures the regulatory focus of an investor's question / comment to an entrepreneur. In models (1) – (3), the dependent variable is *promotion*. In models (4)-(6), the dependent variable is *prevention*. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

		Promotion			**Prevention**	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
investor_eth_minority	-0.025	-0.024		0.024	0.033	
	(0.081)	(0.078)		(0.064)	(0.063)	
entrepreneur_asian	0.029	0.023		0.031*	0.032**	
	(0.034)	(0.034)		(0.016)	(0.016)	
entrepreneur_white	-0.004	-0.005	-	0.016	0.018	-
	(0.031)	(0.031)		(0.013)	(0.012)	
investor_eth_minor.#entrepreneur_asian	0.084	0.090	-0.172	-0.068	-0.081	-0.132
	(0.110)	(0.109)	(0.173)	(0.078)	(0.078)	(0.136)
investor_eth_minor.#entrepreneur_white	0.022	0.021	-0.249	-0.039	-0.049	-0.126
	(0.079)	(0.074)	(0.152)	(0.067)	(0.066)	(0.080)
entrepreneur_prev_ent_exp		-0.016	-		0.003	-
		(0.024)			(0.012)	
entrepreneur_adv_deg		-0.010	-		-0.011	-
		(0.024)			(0.013)	
entrepreneur_ivy_plus		0.005	-		-0.008	-
		(0.018)			(0.008)	
entrepreneur_tech		0.004	-		0.012	-
		(0.028)			(0.013)	
company_age		0.027	-		-0.022**	-
		(0.021)			(0.011)	
Constant	0.339***	0.353***	0.349***	0.047***	0.069***	0.069***
	(0.028)	(0.040)	(0.005)	(0.011)	(0.019)	(0.003)
Observations	3,728	3,686	3,698	3,728	3,686	3,698
R-squared	0.011	0.012	0.207	0.011	0.014	0.182
Event FE	YES	YES	YES	YES	YES	YES
Judge FE	NO	NO	YES	NO	NO	YES
Founder FE	NO	NO	YES	NO	NO	YES
N_clust	320	319	291	320	319	291

Table 2.10: *Regulatory Focus - Promotion (All Ethnicity Combinations)*

Notes: This table reports the linear probability model where the dependent variable measures the regulatory focus of an investor's question / comment to an entrepreneur. The dependent variable is *promotion*. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) **Promotion**	(2) **Promotion**	(3) **Promotion**
investor_ethnic_minority	-0.017	-0.022	
	(0.094)	(0.093)	
entrepreneur_asian	0.006	0.000	
	(0.095)	(0.096)	
investor_ethnic_minority#entrepreneur_asian	0.106	0.113	-0.171
	(0.132)	(0.133)	(0.185)
entrepreneur_white	0.005	-0.005	-
	(0.076)	(0.075)	
investor_ethnic_minority#entrepreneur_white	0.013	0.021	-0.328**
	(0.093)	(0.090)	(0.159)
investor_white	0.010	0.002	-
	(0.073)	(0.073)	
investor_white#entrepreneur_asian	0.026	0.028	0.007
	(0.096)	(0.097)	(0.112)
investor_white#entrepreneur_white	-0.011	0.000	-0.103
	(0.076)	(0.076)	(0.082)
entrepreneur_prev_ent_exp		-0.016	
		(0.024)	
entrepreneur_adv_deg		-0.010	
		(0.024)	
entrepreneur_ivy_plus		0.005	
		(0.018)	
entrepreneur_tech		0.004	
		(0.028)	
company_age		0.026	
		(0.021)	
Constant	0.331***	0.351***	0.413***
	(0.073)	(0.077)	(0.065)
Observations	3,728	3,686	3,698
R-squared	0.011	0.012	0.208
Event FE	YES	YES	YES
Judge FE	NO	NO	YES
Founder FE	NO	NO	YES
N_clust	320	319	291

Table 2.11: *Regulatory Focus - Prevention (All Ethnicity Combinations)*

Notes: This table reports the linear probability model where the dependent variable measures the regulatory focus of an investor's question / comment to an entrepreneur. The dependent variable is *prevention*. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) **Prevention**	(2) **Prevention**	(3) **Prevention**
investor_ethnic_minority	0.012	0.022	
	(0.064)	(0.063)	
entrepreneur_asian	0.010	0.011	
	(0.036)	(0.034)	
investor_ethnic_minority#entrepreneur_asian	-0.048	-0.060	-0.118
	(0.081)	(0.080)	(0.134)
entrepreneur_white	0.006	0.009	-
	(0.029)	(0.027)	
investor_ethnic_minority#entrepreneur_white	-0.029	-0.039	-0.106
	(0.069)	(0.068)	(0.081)
investor_white	-0.015	-0.013	-
	(0.031)	(0.030)	
investor_white#entrepreneur_asian	0.025	0.026	0.018
	(0.043)	(0.042)	(0.059)
investor_white#entrepreneur_white	0.013	0.012	0.026
	(0.034)	(0.034)	(0.048)
entrepreneur_prev_ent_exp		0.003	
		(0.012)	
entrepreneur_adv_deg		-0.011	
		(0.013)	
entrepreneur_ivy_plus		-0.008	
		(0.008)	
entrepreneur_tech		0.012	
		(0.013)	
company_age		-0.022**	
		(0.011)	
Constant	0.059**	0.080***	0.050
	(0.025)	(0.027)	(0.036)
Observations	3,728	3,686	3,698
R-squared	0.012	0.014	0.183
Event FE	YES	YES	YES
Judge FE	NO	NO	YES
Founder FE	NO	NO	YES
N_clust	320	319	291

Table 2.12: *Regulatory Focus - Promotion (White & Non-White Ethnicities)*

Notes: This table reports the linear probability model where the dependent variable measures the regulatory focus of an investor's question / comment to an entrepreneur. The dependent variable is *promotion*. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)
VARIABLES	**Promotion**	**Promotion**	**Promotion**
investor_white	0.019	0.012	
	(0.041)	(0.041)	
entrepreneur_white	-0.010	-0.016	
	(0.043)	(0.042)	
investor_white#entrepreneur_white	-0.020	-0.009	-0.068
	(0.047)	(0.046)	(0.052)
entrepreneur_prev_ent_exp		-0.015	
		(0.023)	
entrepreneur_adv_deg		-0.011	
		(0.024)	
entrepreneur_ivy_plus		0.005	
		(0.017)	
entrepreneur_tech		0.002	
		(0.028)	
company_age		0.027	
		(0.021)	
Constant	0.346***	0.362***	0.383***
	(0.038)	(0.045)	(0.031)
Observations	3,728	3,686	3,698
R-squared	0.010	0.011	0.207
Event FE	YES	YES	YES
Judge FE	NO	NO	YES
Founder FE	NO	NO	YES
N_clust	320.000	319.000	291.000

Table 2.13: *Regulatory Focus - Prevention (White & Non-White Ethnicities)*

Notes: This table reports the linear probability model where the dependent variable measures the regulatory focus of an investor's question / comment to an entrepreneur. The dependent variable is *prevention*. The unit of observation is the question / comment from an investor to an entrepreneur. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. "Investor FE" are investor fixed effects. "Entrepreneur FE" are entrepreneur fixed effects. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) **Prevention**	(2) **Prevention**	(3) **Prevention**
investor_white	0.007	0.008	
	(0.022)	(0.023)	
entrepreneur_white	-	0.002	
		(0.019)	
investor_white#entrepreneur_white	-0.007	-0.007	0.021
	(0.025)	(0.025)	(0.032)
entrepreneur_prev_ent_exp		0.004	
		(0.012)	
entrepreneur_adv_deg		-0.012	
		(0.012)	
entrepreneur_ivy_plus		-0.006	
		(0.008)	
entrepreneur_tech		0.011	
		(0.013)	
company_age		-0.021*	
		(0.011)	
Constant	0.063***	0.084***	0.052***
	(0.018)	(0.023)	(0.019)
Observations	3,728	3,686	3,698
R-squared	0.011	0.013	0.182
Event FE	YES	YES	YES
Judge FE	NO	NO	YES
Founder FE	NO	NO	YES
N_clust	320.000	319.000	291.000

2.7 Concluding Discussion

This study investigates the influence of co-ethnicity between investors and entrepreneurs on the regulatory focus of investors' evaluation of ventures. Narrowing our attention to the questions / feedback from investors to entrepreneurs in the course of venture screening, we evaluated if co-ethnicity increased the likelihood of promotion-focused feedback (which is associated with higher likelihood of investment) and relatedly if co-ethnicity reduced the likelihood of prevention-focused feedback (which is associated with lower levels / likelihood of investment). We hypothesized that the expected advantages of co-ethnicity to investors i.e., reduced pre-investment information asymmetry and improved post-investment monitoring and coordination, would reinforce positive (promotion-focused) evaluation / feedback and reduce negative (prevention-oriented) evaluation / feedback.

We tested and found partial support for our primary hypotheses. Our results reveal that within minority ethnic groups, co-ethnicity between an entrepreneur and investor is associated with more positive evaluation of the entrepreneur's venture by the investor. Specifically, co-ethnicity between ethnic minority investors and entrepreneurs increases the likelihood of receiving promotion-focused questions / feedback by up to 74% above the baseline probability (of receiving a promotion-focused question / feedback). We do not find evidence of this effect among White or Asian co-ethnic investors and entrepreneurs.

There are a number of potential explanations for our results. First, as hypothesized, co-ethnicity is expected to yield pre- and post- investment advantages which are attractive to investors purely from an investment cost perspective. Therefore, we expect to consistently observe the co-ethnicity effect across all the ethnic groups we examine. However, the fact that we observe this co-ethnicity effect only within minority ethnicity groups points to characteristics / dynamics that are unique to group. Thus, it is unlikely that the pre- and post- investment cost advantages fully explain our findings.

A second explanation for our results is that low-status ethnic minority investors face asymmetric investment premiums (not incurred by high-status mainstream investors), when investing outside (above) their status group. In VC and high-growth technology entrepreneurship today, White and Asian investors have largely become mainstream while Black, Native American, Native Hawaiian and other ethnic groups have remained severely under-represented and by definition, low-status. However, the reason why the status differential argument may not apply in this case is because in our setting, the investment cost for each venture is equal for all investors, despite their ethnicity. Therefore, we also find it unlikely that ethnicity – status investment premiums explain our findings.

The final and perhaps most likely explanation for our findings is that of ethnic solidarity, born out of shared adversity. One factor attributed to the limited representation of ethnic minority entrepreneurs in high-growth entrepreneurship is the challenges they face in acquiring financial capital in comparison to their mainstream peers (Kushnirovich &

Heilbrunn, 2008). In the early days of Silicon Valley, these funding challenges were faced by Asian immigrant entrepreneurs who represented the ethnic minority class at the time. In response, these ethnic minority entrepreneurs created entrepreneurial support networks on the basis of their shared cultural and professional experiences (Saxenian, 2002). These networks provided critical resources, including capital, to support the integration of these ethnic minority entrepreneurs into the mainstream technology community (Leng, 2002). In today's high-growth entrepreneurship landscape, the new ethnic minority class has shifted from Asian immigrant entrepreneurs to Black, American Indian / Alaskan Native and Native Hawaiian / Pacific Islander entrepreneurs. Therefore, it is plausible to expect investors from this ethnic minority group to support co-ethnic entrepreneurship using resources available to them. In this case, this translates into more favorable comments / feedback which by itself is associated with higher likelihood of investment but may also indirectly improve the attractiveness of these ventures to other investors.

Previous findings highlight the positive influence of co-ethnicity in investor-entrepreneur matching(Bengtsson & Hsu, 2015; Hegde & Tumlinson, 2014; Zhang et al., 2016). However, while these studies argue that co-ethnicity may override observable venture quality considerations, they are unable to directly observe how these quality signals are interpreted by investors. Our study closes this gap by directly analyzing whether or not co-ethnicity influences investors' evaluation of ventures for investment through direct feedback / questions to entrepreneurs. Our results highlight that rather than being systematically widespread among investors, the likelihood of favoritism in venture evaluation due to co-ethnicity between investors and entrepreneurs is higher among ethnic minorities.

A key implication of this finding for practitioners is that ethnic diversity in venture capital investment decision-making is important. Irrespective of which investors exhibit biases, balanced ethnic representation helps to ameliorate any (negative) effect of these biases on the quality of investment decisions. By minimizing the effect of biases and maximizing the use of available information, this collaborative ethnic diversity could increase the representation of marginalized ethnic groups in entrepreneurship. However, this recommendation is only effective if there is ethnic diversity in the supply pipeline of VC investors.

We acknowledge a number of limitations to the generalizability of our results. First and foremost, while new venture competitions allow close examination of venture evaluation dynamics that are difficult to observe first-hand, there may be other aspects of the evaluation process (for instance, pre-investment due diligence checks), that may influence the final investment decision. In addition, the style / structure of investment decision-making in VC firms may vary. Investment decisions may be made unanimously, by majority vote, veto power, or by individual choices of relevant managing partners. Our research setting and results are most reflective of decision-making by consensus and may not be applicable to other decision-making styles. Finally, our ethnic grouping strategy is not granular enough to account for specific intra-ethnic differences that may exist within ethnic sub-groups. Therefore, there may be heterogeneity in investor behavior within our ethnic groupings that are not visible from our analysis.

Chapter 3

The Role of Self-Promoting Language in New Venture Screening

3.1 Introduction

Entrepreneurship scholars have identified a variety of impression management behaviors which resource-seeking entrepreneurs enact with the objective of securing critical funding from investors. These behaviors function to positively influence investors' perceptions of the entrepreneurs and their ventures, resulting in favorable investment decisions (Bolino *et al.*, 2008). In the context of early-stage venture investing, one noteworthy impression management behavior exhibited by entrepreneurs is self-promotion (Nagy et al., 2012). Self-promotion refers to the practice of highlighting or emphasizing one's qualities and achievements to positively influence the perception of one's competence (Bolino et al., 2008). This behavior, enacted primarily through the use of positive language, has been found to positively influence investor perception, when not overused(Nagy et al., 2012; Parhankangas & Ehrlich, 2014b).

However, extant research rarely highlights the specific dimensions / aspects of language-based self-promotion which influence investors' perceptions of entrepreneurs and their ventures. Thus, the question of which specific personal attributes / traits benefit from language-based self-promotion in the context of new venture financing remains largely unanswered. We argue that answering this question improves our understanding of the mechanism through which self-promotion influences venture funding outcomes. This knowledge is also beneficial for educators and practitioners of entrepreneurship. A clearer understanding of the effect of specific self-promotion language techniques helps educators be more effective in their pedagogical approach to entrepreneurial education. For entrepreneurs, this knowledge is useful for creating and delivering more engaging and effective pitches to investors.

Our study aims to address this research gap by examining specific personal attributes / traits promoted via language by entrepreneurs and their relationship with venture funding decisions by VC investors. For consistency and completeness, we consider the traits identified by the most widely studied and applied model of personality categorization, the Five Factor Model (FFM) (Costa & McCrae, 1992; Digman, 1990) (commonly referred to as the Big Five(Goldberg, 1990)). This comprehensive framework describes a universal and empirically-derived set of enduring and stable behavioral traits which have been linked to entrepreneurial performance outcomes (Zhao et al., 2010; Zhao & Seibert, 2006).

Our research setting is TechCrunch Disrupt, one of the most prestigious competitions in the world for technology startups seeking venture capital. Our analysis covers competition events across 4 locations – New York, San Francisco, London and Berlin – from 2010 to 2017. Using textual transcriptions of entrepreneurial pitch presentations to VC investors, we measure the extent to which the language of a pitch promotes various FFM personality traits, based on prior psycholinguistic research linking personality traits to distinctive linguistic characteristics (Holtgraves et al., 2014). We use these measures to investigate the relationship between traits self-promoted via the language of entrepreneurial pitches and VC funding outcomes, proxied by competition outcomes.

Our results provide evidence that self-promoting language which emphasizes *extraversion* is correlated with positive VC funding outcomes in later stages of the venture screening where variance in venture quality is expectedly lower. In other words, entrepreneurs who communicate higher levels of energy and enthusiasm via language are 13.5% more likely to receive venture funding, provided their ventures meet certain baseline quality standards. In our study, this quality certification requirement is conferred by the ability of a venture to advance through to the final round of the competition. We also find evidence that entrepreneurs who communicate higher levels of *extraversion* are evaluated more positively by investors while those who communicate higher levels of *neuroticism* are evaluated more negatively.

With regard to why *extraversion* yields a significant positive effect on VC funding outcomes and garners more positive evaluation by investors, we argue that beyond having a viable venture, the most important determinant of the success of a venture is the ability of the entrepreneur to communicate persuasively with a diverse range of constituents including investors, partners, employees and customers to secure critical resources that drive venture performance. The inability of an entrepreneur to garner financial and non-financial resources from key stakeholders likely eliminates any chance of venture success. Thus, entrepreneurs who communicate more enthusiasm and energy – key characteristics of *extraversion* -- are likely better at persuading VC investors of the venture's investment potential (see Beukeboom, Tanis and Vermeulen (2013); Clarke, Cornelissen and Healey (2019)).

On the other hand, we argue that the relationship between *neuroticism* and less favorable evaluation by investors is explained by the fact that lack of emotional stability – which characterizes *neuroticism* – is perceived by investors as undesirable to venture success. The often-unstructured work environment of new ventures coupled with the high level of personal responsibility demanded, requires remarkable emotional stability and resilience from the entrepreneur if the venture is to succeed. Thus, entrepreneurs who communicate higher levels of *neuroticism* are likely evaluated by investors as being less likely to succeed. While we do not observe a direct negative relationship between *neuroticism* and venture funding outcomes, our results still suggest that it is detrimental to investment-seeking entrepreneurs.

Our study makes two distinct contributions. We contribute to the impression management literature by providing the first known examination of the relationship between FFM personality traits promoted via the language of entrepreneurial pitches and VC funding outcomes. Previous studies examining language-based self-promotion by entrepreneurs rarely identify any specific dimensions along which the behavior takes place. For the few studies that do (e.g. Balachandra, Fischer and Brush, 2021), no comprehensive behavioral framework is considered. This makes it challenging to coherently synthesize research findings and misses out on identifying more granular elements of the behavior. Our study addresses these research gaps by identifying not only which aspects of language-based self-promotion matter, but also the conditions under which we expect them to be (most) important.

In addition, we contribute empirically to the FFM literature by highlighting the ability of the language of an entrepreneurial pitch to convey personality information. Traditional personality studies rely on self-reported surveys which are "notoriously unreliable" in accurately defining personality traits(Chung & Pennebaker, 2018). Language analysis has the advantage of being more reliable and convenient and benefits from robust computational support. Our study is the first we are aware of that utilizes entrepreneurial pitches to measure FFM personality traits.

The rest of the study proceeds as follows. In Section 3.2, we develop our hypotheses. Section 3.3 describes the empirical setting, data and measures. Section 3.4 presents our main results. Section 3.5 presents the results of additional analyses. Section 3.6 discusses our findings. Section 3.7 highlights the limitations of the study. Section 3.8 concludes.

3.2 Theory & Hypotheses

3.2.1 Entrepreneurial pitches & venture financing outcomes

New ventures are typically faced with severe resource constraints and limited bargaining power. Thus, entrepreneurs expend considerable time and effort to communicate about their ventures to secure investments. Their approach to this communication matters (Bird & Schjoedt, 2009) and entrepreneurs generally use two broad categories of communication to this end: textual and verbal(Clarke, Cornelissen, Healey, et al., 2019). Textual communication takes the form of written text that is designed to be sent to or accessed by investors (Giorgi & Weber, 2015; Martens et al., 2007b) and include email pitches, pitch decks, and business plan documents. Verbal communication takes the form of formal and informal conversations (typically in-person) and include formal pitch presentations and meetings. In this paper, we focus on verbal communication, specifically examining formal entrepreneurial pitch presentations.

The current "industry standard" for entrepreneurial pitches (Clarke, Cornelissen, & Healey, 2019) employed in a considerable number of new venture competitions, investment meetings and incubator programs involves a 5-10 minute presentation given by entrepreneurs to investors to provide an overview of the venture and demonstrate product / service features (Brooks et al., 2014b).   Such pitches are characterized by high levels of uncertainty as investors have to evaluate the viability of the venture based on limited information provided during the presentation and from subsequent time-constrained question-and-answer sessions. Extant research suggests that investors use a combination of formal analysis of venture viability information -- such as market forecasts, financial projections etc. – and subjective assessment of the entrepreneur to make investment selection decisions(Huang & Pearce, 2015).

3.2.2 Impression management in entrepreneurial pitches

Impression management is the process through which an actor attempts to influence the perceptions that an audience forms of the actor in the context of a social interaction (Goffman, 1959). The underlying assumption is that a certain level of uncertainty about the actor exists, resulting in a cognitive gap on the part of the audience(Nagy et al., 2012). This allows the actor to use certain behavioral techniques to bridge the cognitive gap and subsequently influence the audience's perceptions.

In the context of new venture financing, impression management focuses on how resource-seeking entrepreneurs present themselves and their ventures to investors with the objective of being perceived favorably, and ultimately securing investments(Parhankangas & Ehrlich, 2014a). Extant research has identified several impression management behaviors which entrepreneurs employ to positively influence investors' perceptions and subsequent investment-related decisions(Bolino et al., 2008; Nagy et al., 2012; Parhankangas & Ehrlich, 2014a). We focus one of these behaviors – self-promotion.

Self-promotion refers to the practice of highlighting or emphasizing one's qualities, abilities and achievements to positively influence the perception of one's competence(Bolino et al., 2008). Extant literature provides evidence that the use of self-promotion in entrepreneurial pitches is positively correlated with progress in the venture funding process and subsequent outcomes, provided investors do not perceive the entrepreneur's claims to be overblown or dishonest (Nagy et al., 2012; Parhankangas & Ehrlich, 2014a). Self-promotion in entrepreneurial pitches is enacted primarily through the use of positive language that promotes qualities of the entrepreneur that are associated with venture success. In combination with more objective venture viability information, such linguistic choices can improve the ability of investors to identify ventures with return-maximizing potential(Clingingsmith & Shane, 2017).

3.2.3 The Five-Factor Model (FFM) of personality traits and entrepreneurial outcomes

In psychology, the most widely studied and applied model of personality categorization is the Five Factor Model (FFM) (Costa & McCrae, 1992; Digman, 1990) (commonly referred to as the Big Five(Goldberg, 1990)), which describes a universal and empirically-derived set of enduring and stable behavioral traits (Chung & Pennebaker, 2018). The five traits of the model are *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness*, and *Neuroticism*. Extant research provides evidence that these personality traits are correlated with entrepreneurial career intentions (Crant, 1996; Zhao et al., 2005, 2010), venture funding outcomes (Murnieks, Sudek and Wiltbank, 2015) and subsequent venture performance (Zhao et al., 2010).

With respect to VC investment selection, Gompers *et al.* (2020) find that majority of early-stage VC investors rank the ability of the entrepreneur to be the most important determinant of success and failure of a new venture. Therefore, we expect that, given a certain baseline of venture quality, entrepreneurs who convincingly highlight / emphasize those traits that are correlated with venture performance will receive more favorable investment outcomes. In other words, we expect self-promotion of certain personality traits to be beneficial.

Openness (To Experience) is characterized by intellectual curiosity and a tendency to embrace novel ideas and new experiences. A person who ranks high on *openness* tends to be creative, imaginative and unconventional. On the other hand, a person who ranks low on openness tends to be more conventional and have narrow interests(Costa & McCrae, 1992; Zhao & Seibert, 2006). There is evidence that *openness* is strongly positively correlated with both entry into entrepreneurship and venture growth (Zhao et al., 2010) as founding a high-growth new venture often requires an entrepreneur to explore innovative ways to solve problems, develop products / services and choose business strategies. We expect early-stage VC investors to recognize *openness* as an entrepreneurial success factor. Therefore, we predict that:

Hypothesis 1. The level of *openness* communicated via the language of an entrepreneurial pitch is positively correlated with the likelihood of receiving VC funding.

Conscientiousness describes the degree to which a person is organized, persistent, and motivated to accomplish a goal(Costa & McCrae, 1992; Zhao & Seibert, 2006). Conscientiousness is also consistently positively correlated with both entry into entrepreneurship and venture growth (Zhao et al., 2010) as founding a high-growth new venture is often fraught with challenges and resource constraints that require persistence and motivation to surmount. We expect early-stage VC investors to recognize *conscientiousness* as an important factor for entrepreneurial success. Therefore, we predict that:

Hypothesis 2. The level of *conscientiousness* communicated via the language of an entrepreneurial pitch is positively correlated with the likelihood of receiving VC funding.

Extraversion describes the extent to which a person is energetic, enthusiastic and assertive when interacting with others(Costa & McCrae, 1992). Highly extraverted people tend to be cheerful and social. Less extraverted people tend to prefer to spend time alone and are often more reserved (Zhao & Seibert, 2006). Extraversion has been found to be positively correlated with entrepreneurial performance (Zhao et al., 2010) . Entrepreneurs often need to communicate persuasively with investors, partners, employees and customers to ensure venture success. Consequently, we expect VC investors to value *extraversion* in entrepreneurs. Therefore, we predict that:

Hypothesis 3. The level of *extraversion* communicated via the language of an entrepreneurial pitch is positively correlated with the likelihood of receiving VC funding.

Agreeableness describes the interpersonal orientation of an individual. People who score high on agreeableness are characterized as trusting, altruistic and gullible(Zhao & Seibert, 2006). People who score low on agreeableness can be characterized as self-centered, manipulative and ruthless (Costa & McCrae, 1992). For an entrepreneur, while agreeableness may foster trust and cooperation with investors, employees and customers, excessive levels of agreeableness may inhibit their ability to drive hard bargains and make difficult decisions to guarantee venture success. Consequently, we expect VC investors to value moderate levels of *agreeableness* in entrepreneurs. Therefore, we predict that:

Hypothesis 4. The level of *agreeableness* communicated via the language of an entrepreneurial pitch has a curvilinear relationship with the likelihood of receiving VC funding, with both high and low levels of *agreeableness* being associated with a lower likelihood of receiving VC funding.

Neuroticism represents differences in the level of adjustment and emotional stability across individuals (Zhao & Seibert, 2006). People who score high on neuroticism tend to experience a range of negative emotions such as anxiety, hostility, self-consciousness and vulnerability (Costa & McCrae, 1992). On the other hand, people who score low on neuroticism tend to be emotionally-stable and even-tempered(Kerr et al., 2018). Neuroticism has been found to be negatively correlated with entrepreneur performance (Zhao et al., 2010). The often-unstructured work environment of a new venture coupled with the high level of personal responsibility demanded, requires remarkable emotional stability and resilience from the entrepreneur if the venture is to succeed. Consequently, we expect VC investors to consider *neuroticism* to be an undesirable trait for entrepreneurs. Therefore, we predict that:

Hypothesis 5. The level of *neuroticism* communicated via the language of an entrepreneurial pitch is negatively correlated with the likelihood of receiving VC funding.

3.3 Method

3.3.1 Setting & Data

Startup competitions are critical opportunities for entrepreneurs to articulate their venture's business propositions not only to competition judges but also to other potential investors. If the judges / investors form negative impressions of the entrepreneur or venture during these presentations, the entrepreneur is highly unlikely to obtain funding (Lounsbury & Glynn, 2001; Martens et al., 2007a).

"TechCrunch Disrupt is widely regarded as the most prestigious setting in which high-tech startups can launch"(Kanze et al., 2018). Since its inception in 2007, the 763 startups that presented at the competition have raised a total of $8.8 billion in funding, with 109 having been acquired or gone public. Notable TechCrunch Disrupt alumni include Yammer, Dropbox and Qwiki.

The competition takes place across a number of locations, once a year each. These locations include San Francisco, New York, London and Berlin. Online applications to each competition open three months before the actual event. TechCrunch reviews applicants and selects contestants based on their team, product and market potential. Selection is highly competitive and acceptance rates range between 3% to 6%. Typically, the number of accepted startups in each competition ranges between 15 and 30. These startups get the opportunity to pitch to panels of 4 - 6 judges (judges) in a style similar to an investment pitch meeting. These judges are prominent Silicon Valley VCs and technologists and include figures like Marissa Mayer – former CEO of Yahoo, Roelof Botha – a partner at Sequioa Capital, a prominent VC firm - etc.

The competition takes place over the course of 3 days across 2 stages – a semi-final and final round. Competing startups are allocated 6 minutes for their pitch presentation followed by a question-and-answer session with the panel of judges. Each team is scored by each judge and the scores are collated by TechCrunch. The highest scoring startups, typically 4 – 6 in number, proceed to the final round. In the final round, the startup entrepreneurs repeat the presentation to a new independent set of judges, participate in a question-and-answer session and are scored by individual judges. After the scores are collated by TechCrunch, the highest scoring team from the final round wins the competition and the $100,00 prize.

Our sample comprises the data set of startups that participated in TechCrunch Disrupt from 2010 – 2017 across 4 locations: New York, San Francisco, London and Berlin. During this period, a total of 349 startup firms competed with 96 first-round winners and 19 final-round winners.

Our list of participating startups was gathered manually from the TechCrunch Disrupt website. The records of conversations between entrepreneurs and judges were obtained by transcribing publicly available video footage of each pitch session to text via YouTube's automated speech-to-text feature. Supporting information on the profile of the participating startups was obtained manually from Crunchbase, a publicly available database maintained by TechCrunch.

Using TechCrunch Disrupt as our research setting provides a number of important benefits. First, it permits full observation of the pitch presentation and Q&A sessions based on complete and publicly available video footage hosted on YouTube. This has the added benefit of allowing speaker identification and automated speech-to-text transcription of verbal exchanges between entrepreneurs and screening panels. Furthermore, the enforced time limits for both presentation and Q&A sessions across all events minimizes the variability of the conditions across which competing startups are evaluated and allows for robust comparison of screening processes and outcomes across various competitions. Yet another benefit of this research setting is that TechCrunch maintains a database, Crunchbase, which makes background information on the participating startups publicly available. This information includes the names of founders, founding date, business category, operating status and company description. Finally, participation is open only to companies that demonstrate a need for venture capital. Thus, we are able to eliminate variability regarding the founders' intentions and funding needs (Kanze et al., 2018).

3.3.2 Measures

3.3.2.1 Dependent variables

As described in the previous section, competition judges comprise primarily of seasoned VC investors, who select finalists and winners across the 2 rounds of the competition. Thus following prior literature on startup competitions (e.g. Balachandra *et al.*, 2019; Balachandra, Fischer and Brush, 2021), we use finalist/winner selection across the 2 rounds of the competition. This yields 2 dependent variables: *winner_stage_1* is a binary variable which is equal to 1 if a venture succeeds in the 1st round and advances to the final (2nd) round of the competition and; *winner_stage_*2 is a binary variable which is equal to 1 if a venture subsequently emerges from the 2nd round of the competition as the overall winner.

3.3.2.2 Independent variables

Prior psycholinguistic research has established the link between personality traits and use of language (Chung & Pennebaker, 2018; Holtgraves et al., 2014; Pennebaker & King, 1999).

These findings have fueled the development of new personality prediction techniques and tools that use spoken word and written text as inputs. This marks a leap (in terms of scalability and reliability) from the more traditional methods of personality analysis which rely on self-reported surveys. We provide a summary of the FFM personality traits and corresponding linguistic markers in Table 3.1.

We transcribe the pitch presentations and answers given by entrepreneurs into text and analyze the corresponding personality dimensions using *Receptiviti*[5]. *Receptiviti* is the commercial variant of Linguistic Inquiry and Word Count (LIWC) (Chung & Pennebaker, 2013; Pennebaker et al., 2007) which has been used for psycholinguistic research for over 30 years. It quantifies language samples along a number of social, motivational and psychological dimensions based on the structure and content of text inputs. With respect to the FFM measures of personality, its outputs have been validated by comparing them to those from traditional scale-based questionnaires (Obschonka et al., 2017; Yarkoni, 2010). *Receptiviti* generates 5 continuous variables corresponding to the 5 personality traits of the FFM: *Openness, Conscientiousness, Extraversion, Agreeableness* and *Neuroticism.* These variables measure the extent to which the language of a given text input reflects each of the 5 measures of personality traits.

3.3.2.3 Control variables

To control for the informational quality of the entrepreneurial pitches and answers, we construct (using corresponding keywords), 4 dummy variables which measure whether or not an entrepreneur provides information related to each of the 4 primary venture viability assessment criteria demanded by investors i.e. (1) product/service attractiveness, (2) market/competitive conditions, (3) entrepreneur/team capabilities, and (4) financial returns if the venture is successful (Hall & Hofer, 1993; Macmillan et al., 1985, 1987; Tyebjee & Bruno, 1984; Zacharakis & Meyer, 1998). However, since every pitch focuses on the product, we omit the product dummy variable to produce a continuous *completeness* measure based on the mean of the remaining 3 variables. The keywords used are provided in Appendix Table A1.

[5]Available at www.receptiviti.com/personalityinsightsdemo

Table 3.1: *Personality traits and linguistic markers*

Note. Adapted from (Holtgraves et al., 2014; RECEPTIVITI, 2021)

Personality Trait	Description	High Score Definition	Low Score Definition	Linguistic Indicators
Openness	This measure and its facets examine the degree to which a person is open to new ideas or new experiences.	A high score suggests an individual is significantly emotional, creative, and imaginative.	A low score suggests that an individual is more conventional, predictable, and practical.	articles (+), prepositions (+), personal pronouns (-), family (-), home (-), rest (-)
Conscientiousness	This measure and its facets examine the degree to which a person is reliable, organized, disciplined, and deliberate.	A high score suggests an individual is significantly organized, disciplined, and deliberate	A low score suggests that an individual is more impulsive, careless, or disorganized.	swearing (-), negative emotion (-)
Extraversion	This measure and its facets examine the degree to which a person feels energized or uplifted when interacting with others.	A high score suggests an individual is significantly sociable, out-going, and socially assertive.	A low score suggests that an individual is more reserved, reflective, dislikes being the center of attention.	second-person pronouns (+), first-person plural pronouns (+), positive emotion (+), social (+), leisure (+), sex (+), inhibition (-), tentativeness (-)
Agreeableness	This measure and its facets examine the degree to which a person is inclined to please others.	A high score suggests an individual is significantly cooperative, trusting, and well-liked.	A low score suggests that an individual is more critical, demanding, and unsympathetic.	positivity (+), first-person singular pronouns (+), social (+), home (+), family (+), communication (+), death (-), money (-), swearing (-)
Neuroticism	This measure and its facets examine the degree to which a person expresses signs of anxiety, unhappiness, pessimism, or depression.	A high score suggests an individual is significantly anxious, unhappy, pessimistic, or depressed.	A low score suggests that an individual is more calm, resilient, and confident.	first-person singular pronouns (+), negative emotion (+)

Table 3.2: *Description of main variables*

Variable	Description
winner_stage_1	Dummy variable equal to 1 if a startup advances through the 1st round of the competition. 0 otherwise.
winner_stage_2	Dummy variable equal to 1 if a startup advances through the 2^{nd} (final) round of the competition. 0 otherwise.
Openness	Continuous variable that measures the level of Openness of an entrepreneur
Conscientiousness	Continuous variable that measures the level of Conscientiousness of an entrepreneur
Extraversion	Continuous variable that measures the level of Extraversion of an entrepreneur
Agreeableness	Continuous variable that measures the level of Agreeableness of an entrepreneur
Neuroticism	Continuous variable that measures the level of Neuroticism of an entrepreneur
completeness	Continuous variable that measures the extent to which a pitch provides relevant information about venture viability assessment criteria (i.e., market potential, financial information & entrepreneur / team characteristics)
word_count	Continuous variable that measures the (log) length (i.e. number of words) of the pitch.
B2C	Dummy variable equal to 1 if the startup is a Business-to-Consumer (B2C) firm and 0 if it is a Business-to-Business (B2B)
entrepreneur_female	Dummy variable equal to 1 if the entrepreneur is female, 0 for male
entrepreneur_adv_deg	Dummy variable equal to 1 if the entrepreneur has an advanced degree e.g., Masters, MD, JD, PhD etc.
entrepreneur_ivy_plus	Dummy variable equal to 1 if the entrepreneur has a graduate or undergraduate degree from Brown, Caltech, Univ. of Chicago, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, Univ. of Pennsylvania, Princeton, Yale, Stanford, Cambridge, Oxford, Ecole Polytechnique, and Ecole Normale Superieur (Bengtsson & Hsu, 2015).
entrepreneur_tech	Dummy variable equal to 1 if the entrepreneur has previous experience working at the major big tech companies i.e., Facebook, Apple, Amazon, Netflix, Microsoft or Google. 0 otherwise.
promotion	Dummy variable equal to 1 if an investor's question / feedback is predominated by promotion-focused terms. 0 otherwise.
prevention	Dummy variable equal to 1 if an investor's question / feedback is predominated by prevention-focused terms. 0 otherwise.

We identify educational information and previous work experience of the entrepreneurs from profile information from Crunchbase and LinkedIn. Based on this information we construct 4 dummy variables which are equal to 1 if the entrepreneur has an advanced degree e.g. Masters, PhD, MD etc., attended an *Ivy League Plus* school – undergraduate or graduate degree from Brown, Caltech, University of Chicago, Columbia, Cornell, Dartmouth, Duke, Harvard, MIT, University of Pennsylvania, Princeton, Yale, Stanford, Cambridge, Oxford, Ecole Polytechnique, and Ecole Normale Superieur (Bengtsson & Hsu, 2012), worked for any of the top-performing big technology companies – Facebook, Apple, Amazon, Netflix, Google and Microsoft, and has previously been the founder or co-founder of a company. Similarly, we identify gender information for both entrepreneurs and investors and code them using dummy variables that take on values of either 1 (indicating female) or 0 (indicating male).

3.3.3 Summary statistics

We begin in Table 3.3 by examining the composition of entrepreneurs and investors in our sample. In Panel A, out of a total of 349 entrepreneurs, we observe that male entrepreneurs make up 84.8% while female entrepreneurs account for 15.9%. For investors, the gender distribution is more balanced with about female investors accounting for almost a third of the sample, while male investors account for about 68% of the total of 356. With respect to education and work experience summarized in Panel B, 82.2% of the entrepreneurs in our sample have advanced degrees, 35.8% attended prestigious *Ivy League Plus* universities, and 11.46% are former employees of major technology companies.

In Table 3.4, we report firm-level and competition-level statistics across the 19 competition events in our sample. The total number of ventures in the sample is 349 with an average number of 18.4 competing ventures per event. With respect to the business models, 179 ventures are business-to-consumer (B2C) while the remaining 170 are business-to-business (B2B) ventures. A total of 94 ventures advance through the 1st round of the competition and subsequently, there are 19 overall (2nd round) winners. There are a total of 355 distinct screening panels with an average size of 4.7 in the 1st round and 5.3 in the 2nd round.

Table 3.3: *Individual-level Statistics*

The table reports the summary statistics for the sample of entrepreneurs and investors by gender and ethnicity from 19 TechCrunch Disrupt startup competition events between 2010 and 2017. % values represent percentage of group totals in the sample.

Panel A

Entrepreneur			**Investor**		
Gender	Obs.	% of total	Gender	Obs.	% of total
Male	296	84.81	Male	242	67.98
Female	53	15.19	Female	114	32.02
Total	349	100	Total	356	100

Panel B: *Entrepreneur characteristics*

	Obs.	**% of Total**
Advanced Degrees (e.g., PhD, Master's etc.)	287	82.23
Ivy-League-Plus Alma Mater	125	35.82
Previous *Big Tech* Experience	40	11.46

Table 3.4: *Startup- and competition-level statistics*

The table reports the startup-level summary statistics from 19 TechCrunch Disrupt startup competition events between 2010 and 2017.

Panel A: *Startup statistics per competition*

	Obs	**Mean**	**Std.Dev.**	**Min**	**Max**
Startups	349	18.36	6.39	7	28
Business-To-Consumer (B2C)	179	10.60	4.84	3	16
Business-To-Business (B2B)	170	11.01	5.21	2	18
1st-stage winners	94	4.95	1.35	3	7
2nd-stage winners	19	1	0	1	1
Survived (>=3 years)	331	17.42	5.24	9	25
Survived (>= 5 yrs)	208	10.94	7.16	2	22

Panel B: *Competition level statistics*

	Obs	**Mean**	**Std.Dev.**	**Min**	**Max**
Screening Panels	355				
1st stage					
Investors	295	4.72	1.03	2	7
2nd stage					
Investors	60	5.32	1.06	4	7

Figure 3.1: *Distribution of FFM Personality Traits in Entrepreneurs (1st Round)*

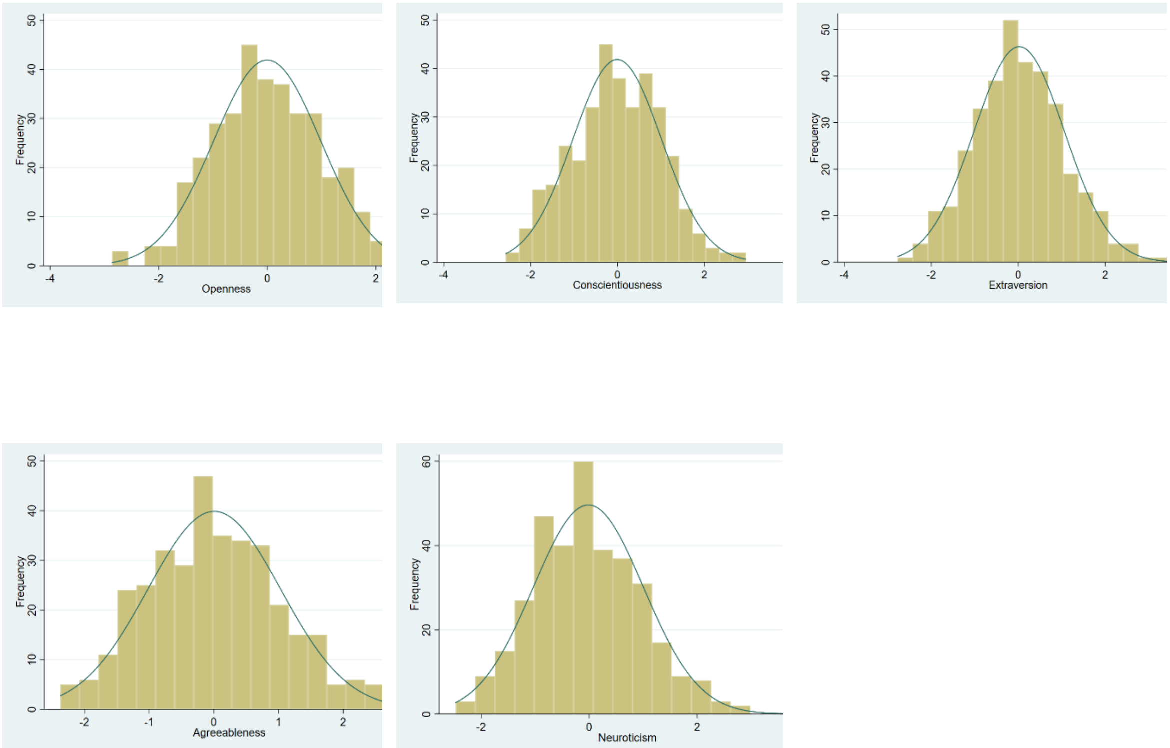
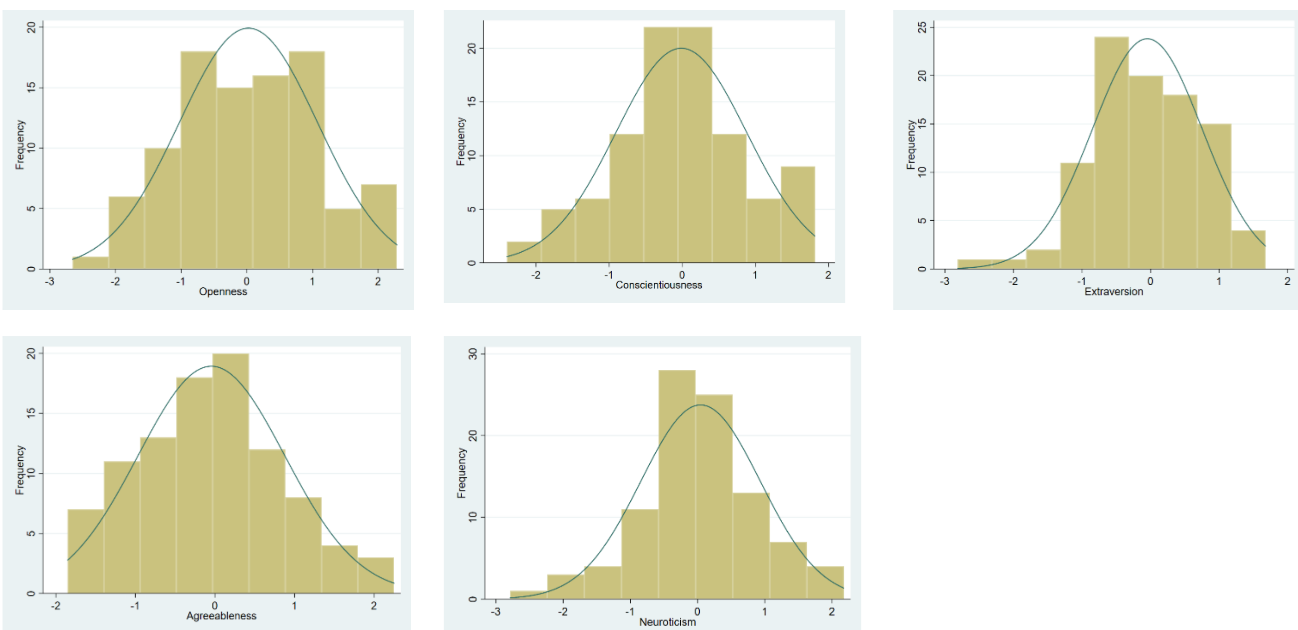


Figure 3.2: *Distribution of FFM Personality Traits in Entrepreneurs (2nd Round)*



Figures 3.1 and 3.2 present graphical representations of the distribution of personality measures for entrepreneurs across the competition. Across all 5 personality traits, the

sample is normally distributed. This provides evidence that our sample has sufficient variation across personality measures to test our hypotheses.

3.4 Results

We test our hypotheses by leveraging regression analysis of competition outcomes (in the 1st and 2nd rounds) against the five measures of personality generated by Receptiviti. We present intercorrelations of our main variables in Table 3.5. The results for 1st round competition are presented in Table 3.6. Models (1) – (4) present the results of analysis using linear probability model while models (5) – (8) use logit. Our results explain about 3% of the variation in the sample. However, across all models of 1st round competition outcomes, we find no significant personality terms.

We conduct similar analyses against 2nd round competition outcomes. This round is restricted to 1st round competition winners. We present our results in Table 3.7. Models (4) and (8) present the full models using both linear probability and logit specifications respectively. Our results explain 13.8% of the variation in the sample. Out of the 5 FFM variables, we find the coefficient of *Extraversion* to be positive and significant across both models. When we calculate the average marginal effects of the regression terms, we find that the use of language that communicates *extraversion* yields a 13.5% increase in the likelihood of receiving VC funding. No other personality measures yield significant results.

Combining the outcomes across both stages of the competition, we do not find support for the effect of *Openness* (Hypothesis 1), *Conscientiousness* (Hypothesis 2), *Agreeableness* (Hypothesis 4) and *Neuroticism* (Hypothesis 5) on VC's decision to invest. However, we find support for the positive association between the level of *Extraversion* communicated by an entrepreneurial pitch and VC investment likelihood (Hypothesis 3).

3.5 Additional Analyses

Kanze et al., (2018) provide evidence from Regulatory Focus Theory (RFT) showing that promotion-focused interactions between VC investors and entrepreneurs are associated with better funding outcomes than prevention-focused interactions. Promotion-focused interactions are characterized by emphasis on growth, advancement and potential rewards of a venture. On the other hand, prevention-focused interactions are concerned with risks, losses and how to avoid / mitigate them.

To gain a more complete understanding of how investors respond to personality traits promoted by entrepreneurs via language, we examine the regulatory focus of investors' questions / feedback following entrepreneurs' pitch presentations. We categorize the questions / feedback as being either promotion-focused or prevention-focused by calculating the proportion of promotion and prevention terms appearing in the transcribed text of each question / comment. These calculations are computed as continuous measures using the Linguistic Inquiry and Word Count (LIWC) software application (Chung & Pennebaker, 2013; Pennebaker et al., 2007). Following Kanze et al., (2018), we classify each question / comment as promotion-focused if the proportion of promotion terms is higher than the proportion of prevention terms. Similarly, a question / comment is prevention-focused if the proportion of prevention terms is higher than the proportion of promotion terms (see Appendix Table A2). This yields 2 binary variables: *promotion* and *prevention*. *Promotion* takes on the value of 1 if a question / comment is promotion-focused, 0 otherwise. Similarly, *prevention* is set to 1 for questions / comments that are prevention-focused, 0 otherwise. Using these 2 measures as dependent variables, we explore their relationship with the FFM personality traits promoted via the language of entrepreneurial pitches.

We use a logit model to estimate the likelihood of receiving either promotion-focused or prevention-focused feedback. We present our results in Table 3.8.

In models (1) - (3), the dependent variable is *promotion*. Controlling for entrepreneur and venture characteristics, we find the effect of *Extraversion* to be positive and significant, accounting for a 2% increase in the likelihood of receiving promotion-focused questions / feedback. We interpret this finding to indicate that investors evaluate entrepreneurs who communicate higher levels of *extraversion* more positively. We argue that this is likely because investors consider *extraversion* to be a desirable entrepreneurial trait. This provides additional evidence for our previous finding linking higher levels of *extraversion* to positive investment decisions by investors.

Similarly, in models (4) – (6), the dependent variable is *prevention.* Controlling for entrepreneur and venture characteristics, we find the effect of *Neuroticism* to be positive and significant, accounting for a 1.2% increase in the likelihood of receiving prevention-focused questions / feedback. This finding suggests that investors evaluate entrepreneurs who communicate higher levels of *neuroticism* more negatively. We argue that this likely because investors consider *neuroticism* to be undesirable for the entrepreneurs. While we do not find this trait to be negatively correlated with (positive) investment outcomes, its negative perception may still be detrimental to investment-seeking entrepreneurs.

3.6 Discussion

Our study examines the relationship between the Five Factor Model (FFM) personality traits self-promoted by entrepreneurs via the language of entrepreneurial pitches and subsequent venture funding decisions. Our results indicate a positive relationship between the level of *extraversion* communicated via the language of an entrepreneurial pitch and the likelihood of receiving VC funding. However, we find this relationship materializes only in later stages of the investment selection process. Furthermore, we find evidence that investors evaluate entrepreneurs who communicate higher levels of *extraversion* more positively and those who communicate higher levels of *neuroticism* more negatively.

As discussed earlier, the primary objective of VC investors is to identify return-maximizing venture investment opportunities. Therefore, in line with findings from prior research, we expect VC investors to prioritize objective venture quality information such as financial records and market projections (Huang & Knight, 2017). However, VC investors may rely on additional qualitative factors such as the ability and behavior of the entrepreneur, to complement objective venture quality information in the decision-making process. In other words, VC investors establish that ventures meet a certain viability standard before other decision-making factors are considered.

We argue that winning the 1st round of the competition functions as a certification of the quality of a venture (de Rassenfosse & van den Heuvel, 2020; Howell, 2019). By implication, in the 2nd (final) round of the competition, the variance of quality of competing ventures is expectedly lower than in the 1st round.

Table 3.5: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) winner_stage_2	1													
(2) winner_stage_1	0.303*	1												
(3) Openness	-0.081	0.017	1											
(4) Conscientious	0.052	0.009	-0.346*	1										
(5) Extraversion	-0.011	-0.018	0.055	0.469*	1									
(6) Agreeableness	-0.045	-0.017	0.084	0.493*	0.611*	1								
(7) Neuroticism	0.036	0.035	-0.101*	-0.247*	-0.474*	-0.454*	1							
(8) completeness	0.017	0.082	-0.010	0.075	0.122*	0.094	-0.074	1						
(9) word_count	0.061	0.186*	0.062	-0.038	-0.102*	-0.029	0.119*	0.233*	1					
(10) b2c	0.088	-0.018	-0.090	-0.036	-0.036	0.006	0.036	0.035	-0.100*	1				
(11) ent_female	-0.017	-0.119*	-0.039	0.029	0.027	0.014	-0.094	-0.029	-0.055	0.038	1			
(12) ent_adv_deg	-0.035	-0.036	0.045	0.059	0.060	0.038	-0.054	0.063	-0.014	-0.045	0.093	1		
(13) ent_ivy_plus	-0.021	0.035	0.043	0.011	0.028	0.023	-0.058	0.045	0.027	-0.052	0.118*	0.197*	1	
(14) ent_tech	0.099*	0.050	0.038	-0.050	-0.027	-0.030	-0.018	0.086	-0.040	0.049	-0.021	0.095*	0.126*	1

* shows significance at the .05 level

Table 3.6: *FFM Personality Traits and 1st round competition outcomes*

Notes: This table reports the Linear Probability (LPM) and Logit models where the dependent variable is 1 if the startup wins the first (semi-final) round of the competition. The unit of observation is a startup which participated in the competition. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) LPM	(2) LPM	(3) LPM	(4) LPM	(5) Logit	(6) Logit	(7) Logit	(8) Logit
Openness	0.005	0.006	0.005	0.002	0.051	0.057	0.056	0.029
	(0.028)	(0.028)	(0.028)	(0.029)	(0.145)	(0.145)	(0.150)	(0.155)
Conscientiousness	-0.005	-0.003	-0.003	-0.001	0.022	0.030	0.032	0.036
	(0.031)	(0.030)	(0.031)	(0.031)	(0.157)	(0.157)	(0.159)	(0.168)
Extraversion	0.022	0.021	0.023	0.026	0.070	0.060	0.074	0.079
	(0.032)	(0.032)	(0.033)	(0.033)	(0.166)	(0.168)	(0.173)	(0.174)
Agreeableness	-0.033	-0.579	-0.580	-0.583	-0.057	-2.237	-2.270	-2.438
	(0.035)	(0.380)	(0.382)	(0.383)	(0.176)	(1.726)	(1.727)	(1.783)
Agreeableness^2		0.547	0.546	0.545		2.185	2.204	2.365
		(0.377)	(0.379)	(0.380)		(1.720)	(1.720)	(1.771)
Neuroticism	-0.002	-0.003	-0.005	-0.009	0.066	0.062	0.054	0.036
	(0.026)	(0.026)	(0.027)	(0.027)	(0.132)	(0.132)	(0.133)	(0.138)
completeness			0.084	0.033			0.696	0.635
			(0.190)	(0.183)			(1.160)	(1.148)
word_count_log			0.093	0.108			0.456	0.521
			(0.087)	(0.086)			(0.469)	(0.481)
B2C			0.014	0.017			0.064	0.072
			(0.050)	(0.050)			(0.252)	(0.257)
entrepreneur_female				-0.180***				-0.969**
				(0.054)				(0.443)
entrepreneur_adv_deg				-0.045				-0.168
				(0.065)				(0.331)
entrepreneur_ivy_plus				0.035				0.178
				(0.052)				(0.272)
entrepreneur_tech				0.149*				0.492
				(0.084)				(0.388)
company_age				0.042				0.314
				(0.059)				(0.304)
Constant	0.258***	0.256***	-0.548	-0.590	-1.06***	-1.06***	-5.275	-5.732
	(0.023)	(0.023)	(0.638)	(0.644)	(0.123)	(0.124)	(3.543)	(3.678)
Observations	349	349	349	349	349	349	349	349
R-squared	0.073	0.079	0.084	0.120	0.0013	0.005	0.01	0.03
Event FE	YES	YES	YES	YES	YES	YES	YES	YES
N_clust	349	349	349	349	349	349	349	349

Table 3.7: *FFM Personality Traits and 2nd round competition outcomes*

Notes: This table reports the Linear Probability (LPM) and Logit models where the dependent variable is 1 if the startup wins the 2nd (final) round of the competition. The unit of observation is a startup which participated in the competition. "Event FE" are event (competition) fixed effects that take account for both the year and location of the competition. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

VARIABLES	(1) LPM	(2) LPM	(3) LPM	(4) LPM	(5) Logit	(6) Logit	(7) Logit	(8) Logit
Openness	-0.047	-0.047	-0.029	-0.038	-0.288	-0.256	-0.227	-0.354
	(0.054)	(0.054)	(0.054)	(0.057)	(0.306)	(0.297)	(0.300)	(0.344)
Conscientiousness	-0.039	-0.039	-0.030	-0.037	-0.118	-0.069	0.012	-0.072
	(0.079)	(0.082)	(0.078)	(0.083)	(0.422)	(0.416)	(0.414)	(0.498)
Extraversion	0.086	0.086	0.147*	0.158*	0.510	0.468	0.842**	0.983**
	(0.070)	(0.072)	(0.086)	(0.088)	(0.390)	(0.413)	(0.427)	(0.460)
Agreeableness	-0.057	-0.045	0.067	0.675	-0.333	-4.460	-4.666	-2.432
	(0.071)	(1.038)	(1.015)	(1.133)	(0.407)	(5.201)	(5.089)	(5.875)
Agreeableness^2		-0.012	-0.152	-0.771		4.198	4.158	1.950
		(1.041)	(1.025)	(1.144)		(5.226)	(5.094)	(5.911)
Neuroticism	0.007	0.007	0.015	-0.006	0.114	0.169	0.220	0.210
	(0.061)	(0.061)	(0.063)	(0.062)	(0.289)	(0.298)	(0.305)	(0.334)
completeness			-0.813	-1.034			-3.937	-3.793
			(0.756)	(0.847)			(4.465)	(4.935)
word_count_log			-0.105	-0.085			-0.634	-0.570
			(0.170)	(0.181)			(0.923)	(1.026)
B2C			0.206**	0.201*			1.345**	1.448**
			(0.093)	(0.103)			(0.607)	(0.608)
entrepreneur_female				-0.025				-0.100
				(0.170)				(1.062)
entrepreneur_adv_deg				0.040				-0.011
				(0.119)				(0.814)
entrepreneur_ivy_plus				-0.023				-0.187
				(0.115)				(0.668)
entrepreneur_tech				0.298*				1.295
				(0.167)				(0.817)
company_age				-0.043				0.876
				(0.122)				(0.787)
Constant	0.202***	0.202***	1.720	1.752	-1.45***	-1.43***	6.601	5.324
	(0.043)	(0.044)	(1.385)	(1.470)	(0.262)	(0.262)	(7.451)	(7.998)
Observations	95	95	95	95	96	96	96	96
R-squared	0.188	0.188	0.263	0.317	0.028	0.035	0.102	0.138
Event FE	YES	YES	YES	YES	YES	YES	YES	YES
N_clust	95	95	95	95	96	96	96	96

Table 3.8: *FFM Personality Traits and Regulatory Focus*

Notes: This table reports the logit models where the dependent variable is variable is 1 depending on the regulatory focus of the question / feedback received by an entrepreneur from an investor. In columns (1) – (3), the dependent variable is the likelihood of receiving a promotion-focused question / feedback. In columns (4)-(6), the dependent variable is the likelihood of receiving a prevention-focused question / feedback. The unit of observation is the question / feedback an entrepreneur receives from an investor / judge. Robust standard errors reported in parentheses. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

		Promotion			Prevention	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Openness	0.062	0.062	0.057	0.016	0.016	0.006
	(0.046)	(0.046)	(0.046)	(0.081)	(0.081)	(0.083)
Conscientiousness	0.100**	0.099*	0.083	0.027	0.028	0.019
	(0.051)	(0.051)	(0.051)	(0.097)	(0.096)	(0.097)
Extraversion	0.088*	0.089*	0.097*	-0.129	-0.130	-0.134
	(0.053)	(0.053)	(0.054)	(0.084)	(0.085)	(0.088)
Agreeableness	-0.064	0.204	0.242	-0.009	-0.079	-0.050
	(0.056)	(0.606)	(0.603)	(0.112)	(1.606)	(1.582)
Agreeableness^2		-0.268	-0.304		0.071	0.063
		(0.613)	(0.609)		(1.665)	(1.642)
Neuroticism	0.063	0.063	0.073	0.206**	0.206**	0.212**
	(0.047)	(0.046)	(0.048)	(0.083)	(0.083)	(0.082)
entrepreneur_female			0.148			0.017
			(0.095)			(0.208)
entrepreneur_adv_deg			-0.081			-0.142
			(0.098)			(0.181)
entrepreneur_ivy_plus			-0.052			-0.127
			(0.082)			(0.165)
entrepreneur_tech			0.067			0.148
			(0.113)			(0.204)
company_age			0.063			-0.021
			(0.105)			(0.173)
Constant	-0.647***	-0.647***	-0.616***	-2.699***	-2.699***	-2.469***
	(0.039)	(0.039)	(0.100)	(0.073)	(0.073)	(0.197)
Observations	3,486	3,486	3,486	3,486	3,486	3,486
R-squared	0.026	0.032	0.037	0.010	0.013	0.014
N_clust	328	328	328	328	328	328

Therefore, the 2nd round effect indicates that self-promoting language is (more) beneficial to entrepreneurs whose ventures already satisfy minimum viability standards. In other words, self-promotion is not a substitute for objective venture quality. This explanation is supported by extant research (e.g. Clingingsmith and Shane, 2017) which shows that entrepreneurial pitches, no matter how well delivered, do not affect assessment of underlying venture quality.

With regard to why *extraversion* yields a significant positive effect VC funding outcomes and garners more favorable evaluation by investors, we argue that beyond having a viable venture, the most important determinant of the success of a venture is the ability of the entrepreneur to communicate persuasively with a diverse range of constituents including investors, partners, employees and customers to secure critical resources that drive venture performance. The inability of an entrepreneur to garner financial and non-financial resources from key stakeholders likely eliminates any chance of venture success. Thus, entrepreneurs who communicate with more enthusiasm and energy – key characteristics of *extraversion* -- are likely better at persuading VC investors of the venture's investment potential (see Beukeboom, Tanis and Vermeulen (2013); Clarke, Cornelissen and Healey (2019)).

On the other hand, we argue that the relationship between *neuroticism* and less favorable evaluation by investors is explained by the fact that lack of emotional stability – which characterizes *neuroticism* – is perceived by investors as undesirable to venture success. The often-unstructured work environment of new ventures coupled with the high level of personal responsibility demanded, requires remarkable emotional stability and resilience from the entrepreneur if the venture is to succeed. Thus, entrepreneurs who communicate higher levels of *neuroticism* are likely evaluated by investors as being less likely to succeed. While we do not observe a direct negative relationship between *neuroticism* and venture funding outcomes, our results still suggest that it is detrimental to investment-seeking entrepreneurs.

We contribute to the impression management literature by providing the first known examination of the relationship between FFM personality traits promoted via the language of entrepreneurial pitches and VC funding outcomes. Previous studies examining language-based self-promotion by entrepreneurs rarely identify any specific dimensions along which the behavior takes place. For the few studies that do (e.g. Balachandra, Fischer and Brush, 2021), no comprehensive behavioral framework is considered. This makes it challenging to coherently synthesize research findings and misses out on identifying more granular elements of the behavior. Our study addresses these research gaps by identifying not only which aspects of language-based self-promotion matter, but also the conditions under which we expect them to be (most) important. This provides opportunities for further research that examines moderators and mediators of the relationship between language-based self-promotion and new venture funding outcomes.

In addition, we contribute empirically to the FFM literature by highlighting the ability of the language of an entrepreneurial pitch to convey personality information. Traditional personality studies rely on self-reported surveys which are "notoriously unreliable" in accurately defining personality traits(Chung & Pennebaker, 2018). Language analysis has the advantage of being more reliable and convenient and benefits from robust computational support. Our study is the first we are aware of that utilizes entrepreneurial pitches to measure FFM personality traits.

Our findings may also be of practical relevance to entrepreneurship educators and entrepreneurs. There is a plethora of entrepreneurship training resources, ranging from online courses to executive programs. However, these programs predominantly focus on hard skills rather than soft skills(Kerr et al., 2018). A clearer understanding of the effect of specific self-promotion language techniques may help educators be more effective in their pedagogical approach to entrepreneurial education. For entrepreneurs, our results may guide them in crafting and delivering more engaging and effective pitches to investors.

3.7 Limitations

Our study is not without limitations. First, while computational text analysis software such as Receptiviti can offer valuable insights into the personality dynamics of language, this approach has its shortcomings. Language can be contextually-dependent and while software like has been shows to outperform human coders in content analysis (Ober & Alexander, 1999), it cannot always identify nuances in language (Balachandra et al., 2021). Ongoing improvements in computational text analysis aim to address this shortcoming.

Furthermore, our study focuses on the linguistic elements of the entrepreneurial pitches but is unable to account for paralinguistic elements such as intonation, pitch, etc. and other non-verbal modalities such as facial expressions and physical appearance which may also shape the interaction between entrepreneurs and investors (e.g. Brooks *et al.*, 2014).

3.8 Conclusion

Our study contributes to a deeper understanding of the relationship between specific aspects of self-promoting language used by entrepreneurs and subsequent venture financing outcomes. Our results suggest that level of *extraversion* -- enthusiasm, energy and assertiveness -- communicated by an entrepreneur appears to have a positive impact when pitching for investor funding. We also find that *neuroticism* is associated with more negative evaluation by investors. While we do not argue that self-promoting language alone is sufficient, we provide early evidence of its importance within the constellation of factors that affect entrepreneurial funding outcomes.

Conclusion

This dissertation advances knowledge of the VC decision-making process. It identifies sources of variation in attention allocation by VC investors during the venture selection process and the consequent funding outcomes at the venture level. By examining the behavior and interactions between VC investors and investment-seeking entrepreneurs, it uncovers the influence of subjectively-evaluated qualitative factors such as entrepreneur gender, ethnicity and personality traits on venture funding decisions.

With respect to gender, it provides evidence that female VC investors focus their attention on entrepreneur / team - and product – related upsides when evaluating female entrepreneurs, particularly those whose product / service offerings are oriented primarily toward a female customer base. Whether through gender advocacy by female VC investors or as a consequence of being more skilled at evaluating the potential of female-oriented products and the female entrepreneurs behind them, this finding highlights the importance of female VC representation in the venture screening process and its potential to address the well-documented gender gap in new venture funding and more generally, in high-growth entrepreneurship. Increased female VC representation in investment decision-making directly implies higher likelihood of female entrepreneurs receiving VC funding. However, it may also have the indirect effect of encouraging more women to participate in high-growth entrepreneurship as success stories of female-led ventures become more common.

With respect to ethnicity, it highlights the extent to which co-ethnicity between VC investors and investment-seeking entrepreneurs influences venture funding outcomes. The results reveal that within minority ethnic groups, co-ethnicity between an entrepreneur and investor is associated with more positive evaluation of the entrepreneur's venture by the investor. However, while similar effects are not observed among mainstream White and Asian investors and entrepreneurs, the importance of ethnic / racial diversity in VC investing cannot be overstated. The ethnic distribution of VC investors in technology entrepreneurship in the US almost perfectly mirrors the ethnic distribution of the investment-seeking entrepreneurs. Irrespective of which investors exhibit biases, balanced ethnic representation helps to ameliorate any (negative) effect of these biases on the quality of investment decisions. By minimizing the effect of biases and maximizing the use of available information, collaborative ethnic diversity in VC investment decision-making could increase the representation of marginalized ethnic groups in high-growth entrepreneurship.

Regarding personality factors, it uncovers the positive relationship between the level of *extraversion*, i.e., enthusiasm, energy and assertiveness, communicated by entrepreneurs during pitch presentations and the likelihood of receiving venture funding. Furthermore, it highlights the negative perception of *neuroticism* (i.e., lack of emotional stability) by investors. These findings serve as empirical evidence of the importance of impression management behavior by entrepreneurs (i.e., as a complement for venture quality), within the constellation of factors that influence VC funding decisions. This knowledge is especially beneficial to investment-seeking entrepreneurs as it yields practical recommendations that can be implemented (e.g., via coaching, human resourcing etc.) to improve the likelihood of receiving investment.

Taken together, these findings highlight the relationship between variation in attention allocation by VC investors and the heterogeneity of VC firm performance. Sources of variation in attention allocation by VC investors during venture screening directly influence investment selection decisions. These decisions in turn influence VC investment performance and ultimately VC firm performance. As the volume and velocity of VC investing continues to increase worldwide[6], these findings highlight areas of improvement for investors seeking to make better investment decisions and policy-makers seeking to promote more vibrant and diverse entrepreneurial ecosystems.

This dissertation also makes important methodological contributions. By applying novel Natural Language Processing and Machine Learning techniques to tasks such as product gender categorization and personality profiling, it presents fruitful research opportunities for scholars to creatively examine large text-based corpuses in ways that were previously

[6] According to The Economist, in 2021, venture capital investment was roughly $600 billion worldwide, a 50% increase over 2020 figures and 10 times the total amount invested a decade ago. Source: https://www.economist.com/podcasts/2021/11/24/veni-vidi-vc-the-new-age-of-venture-capital

prohibitively costly. With respect to personality profiling specifically, it opens up avenues for researchers to investigate the severely understudied role of behavioral traits on various firm outcomes. These studies have the potential to yield actionable insights that translate to improved firm performance.

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Appendix

Table A1: *Criterion-keyword mappings*

Notes: This table lists the keywords used to identify the screening criterion / topic of questions.

Criterion	Keywords
Finance	*return, cashout, liquid, cash out, financ, loan, termsheet, raise, round, invest, seed, series, valuation, term sheet, equity, capital, vc, venture, debt, ipo*
Market	*business, model, growth, barrier, compet, player, who else, up against, crowd, fight, battle, war, price war, undercut, market, user, customer, revenue, rev, size, sale, how many, how much, invest, money, pay, earn, cash, cost, distribut, price, segment, retain, reten, market share, margin, expand, earn, increas*
Product	*tool, design, device, concept, attribute, differentiat, proprietary, patent, trademark, ip, prototype, property, product, content, service, platform, tech, system, server, network, process, launch, feature, beta, alpha, test, form factor*
Team	*personal, motivat, entrepreneur, ceo, cfo, vp, skill, manage, engineer, developer, geek, president, team, background, experience, college, grad, engineer, genius, expert, major, school, employ, research, phd, university*

Table A2: *Regulatory-focus keyword mappings*

Notes: This table lists the keywords used to identify the risk/reward focus of questions. The list is based on the dictionary entries contained within the LIWC tool (Pennebaker et al., 2015).

Regulatory Focus	Keywords
Prevention (Risk)	*abstain**, alarm*, apprehens*, averse, aversi*, avert*, avoid*, bad, balk, beware, careful*, caution*, cautious*, cease*, concern, consequen*, crises, crisis, curb*, danger, dangerous, dangerously, dangers, defend*, defense, difficult, difficulties, difficulty, disadvantag*, disaster*, distrust*, doom*, doubt*, dread*, escap*, evad*, expense, expenses, fail*, fault*, fled, flee, fleeing, flees, flunk*, guard*, hazard*, hesita*, hid, hide, hides, hiding, hinder*, inhibit*, lack, lacked, lacking, lacks, liabilit*, lose, loses, losing, loss*, pessimis*, prevent*, problem*, protect*, refrain*, reluctan*, risk*, safe, safely, safer, safest, safety, secur*, stop, stopped, stopping, stops, suppress*, tentativ*, threat*, troubl*, trust, trusted, trusting, trusts, trustworthiness, trustworthy, undesir*, unproduc*, unprotected, unsafe, unsure*, unwanted, vigilan*, warn*, worse, worst, wrong, yield*
Promotion (Reward)	access*, accrue*, accumul*, achievable, achieve*, achievi*, acquir*, add, added, adding, adds, advanc*, advantag*, adventur*, amass*, approach, approached, approaches, approaching, award*, benefit, benefits, best, bet, bets, better, betting, bold, bonus*, confidence, confident, confidently, crave, craving, dare, dared, dares, daring, desir*, eager, eagerly, eagerness, earn, earned, earning, earnings, earns, enthus*, excite, excited, excitedly, excitement, exciting, fearless*, fulfill*, gain*, get, gets, getting, goal*, good, got, gotten, great, greed*, invigor*, jackpot*, luck, lucky, obtain, obtainable, obtained, obtaining, obtains, opportun*, optimal*, optimism, optimistic, perfect, perfected, perfecting, perfection, perfectly, plus, positive, positively, positives, positivi*, prize*, profit*, promot*, reward*, score*, scoring, seize*, snag*, steal*, stole, succeed*, success, successes, successful, successfully, surpass*, take, taken, takes, taking, took, triumph*, victor*, wager, wagered, wagering, wagers, willing, win

A Note on the Author

Terwase I Viashima was born in Jos, Nigeria. He completed his bachelor's degree in Computer Science at the University of Jos, Nigeria in 2010 and a master's degree in Advanced Computer Science at the University of Leicester, UK in 2012. Between 2013 and 2018, he worked as an IT business and security analyst for the Shell Petroleum Development Company in Lagos, Nigeria. In 2018, he joined the Master of Research in Management (MRM) program at IESE Business School, Barcelona in the Strategic Management department. After successfully completing the MRM in 2020, he joined the Doctor of Philosophy program in Management at IESE Business School, completing his dissertation under the supervision of Prof. Giovanni Valentini and Prof. Sampsa Samila, in 2022. His work has been presented at a number of academic workshops and conferences including the 2021 Strategy Science Doctoral Workshop (Harvard Business School, USA), 2021 Ghoshal Conference (London Business School, UK) and the 2021 Strategic Management Society Conference (Rotman Business School, Canada).