Funding Innovative Products:

The Impact of Non-Pecuniary Income on Choice

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Abstract

We build a choice model for angel investors, who maximize expected utility over monetary *and* non-monetary income, and estimate the model parameters using angel investment decision data. Estimates indicate that risk preferences are a function of education, experience (investing and entrepreneurship) and how active angels are in interacting with venture companies. Moreover, we find empirical support for the inclusion of non-monetary income in an angel investor's utility function, with active investors benefiting from non-pecuniary sources. A counterfactual exercise determines the likelihood of active angels investing in new ventures without non-pecuniary sources of income would fall by 6.92%, which equates to a 14.65% decrease in the new portfolio's mean return.

Keywords: Risk Preferences, Angel Investors, Targeting

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1 Introduction

Marketing researchers have extensively studied new product introductions. Numerous methods and empirical papers have examined various facets of the new product introduction process from ideation to test marketing to channel development. Yet, little research exists on one of the most powerful new product mechanisms, namely, angel investing. Such investors are a critical source for funding the development of numerous breakthrough products. For Instance, Jeff Bezos invested in Google in 1998 and a year later so did Tiger Woods.[1] The process of raising external funds for a startup typically begins with the entrepreneur's friends and family, which raises between $25,000 and $150,000 and is relatively easy to complete. Difficulty arises after the startup burns though this initial investment and seeks additional funds. Entrepreneurs then turn to angel investors, individuals who have a high-net-worth and who invest directly with private companies using their own money, to secure further funding.[2]

While research on angel investors has slowly grown with time, it has been mostly limited to understanding the demographics of angel investors (Morrisette [2007]; Wright et al. [1998]; Lindsay [2004]; Sohl and Hill [2007]). Our research moves the literature forward by leveraging an angel investment data set in order to understand angel investor choice preferences for the funding of innovative products or services. Particularly, we are interested in understanding what factors impact an angel investor's risk aversion for highly uncertain outcomes **and** the impact non-pecuniary income has on choice. Given the importance of angel investing to the development of new products, the baffling paucity of research that looks past demographics is surprising and is potentially due to the difficulty of obtaining data. Even when data is available, researchers who are accustomed to comprehensive and detailed data, find angel investing data to be limiting. Yet, at the margin, this line of research has a great deal of value to the field of marketing by understanding the choices of angel investors, who are an important and growing source of capital for technology strartups (e.g. U.S. angel investments totaled $22.5 billion across 66,230 investments by 318,480 investors in 2011 [Han and Strebulaev, 2012]).

[1] https://www.crunchbase.com/organization/google/investors/investors_list

[2] An angel investor or angel (also known as a business angel, informal investor, angel funder, private investor, or seed investor) is an affluent individual who provides capital for a business start-up, usually in exchange for convertible debt or ownership equity. These investors typically bridge the gap in financing between the friends and family round and the first round of venture capital financing.

The marketing field is well positioned to answer the above questions given its emphasis on understanding decision making under uncertainty through laboratory studies and empirical models. Such examples include whether to purchase an innovative product, an extended warranty for a durable good, or whether an angel investor should provide capital to a startup company. In each case, it is important for the firm (entrepreneur) to understand the consumer (angel) in order to target the most profitable segment. For the latter case, the entrepreneur should understand how different angel investors react to uncertainty in order to more successfully convert potential financial backers. Specifically, they should understand how heterogeneous angel investors are in their attitudes toward risk (the degree of risk aversion) and how risk preferences vary with investor characteristics. Furthermore, with angel investors, non-pecuniary sources of income may be of importance and thus the entrepreneur should also comprehend how this source of income impacts investment choice.

While all angel investors invest in search for high returns, some angels also do so for personal reasons. For instance, they may value being a part of the exciting development process of launching a new venture and want to aid in this process by sharing their own experiences with the firm's management. They also may value this interaction for networking benefits, intellectual challenge, and for altruistic reasons.[3] These non-financial benefits are categorized as non-pecuniary income. When modeling angel investment decisions it is important that these sources are accounted for, as they may impact an angel's choice. *Specifically, we look to answer if non-pecuniary sources of income impact investment choice and whether they change investment decisions in such a way that angels invest in more risky ventures than otherwise would have occurred without the added benefit.* We follow Prowse [1998] and distinguish between "active" and "passive" angels within angel groups. We define active investors as investors who invest for more than pure monetary reasons (e.g. altruism, network group, etc.) and value their time interacting with entrepreneurs whereas passive investors mainly seek financial returns.

We find it important to push this field of research forward by modeling angel choice and estimating model parameters with angel choice data from deals that were sourced and funded through angel groups. Our model and estimation is able to uncover how risk preferences and non-financial benefits impact investment decisions, which ultimately allows us to understand investor choice and

[3]See Southwest Florida Regional Angel Fund Assessment" (2008)
http://www.tamiamiangels.com/uploads/5/0/7/0/5070153/2008_raft_assessment.pdf

who entrepreneurs should target when seeking capital funds. Yet, such analysis is challenging to implement given the typical data set available for research only includes completed deals, rather than the pool of start-ups considered by investors. Without data on the characteristics of companies that were turned down by investors, it is difficult to learn about the investor's decision-making process. We therefore turn to the 2007 Angel Investment Performance Project (AIPP) survey to construct our own panel data set of individual investment choices. We focus on angels who are members of angel groups as well as deals that were sourced by angel investment groups in order to construct a list of potential ventures.[4] While there are limitations with this data, which we discuss below, this angel investing data is among the most comprehensive that is available to researchers to date.

In order to estimate an angel's risk preference and the benefit from non-pecuniary income, we employ a model of portfolio choice, similar to Bao and Ni [2017]. An investor's existing portfolio is assumed to be a mixture of angel investments and the S&P 500 index fund. Our setting is characterized by a situation where angel investors are faced with large stakes and low probability of a very high return, and not small or modest stakes. Specifically, we build a choice model for angel investors who maximize expected utility over monetary and non-monetary income, and estimate the model parameters using angel investment decision data. Estimates of our model of portfolio choice determine that the medium relative risk aversion preference parameter is -0.60 for passive investors versus -1.79 for active illustrating that the majority of angel investors are risk loving.

Model results also indicate that risk preferences are impacted by several factors related to education, experience (years investing, total number of investments, years as an entrepreneur, and the number of years in a large firm) and angel investor type (active or passive). We observe no significant gender differences in risk preferences, which is consistent with the results of Johnson and Powell [1994]. In addition to analyzing how risk preferences vary by individual characteristics, we look to understand how non-pecuniary income impacts choices for passive and active investors. We accomplish this by running a counterfactual exercise where non-pecuniary income for active investors is set to zero while their risk preferences remain at the estimated levels. Counterfactual exercises determine that active angel investor choices are affected and are due to active angel investors valuing non-pecuniary sources of income. Without such a source of income, an active investor's likelihood

[4] Note, the list will only include ventures that at least one angel from group "G" invested in. This is the same methodology used to construct the choice set for product level demand models using individual level purchase data in marketing.

of investing would fall by roughly 6.92%, which equates to a 14.65% decrease in the new portfolio's mean return.

Our work is related to several marketing papers that incorporate agent uncertainty to estimate risk preferences. Bao and Ni [2017] develop and estimate a strucutral model of the banking market to estimate consumer risk preferences for a portfolio of investments consisting of deposits in a bank (along with any included depository services) and traditional financial investments (public stock and corporate bonds). The authors determine that consumers are less risk tolerant after the 2009 economic downturn and that an increase in bank deposit insurance erodes market discipline and increases banks' moral hazard. Ni and Xin (2019) also estimate investor risk preferences in order to understand the impact of information and marketing on the financing of innovation. Their research is centered around the indentification of and the reason for local biases to be present in marketplaces that finance innovation. Specifically, they look to address whether such bias is driven by preferences or information with the use of a structural model to capture an agent's investment behavior. They determine that investment behavior does exhibit a local bias and is attributed in part to information frictions and not only from local preferences.

The estimation of risk preferences in marketing is also seen in research on salesforce and in modeling consumer warranties. Within the salesforce literature, Chung et al. [2014] estimates a dynamic model of salesforce response to a bonus based compensation plan. Their paper provides insights on how different elements of the compensation plan enhance productivity, which is partially driven by salespersons risk preferences. Another such paper is by Padmanabhan and Rao [1993] who studied warranty policy and extended service contracts (ESC) in the automobile market to find that risk-averse consumers are more likely to buy ESC if the manufacturer base warranty is less than three years old. They also determine that the "optimal warranty policy consists of offering a base warranty desired by a risk-averse consumer, and then provid[e] a certain level of over insurance for more risk-averse consumers through ESC." Chen et al. [2009] also studies the ESC market with respect to consumer electronics. They do so in order to understand how the likelihood of ESC purchases can be influenced by product characteristics and the marketing actions taken by retailers. They find evidence that unadvertised promotions increase risk aversion. Jindal [2015] researches warranty policy and extended service contracts (ESC) in the washing machine industry. He identifies heterogeneity in consumer risk preferences to assist in explaining ESC purchases. While there is growing work in marketing on estimating risk preferences, our work contrasts with these papers by estimating the impact non-pecuniary sources of income has on choice. We believe we are the first to estimate risk preferences and non-pecuniary income jointly.

Finally, the literature at the intersections of marketing and finance is also related to our work. Liu et al. [2019] studies decision making related to target retirement funds (TRF) and determine that investors have sizeable zero bias which lead to strong preferences for TRFs that end with zero rather than five. They further determine the effects of this zero bias on consumer welfare using a constant relative risk aversion formulation assuming different values of risk aversion given this model parameter is not estimated. The authors find investors are worse off when deviating from the matched TRF, whereby the extent of the loss is a function of the level of risk aversion. Slightly different but also within the marketing/finance interface is the work Lovett and MacDonald [2005]. This paper determines that firms market to financial markets in order to alter the perceptions of stock analysts and increase the stock price of the firm through more optimistic ratings.

2 The Angel Investment Market

2.1 Angel Investors

Angel investors are individuals who have a high-net-worth who invest directly with private companies using their own money. During our data period these individuals are accredited investors, with wealth over $1 million and annual income in excess of $200,000 in the two most recent years or over $300,000 in joint income with a spouse. Such accreditation is used to protect individuals from excessive risk and ensure they have the financial sophistication to participate in certain investment vehicles. Below in Figure 1 is a histogram of the number of accredited investors by wealth in 2010. It highlights the wealth that many of these angel investors have. Typically, the investments these individuals make are with companies that are technology startups, but they need not be. As we show below in the data section, angels invest in a wide array of industries and stages. Unlike venture capitalist who are pressured by fund investors, angel investors may also invest for more than pure economic/financial reasons. For instance, some angel investors may value being a part of the exciting development process of launching a new venture and want to aid in this process by sharing their own experiences with the firm's management. They also may value this interaction for networking benefits, intellectual challenge, and for altruistic reasons. Such reasons may impact an angel investor's decision to invest in ventures with higher risk. All of these non-financial benefits are categorized as psychic or non-pecuniary income and need to be accounted for in modeling angel investment choice decisions to properly identify risk preferences. Angel investors may also become involved with an investment due to the potential value they or their co-investors from their angel group may add to the return on the investment from acting as a sounding board for management, providing strategic advice, acquiring additional resources, mentoring entrepreneurs to name a few.

Segmenting Angel Investors: Active vs Passive

Angel investors typically fall into two types: active and passive with each taking a different approach to their investing. First, let us define what active and passive investors are and then discuss how each are involved with a venture. A report by Shane (2008) for the Small Business Association define the two types of investors as:

- Active angel investor: An individual who uses his or her own money to provide capital to a private business owned and operated by someone else, who is neither a friend nor family member, and who invests time as well as money in the development of the company.
- Passive angel investor: An individual uses his / her own money to provide capital to a private business owned and operated by someone else, who is neither a friend nor a family member, but who does not invest time in the development of the company.

These definitions clearly highlight the difference between the two investor types–time spent engaged with the company. Typically, active investors interact frequently with the entrepreneurial team to provide value added advice and/or services and to receive non-pecuniary benefits by being more closely affiliated with the venture for networking benefits, intellectual challenge, and for altruistic reasons.

2.2 Angel Groups

In the past, most angel investors invested individually with companies, but starting in the 1990s, individuals began to form groups in order to take advantage of their collective wisdom. The formation of groups helped aid individuals in evaluating and sourcing deals as well as provided access to larger ventures that otherwise might have required too much capital for one individual, by pooling capital from interested members. The formation of groups also allowed investors to invest smaller amounts with each individual venture, enabling angels to participate in more investments to diversify their investment risk. The prominence of angel groups is reflected in the fact that The Angel Capital Association (ACA) lists 300 U.S. groups in its database. "In 2007, the average ACA angel group had forty-two member angels and invested a total of US$1.94 million in 7.3 deals. Between 10,000 and 15,000 angels are believed to belong to angel groups in the United States [Kerr et al., 2014]." If we broaden the scope to include those angels not affiliated with a group, the U.S. angel investments totaled $22.5 billion across 66,230 investments by 318,480 investors in 2011 [Han and Strebulaev, 2012]. We put that number in perspective with the fact that, in the same year, U.S. venture capitalists invested $28.4 billion across 3,673 deals. Moreover, for an individual to join an angel group the investor must be accredited as discussed above, and is usually invited by another member of a group.

[Insert Figure 1 here]

The focus of our paper is on angel investors who are affiliated with an angel group, but where angels make individual investment decisions. We do not study groups that act as venture funds and pool member *dues* to invest, nor do we study individual angels making investment decisions outside an angel group as we do not have this data. That said, our data does provide the number of angel investments made regardless of source (group or individual) and the fraction of wealth tied to angel investments. Most angel groups follow a similar process for sourcing, evaluating, and funding deals. The flow of this process starts with the entrepreneur submitting an application to the angel group. The application includes a request for the firm's business plan for angels to review. Once the initial screening has taken place, entrepreneurs are invited to give a short presentation to a committee of angel investors affiliated with the angel group. The presentation is quite short and includes a question and answer period. After screening, ventures with sufficient interest move to due diligence, which is often done by a small committee of angel members for the benefit of the entire group. After the due diligence process, there exist a dinner meeting for companies that pass the due diligence phase to present to the entire group to secure funds. At this stage, angel investors make investments decisions individually with only a small number of group members needed to participate for the venture to be funded. With most angel groups, individuals have a minimum level of allocation per deal. After, investment funds are distributed (typically three months post the dinner presentation). Figure 2 provides a detailed template of this process.

[Insert Figure 2 here]

One important concern associated with angel groups is that sorting may occur in the marketplace, where successful angel groups have access to higher quality ventures than less successful groups. For instance, those groups who have access to high quality ventures, their expectation about returns will be higher (and/or possibility with less variance) than those without such access. Controlling for such difference is important as the mean and variance of the expected venture returns is an important variable in our model below. This concern is relevant in locations where there are multiple, if not many, angel groups (e.g Silicon Valley). Our data, unfortunately, is blind with respect to the identification and location of each angel group. However, as we discuss below there is a simple method to control for such sorting without building a two-sided matching model.

2.3 How Venture Capitalist Compare to Angel Investors

In order to provide clarity to the setting we study, we discuss how a venture capitalist differs from an angel investor as readers maybe more knowledgeable of the venture capital world due its recent publicized growth.[5] First, let us start with the definition of a venture capitalist. The Rockies Venture Club states "venture capitalists are typically formed as Limited Partnerships in which the Limited Partners invest in the Venture Capital fund. The fund manager is sometimes called the General Partner and the job of the General Partner is to source good deals and to invest in the ones that they think will return the most money to the Limited Partners."[6] This definition highlights several prominent differences from angel investors. The first being that venture capitalist do not invest

[5] https://pitchbook.com/news/articles/16-charts-that-illustrate-current-us-venture-capital-trends

[6] https://www.rockiesventureclub.org/colorado-capital-conference/how-do-angel-investors-differ-from-venture-capitalists/

their own money. Rather they receive funds from limited partners such as university endowment funds, corporations, etc for them to invest. The fact that funds originate from outside sources generates a fiduciary duty for the venture capitalist, whereas the fiduciary duty is not present with angel investors as they invest their own capital making their own decisions (even when ventures are sourced through an angel group). Thus, the venture capitalist has an obligation to his/her limited partners to invest in ventures that generate the highest expected monetary return. Angel investors on the other hand do not and can invest for non-monetary reasons (as discussed above). This fiduciary duty also requires the venture capitalist to perform an extremely high level of due diligence, spending as much as $50,000 or more to conduct thorough research on their prospective growth stage ventures of which they are investing an average of $7 million per deal. Contrast this with angel investors whose average investment is roughly $30,000 per angel investment in a company who is either in the seed or startup phase. Our model below is thus quite different from a model that would be constructed for a venture capitalist. The model that we describe below is tailored to the setting of an angel investor who sources potential ventures through an angel group, but invests his/her own money and make his/her own investment decisions based upon expected monetary and non-monetary returns.

3 Data

The data we use originates from the Angel Investment Performance Project (AIPP) survey, which surveyed 539 investors from 86 different angel groups in 2007. Through an online questionnaire, the survey asked for information about investor demographics (age, gender, education, angel group), experience (years angel investing, number of angel investments, number of exits, years as entrepreneur, years at large firm) as of 2007, and to list in detail their specific angel investments (investment level, year invested, year exited, number of co-investors at time of first investment, stage of the company, experience in the venture industry, and return multiple).[7]

[7] Years experience is observed only if an investment was made. Given the inability to recover years experience for non-investments, we employ this variable only when analyzing investment levels, not the investor's investment decision.

3.1 Panel Data Set Formation

The AIPP data is not explicitly used in its reported form for our analysis, given that much of the information is specific to the investor in 2007. Instead, we construct a panel data set of angel investments and non-investments decisions. The formation of all individual investment decisions is relatively straight forward. We simply use the reported decisions in the original survey which were initiated after 1997 and were sourced through an angel group. In order to obtain the non-investment decision, we use the fact the data lists the investor's group membership code. This enables us to identify a set of angels who were privy to a potential investment. For instance, for group G, if we see 20 investments reported in the raw data between 1998 and 2007, then these 20 investments become the set of potential investments for members of group G. These investments are also naturally linked to 20 individual angels (who made actual investments), which identifies the set of individuals who were able to make investment decisions. Note, we do not view the entire set of angel investors for a given group. Rather only the set of investors who completed the original survey. Such data formation is similar to the process used in empirical microeconomics that employs individual level choice data. Note, that if no angel invests in a venture, this venture does not appear in any angel's consideration set. This lack of inclusion in the choice set is also similar to how micro-economist treat stock-outs.

With the original data providing the number of years an investor has been investing in angel ventures relative to 2007, we are able to form a time varying set of potential investors associated with group G as we use this variable as a natural proxy for the number of years associated with his/her angel group. For example, if angel i has only five years of angel investing relative to 2007, but there was a venture that was initiated in 2000 in the venture set, angel i would not be permitted to enter the potential set of angel investors for venture f from group G. Thus, the opportunities are angel-group specific and are constructed by using all observed deals made by any surveyed group member. After the set of potential ventures and investors are formed, we create deal/venture specific investor experience variables. We specifically use the original data reported in 2007 and the initiation date of an investment to form deal, angel specific variables such as *Total Years as an Entrepreneur*, *Years Angel Investing, Total Angel Investments,* and *Total Number of Investments Outstanding without a Liquidity Event*, to name a few.

Mapping the static survey response in 2007 to a specific venture in a given year is straightforward but tedious. For instance, the survey asks for the number of years the investor has participated as an angel investor at the time the survey was initiated. We adjust the 2007 value to correspond to the year the potential investment decision was made. A similar methodology is used for other variables such as Total Years as an Entrepreneur and Years at a Large Firm. But, with these two variables explicitly, the mapping is not as straight forward as the number of years investing, due to the likelihood that the angel investor did not have a continuous run of being an entrepreneur or working in a large firm.[8] We also require the assumption of complete reporting of investments as it is vital in constructing venture specific variables, especially pertaining to the number of investments made and the number of exits by any angel investor. Thus, it is assumed that all ventures are reported in our data set. Finally, we do make additional assumptions regarding the data (e.g. return distribution, implicit investment amount for investors we don't see invest), but these assumptions are discussed in the modeling section.

3.2 Summary Statistics

Below we present summary statistics of the constructed data set, which focuses on deals between 1998-2007. We first present statistics of investor demographics followed by investment-related statistics. Table 1 presents summary statistics for each type of angel investor. Table 1 highlights the fraction of passive investors in the data set is roughly 56%. Given the definition above, we identify passive and active investors through an original survey question that identifies the frequency of interaction the angel investor had with venture f–responses were rarely if at all, annually, quarterly, monthly, weekly, daily. We denote passive investors as investors who's average frequency of interaction for all reported ventures was quarterly or less and active if it was greater. Moreover, we assume this classification is exogenous due to little variation in time spent interacting with an entrepreneurial team across ventures for a given angel investor. Angel investors are therefore assumed to know their future degree of involvement before they make an investment decision.

The most notable differences between investor types is that passive investors have invested more ventures, roughly five more than active investors. Additionally, active angels have three more

[8]We use the 2007 response and the adjusted values in our analysis below and determine that the results are qualitatively robust. For simplicity's sake, we assume that all measures are adjusted in practice.

years of experience as an entrepreneur and as an angel investor, and have fewer exits than passive investors. Finally, active investors tend to have earned a JD or a PhD degree more often than a passive investor.

[Insert Table 1 here]

Table 2 analyzes important investment measures. We first present the distribution of companies by stage: seed stage comprises 31% of investments, with startups at 45%, early growth at 22%, and late growth and turn around rounding out the sample each with 1.5%. The average log investment for an individual was \$10.31 (\$30,031 in levels), with roughly eight co-investors participating alongside.

[Insert Table 2 here]

In Table 3 we present the distribution of transactions by industry. A wide array of industries is represented in the data set. Media & Entertainment and Biotechnology are the largest industries, each representing 16.84% and 13.75% of the sample, respectively, whereas the computer and peripherals industry is the smallest.

[Insert Table 3 here]

Figure 3 presents the probability mass function for log investment levels. The empirical density appears normal, with a mean investment level of roughly \$30,000.

[Insert Figure 3 here]

Finally, Figure 4 presents the empirical density of the non-normalized (by the number of years held) asset return multiple. For instance, if the investor invested \$10,000 and received \$20,000 in return at the time of the liquidity event, the return multiple equals 2x, but if the venture returned zero cash flows, its multiple would equal zero regardless of holding time. Clearly, this figure illustrates that there is a positive and large likelihood that an investment will return zero dollars to the angel. This finding creates an empirical issue when modeling investor returns. In section 5.1.2, we discuss this issue and present the approach used to mitigate such a concern.

[Insert Figure 4 here]

4 The Investor Decision Model

Studying how agents make decisions under uncertainty requires the inclusion of risk preferences. But much of the research concerning risk preferences is theoretical, laboratory based, or uses preference indifference data. Nonetheless, there is a small and burgeoning stream of literature that estimates risk preferences from the field by employing choice data. For instance, in a binary choice setting where the agent chooses between investing in a risk-less choice and a risky choice, a researcher is able to determine a bound on the the agent's risk preference. As an example, analyze the simple setting where a person chooses between a sure \$3 and a 80% chance of \$4. Assuming a constant relative risk aversion utility function, one can determine the relative risk aversion parameter. For a consumer who chooses the safe option, his risk preference is $\gamma \geq .22$. Below we present our investor decision model where the investor invests his/her own capital. Our model is motivated by this simple example; yet, modifications are made in order to account for the more complex and specific field setting, particularly the inclusion of non-financial utility and portfolio returns.

4.1 Model Setup

The sequence of events for our model is as follows: investor $i \in \mathbf{I}$ has a total of D_i dollars of wealth. He/She currently holds portfolio $P_i(F,\ S\&P)$, which includes $j_i \in \mathbf{J}$ investments with a total F_i dollars invested in private angel ventures and the residual investment amount $(D_i - F_i)$ in the S&P 500 index. Angel i becomes aware of angel venture f through his/her angel group screening process and considers whether or not to invest at the funding stage. Thus, we assume the venture has already completed the screening process and due diligence at the time of an angel's investment decision, as is illustrated in Figure 2. Moreover, at the funding stage of the investment process, angel investors make investments decisions individually with only a small number of group members needed to participate for the venture to be funded. Given this fact, we abstract away the collective group dynamics required to fund ventures, but do allow for multiple angels to invest in the same company at the same time. The decision investors face is therefore a discrete/continuous choice of whether to invest or not and if they invest, how much.[9] If the investor invests, he forms a new

[9] We also ignore the possibility that entrepreneurs may have multiple concurrent offers from different angel groups. Fehder et al. [2018] determine from a sample of roughly 500 startups that only 8% ever were faced with concurrent offers. As a result, we model the entrepreneur as a passive player in this model.

portfolio of $P_i(F',\ S\&P')$ and if the angel investor elects to not invest in company f his portfolio remains at $P_i(F,\ S\&P)$. Additionally, the outcome associated with each investment decision is a continuously compounded return, in which investors have expectations about the likelihood of each possible outcome for a given investment.[10]

4.2 Investor Utility

We model investor utility from portfolio P with a constant relative risk aversion (CRRA) utility function. We do so for several reasons. First, researchers usually believe that individuals exhibit decreasing absolute risk aversion. That is, as individuals becomes more wealthy, they becomes less averse to risk. A CRRA utility function implies such a relationship, while a CARA utility function does not. Second, the CRRA utility function brings tractability to estimation (as will be presented below) while retaining the decreasing absolute risk aversion property.

The utility the angel receives from portfolio P is,

$$U_i(A_P, \mathit{\Gamma}_P) = \begin{cases} \frac{W_P^{1-\gamma_i}}{1-\gamma_i} = \frac{\left(\overbrace{A_P}^{\text{Monetary Benefit}} * \overbrace{\Gamma_P}^{\text{Non}-\text{Monetary Benefit}}\right)^{1-\gamma_i}}{1-\gamma_i} & \text{if } \gamma < 1,\ \gamma \neq 1\, \gamma > 1 \\ ln\, W_p & \text{if } \gamma = 1 \end{cases}$$

where W_P is a function of $A_P = D_i e^{r_{P,i}}$, the total monetary return of portfolio P, and $\mathit{\Gamma}_P$, the non-financial utility associated with the investor's portfolio, which is a function of the number of illiquid investments held by investor i ($\Gamma_P = exp(\alpha j_i^2)$). The number of illiquid investments is used to proxy for time given time is what is needed to capture the benefits associated with networking, intellectual challenge, and for altruistic reasons. Thus, the utility specification models the non-monetary utility as a multiplicative effect of the monetary utility. We assume a multiplicative utility model due to the fact that an additive model implies a marginality property where the marginal utility of one extra pecuniary or non-pecuniary benefit consumed is independent of the the other amount consumed. This is clearly not the case in our model where non-pecuniary income is only possible when pecuniary income (positive or negative) is present. Therefore, preferences cannot be additively

[10] Below we will discuss how consumers form expectation as to the returns for venture f, the S&P 500, and the portfolio.

separable.

Assume investors are uncertain over the return on the portfolio as well as the individual investments, which are continuously compounded, with investment returns equaling $A_v = A_{0,v}e^{r_v}$, where $A_{0,v}$ is the *initial investment* in asset v, $v = (f, s, P)$ where f corresponds to individual angel investments, s to the S&P 500, and P to the portfolio consisting of f and s. Consequently, $r_v = ln\left(\frac{A_v}{A_0}\right)$ for asset v. We further assume all investors believe instantaneous return rates are normally distributed $r_v \sim N(\mu_v, \sigma_v^2)$ with bounds $r \in (-\infty, \infty)$.

Remark 1. We assume that angel investments are independent of one another, which is due to the difficulty of identifying the correlation parameters associated with individual asset returns from our data.

Given this information, the utility of portfolio P can be rewritten as

$$U_i(A_P, \mathit{\Gamma}_P) = \frac{W_P^{1-\gamma_i}}{1-\gamma_i} \quad = \tfrac{1}{1-\gamma_i}e^{(1-\gamma_i)ln(W_p)}$$

$$W_P = \underbrace{D_i e^{r_{P,i}}}_{A_P} * \underbrace{e^{\alpha j_i^2}}_{\Gamma_P}$$

$$U_i(A_P, \mathit{\Gamma}_P) = \frac{1}{1-\gamma_i}\left(e^{(1-\gamma_i)(ln(D_i)+r_{P,i}+\alpha j_i^2)}\right)$$

$$U_i(A_P, \mathit{\Gamma}_P) = K_i\left(e^{(1-\gamma_i)(r_{P,i}+\alpha j_i^2)}\right) \text{ with } K_i = \tfrac{1}{1-\gamma_i}e^{(1-\gamma_i)ln(D_i)},$$

where α is the nonlinear effects of adding one more outstanding venture without a liquidity event on non-pecuniary income. More specifically, the functional form of $\mathit{\Gamma}_P$ assumes non-pecuniary income is increasing in the number of outstanding investments without a liquidity event. This relationship captures the idea that as more interactions occur with multiple entrepreneurs, the more utility the investor receives. The use of the quadratic form is albeit a reduce form approach to capturing the net effect associated with all the above reasons why investors may value non-pecuniary benefits. This model by no means is able to separately identify the impact each reason has on choice nor is it within the scope of this paper. Finally, note that if α is zero then an investor only values the monetary return and the non-pecuniary value equals one.

For any given angel, $(1-\gamma_i)r_P$ is normally distributed, which provides a closed form solution for consumer i's expected utility, $E\left[U_i(A_P, \mathit{\Gamma}_P)\right]$. It takes the form

$$E\left[U_i(A_P, \mathit{\Gamma}_P)\right] = K_i\left(e^{(1-\gamma_i)\mu_{P,i}+\frac{1}{2}(1-\gamma_i)^2\sigma^2_{P,i}+(1-\gamma_i)\alpha j_i^2}\right).$$

The expected utility of individual $i's$ portfolio P is a function of the angel's relative risk aversion parameter, the mean and variance of the portfolio returns, and function of the number of angel investments outstanding for investor i. We should note that the above equation also captures the impact angel investors have on expected portfolio returns through the value added services that they may bring to the venture. These effects are captured via the portfolio mean and variance as they are a function of the underlying ventures' expected mean and variances.

4.3 Investor Decision Problem

Investors are assumed to maximize expected utility and are short-term myopic decision makers. We realize this is an abstraction of reality, but in making such an assumption we are not required to track the time left to exit for each angel investment f.[11] In doing so, we ensure a simple threshold decision rule whereby investors consider the expected return on the portfolio in period t+1 (a year).[12] An investor elects to invest in company f if the expected utility of the portfolio with the new investment is greater than the outside option of not investing and holding the existing portfolio, $E\left[U_i(A_{P'}, \mathit{\Gamma}_{P'})\right] > E\left[U_i(A_P, \mathit{\Gamma}_P)\right]$.

Investor i's decision is

$$Max\left(\underbrace{K_i\left(e^{(1-\gamma_i)(\mu_{P',i}+\frac{1}{2}(1-\gamma_i)\sigma^2_{P'}+\alpha(j_i+1)^2)}\right)}_{\text{Invest}}, \underbrace{K_i\left(e^{(1-\gamma_i)(\mu_{P,i}+\frac{1}{2}(1-\gamma_i)\sigma^2_{P,i}+\alpha j_i^2)}\right)}_{\text{Do Not Invest}}\right)$$

which simplifies to

11

This eliminates the concern associated with the impact of the remaining holding period of the investment $(T-(t-t_0))$ and how returns (if any) are reinvested after exit.

12

Note, we normalize returns to one year for simplicity. Given angels are myopic decision makers, the qualitative results would not change if we normalized returns to t+x periods.

$$Max\ [(1-\gamma_i)\mu_{P',i} + \frac{1}{2}(1-\gamma_i)^2\sigma^2_{P',i} + (1-\gamma_i)(\alpha(j_i+1)^2),\ (1-\gamma_i)\mu_{P,i} + \frac{1}{2}(1-\gamma_i)^2\sigma^2_{P,i} + (1-\gamma_i)\alpha j_i^2]. \quad (1)$$

In order to proceed, we must map the log portfolio return r_P back to the underlying returns of the individual assets. We are keenly aware that the log return on the portfolio is the log of a linear weighted combination of the simple asset returns R_v, and is not the same as a linear weighted combination of logs. We thus need to approximate the nonlinear function relating to log portfolio returns. We use a variant of the Fenton-Wilkinson approximation by Mehta et al. [2007] that constructs a "simple, novel, and general method... to approximat[e] the sum of independent or arbitrarily correlated log-normal random variables (RV) by a single log-normal RV." "The method uses the moment generating function (MGF) as a tool in the approximation and does so without the extremely precise numerical computations at a large number of points that were required by the previously proposed methods in the literature," [Mehta et al., 2007].[13]

With the assumptions and approximations discussed above, we construct the angel investor's investment rule. If γ_i is greater than some threshold,

$$\begin{array}{ccc}
(1-\gamma_i)\mu_{P',i} + \frac{1}{2}(1-\gamma_i)^2\sigma^2_{P',i} + (1-\gamma_i)(\alpha(j_i+1)^2 &) > & (1-\gamma_i)\mu_{P,i} + \frac{1}{2}(1-\gamma_i)^2\sigma^2_{P,i} + (1-\gamma_i)(\alpha {j_i}^2) \\
\mu_{P',i} + \frac{1}{2}(1-\gamma_i)\sigma^2_{P',i} + (\alpha(j_i+1)^2) & > & \mu_{P,i} + \frac{1}{2}(1-\gamma_i)\sigma^2_{P,i} + (\alpha {j_i}^2) \\
\frac{2(\mu_{P',i}-\mu_{P,i})}{(\sigma^2_{P,i}-\sigma^2_{P',i})} + \alpha\frac{2(2j_i+1)}{(\sigma^2_{P,i}-\sigma^2_{P',i})} & > & 1-\gamma_i \\
\gamma_i & > & 1-\frac{2(\mu_{P',i}-\mu_{P,i})}{(\sigma^2_{P,i}-\sigma^2_{P',i})} - \alpha\frac{2(2j_i+1)}{(\sigma^2_{P,i}-\sigma^2_{P',i})}
\end{array} \quad (2)$$

the angel invests, and does not invest if

$$\gamma_i \leq 1 - \frac{2(\mu_{P',i}-\mu_{P,i})}{(\sigma^2_{P,i}-\sigma^2_{P',i})} - \alpha\frac{2(2j_i+1)}{(\sigma^2_{P,i}-\sigma^2_{P',i})}.$$

Note, embedded in this threshold model is the amount the angel invests in venture f through the formation of new investment weights for the new portfolio P'.

[13] It is important to highlight that the above theoretical and below empirical model both account for the impact a large number of angel investments has on the portfolio variance.

5 The Econometric Model and Estimation

5.1 Beliefs on Asset Returns

In order to estimate the above model we must translate the choice environment into a choice between a well defined set of lotteries. A particularly important and difficult step is the formation of lotteries, as estimation of risk preferences requires information about investor beliefs on asset returns. Therefore, what does the econometrician assume about an agent's subjective beliefs about the likelihood of the possible outcomes? In some instances, there are clear objective probabilities, such as state or national lottery contests and therefore the beliefs are specified, but in many other cases they are not. In our setting, we follow the literature of Barseghyan et al. [2016] and assume agents have *rational expectations*, in that beliefs correspond to objective probabilities. This is due to the fundamental identification problem associated with the estimation of subjective beliefs and preferences simultaneously. Specifically, we follow the literature centered around evaluating private equity returns [Franzoni et al., 2012] and employ a Fama and French [1993] factor model with additional non-traded macroeconomic factors tailored to the entrepreneurial environment in order to recover the mean (μ_v) and variance $\left(\sigma_v^2\right)$ of the expected asset return for use in the Fenton-Wilkinson approximation. Like private equity, angel investments are scarcely traded, if at all, and so we cannot use time series variation to identify factor loads. Instead, we exploit the cross-sectional variation of returns, which was first used by Cochrane [2005] and later used by Driessen et al. [2012], and Franzoni et al. [2012] for studying abnormal returns of non-traded assets.

Given that we see total investment dollars from angel i, in investment f, at period t, and the total dollars returned by that same investment at the time of exit T, we employ a variant of Franzoni et al. [2012], where one-period log returns are log normally distributed and exhibit a linear factor structure. We do not express our factors in log terms (as in Cochrane, 2005), but rather in levels, as the factor data can take negative values. In the most simple case, where an investment occurs in period t and the venture exits in $t+1$, the model follows

$$ln\left(\frac{A_{f,g,t+1}}{A_{f,g,t}}\right) = \tau_g + ln\left(R^f_{t+1}\right) + \delta' \mathcal{F}_{\mathrm{t+1}} + \eta_{f,g,t+1} \tag{3}$$

where $A_{f,g,t}$ is the initial investment in angel venture f through angel group g, in period t. $A_{f,g,t+1}$ is the return in period $t+1$ of venture f through angel group g, τ_g is an angel group fixed effect, R^f is the gross risk free rate, $\mathcal{F}$ is a vector of k risk factors, δ is a k-vector of factor loadings, and $\eta \sim N(0, \sigma_r^2)$ is independent of the risk factors. Note, the error term is venture-specific and not individual. Consequently, we assume there is no individual level unobserved heterogeneity with regard to an angel's subjective belief on investment returns. Such an assumption is supported by the fact that with our data all investments are sourced through angel group screenings and that it is typical for a group of angels within each angel investment group to perform due diligence for all members. However, sorting in the marketplace, where successful angel groups have access to different quality of ventures than less successful groups may occur in practice and have an effect on our model results. For instance, those groups who have access to high quality ventures, their expectation about returns will be higher (and/or possibility with less variance) than those without such access. Controlling for such difference is important as the mean and variance of the expected venture returns is an important variable in our model. While our data is blind with respect to the location of each angel group which therefore eliminates the ability to implement a two-sided matching model to correct for sorting, we can control for variation in returns conditional on angel group as our data does identify angel groups. Moreover, with the ability to view multiple returns for each angel group we are able to implement an angel group fixed effect, τ_g, to control for any possible sorting in the marketplace. In the end, our model relies on correctly estimating angel expectations to estimate and investigate investor behavior.

An additional issue that arises with angel investors is the belief that angel investors add value to the company and thereby impact investment returns–this maybe particularly true for active investors as well as passive investors with active co-investors. To control for this effect on returns, we again use the angel group fixed effects. In doing so, the fixed effect also captures the average value added benefit associated with investors from a given angel group.[14]

For investments that live longer than one period, we determine the geometric average return on investment. This is because we do not observe any intermediate valuations of the venture, allowing

[14] Note, that sorting and the benefit from the value added work by the angel on returns is not separately identified from each other.

us to construct a time series of investment returns. The geometric average return takes the form

$$\frac{1}{T_f} ln\left(\frac{A_{f,g,T}}{A_{f,g,0}}\right) = \tau_g + \frac{1}{T_f}\sum^{T_f} ln\left(R^f_{t+1}\right) + \delta' \frac{1}{T_f}\sum^{T_f} \mathcal{F}_{t+1} + \frac{1}{T_f}\sum^{T_f} \eta_{f,g,t+1}$$

with the variance of the error equaling $\frac{1}{T_f}\sigma_r^2$ and T is the length of the investment holding. We eliminate the heteroskedasticity by using a weighted least squares estimator with weights equal to $\sqrt{T_f}$. The dependent variable is the scaled natural logarithm of gross returns, and the independent variables are the time-series averages of the risk factors over the investment's life.

5.1.1 Factors

An important assumption that enables us to price the risk factors using a public equity factor model is the that there exists a link between the private and public equity markets [Franzoni et al., 2012]. Our factor model augments the Fama-French three factor model with additional macroeconomic factors that we believe are central to the startup world and capture the macro level risk associated with angel investing: The Kaufman Foundation Startup Activity Index,[15] the Kaufman Foundation 5-year survival rate for startups and the Bureau of Labor Statistics (BLS) startup growth rate.[16] We believe that each of these entrepreneurial factors could impact valuations and thus firm performance and returns.

In Table 4, we present the underlying data (in levels) that is used to construct our non-traded entrepreneurial factors, and in Table 5 we present the factors themselves, which is the difference between the yearly level and the three year moving average. Two of the most prominent facts pertaining to these tables are that the 5-year survival rate of a startup increased as it approached year 2001 and then declined, perhaps indicating an underlying shift in the entrepreneurial conditions pertinent to startups.[17] Similarly, the Kaufman Index increased and then declined post 2001.

[Insert Table 4 here]

[Insert Table 5 here]

[15] Index measure of new venture creation.

[16] Each of these factors are created by forming a 3-year moving average of the underlying variable and differencing the year specific variable from its moving average.

[17] This variable is measured in the 5th year. For instance, the 2000 measure corresponds to the 1996 cohort of startups.

5.1.2 Accounting for Zero Return Data

Equation 3 requires a measure of the geometric return. Yet, in some instance, in our data, the natural logarithm of this return is not defined (ventures with a return multiple of 0). We also make the assumption above that log returns are normally distributed, but given the large number of undefined log venture returns, such an assumption fails the Shaprio-Wilk's test of normality. This is because roughly 30% of the observed angel ventures returned zero cash flow. In order to mitigate these concerns, "we adopt the typical approach in the asset pricing literature and group individual investments into portfolios" [Franzoni et al., 2012]. Specifically, for an individuals investment that returned 0x, we group other positive return investments that were initiated in the same year and by the same angel group together with the 0x return asset to form a portfolio. Moreover, within any set of initial investments, if all investments in that year returned positive cash flows then each investment is treated as a "portfolio" in order to increase the power of the return analysis.[18] Thus, the log asset returns presented in Figure 5 includes individual venture asset returns (when all of the other investments in the same angel group year cohort returns were positive) and the portfolios just described. These new returns are indeed normally distributed.[19] Finally, it should be noted that we cannot simply assume returns that were zero were paid some fraction on the dollar (e.g. $0.05 on the dollar) as doing so would lead to a non-normal distribution of log return and a failure of the primary assumption of the above model.

[Insert Figure 5 here]

5.2 Portfolio Choice

In the theoretical model above, we assume, investor risk preferences are individual specific. In the empirical application we also allow the relative risk aversion parameter to vary by demographic, experience and type (active and passive), which takes the form

$$\gamma_i = x'_{1,i}[\beta_1 + \beta_2 \mathrm{I}(Active)] + \varepsilon_{1,i}. \tag{4}$$

[18]If we simply formed portfolios by initial investment year and angel group, the number of observations would decrease substantially, and statistically precise estimates would have been difficult to obtain.

[19]We test using the Shapiro-Wilks test and determine that we cannot reject the null hypothesis that returns are normally distributed.

Furthermore, the impact of non-pecuniary income, α, is specified as

$$\alpha = \alpha_1 + \alpha_2 \mathrm{I}(Active)$$

and accounts for the impact non-pecuniary income may have for differing investor types. Assume there is unobserved heterogeneity in risk preferences in the form of $\varepsilon_{1,i}$.[20] This implies that observationally equivalent investors facing the same choice set are allowed to make different investment decisions. Thus, by specifying a distribution for ε, we can estimate the distribution for γ_i, even though the risk preference parameter is unobserved to the econometrican. In order to overcome this empirical issue, we use the natural threshold of the relative risk aversion coefficient in the theoretical model above to estimate investors' relative risk preferences. However, in order to proceed we make a few additional assumptions that pertain to the formulation of angel $i's$ asset class weights for use in determining the expected return of the new and old portfolios and potential investment dollars for angels we do not see invest.

Remark 2. We make an assumption regarding the potential investment dollars in venture f for angels whom we do not see invest in venture f. Our assumption is to set this potential investment amount to $d = \$30,000$. This assumption originates from Figure 3, which illustrates a large mass of angels making roughly a similar level of investment into each venture. For those angels who do invest, we employ the actual dollar amount, with the residual amount of the angel's wealth $(D_i - d * j_i)$ invested in the S&P 500, where j represents the total number of angel investments outstanding. Additionally, D_i or wealth is an important variable in our model as it dictates the weights associated with each class of investment, angel and S&P 500. The original data does not provide such a measure for a specific time period. Rather, it provides the percent of wealth held in angel investments at the time of the survey (in 2007), as we mentioned in Section 4. Given this percent along with the assumptions that investors invest roughly $30,000 per venture and that the investors wealth does not widely vary over time, we are able to approximate the investor's total wealth (D_i), $\%W_i = \frac{J_i * d}{D_i}$, and form weights for each year given the number of outstanding angel ventures for each investor is available.

[20]The subscript 1 will become clear after presenting the investment level model

The latent variable model we take to the data and estimate, with the binary investment choice variable y_i taking the value 1 if $\gamma_i > Z$ and 0 if $\gamma_i \leq Z$, and with the assumption of ε being normally distributed, is

$$Pr(choice = 1) = Pr\left(\gamma_i > 1 - \frac{2(\mu_{p',i} - \mu_{P,i})}{(\sigma^2_{P,i} - \sigma^2_{P',i})} - [\alpha_1 + \alpha_2 \mathrm{I}(Active)]\frac{2(2j_i+1)}{(\sigma^2_{P,i} - \sigma^2_{P',i})}\right)$$
$$= Pr\left(x'_{1,i}[\beta_1 + \beta_2 \mathrm{I}(Active)] + \varepsilon_{1,i} > 1 - \frac{2(\mu_{p',i} - \mu_{P,i})}{(\sigma^2_{P,i} - \sigma^2_{P',i})} - [\alpha_1 + \alpha_2 \mathrm{I}(Active)]\frac{2(2j_i+1)}{(\sigma^2_{P,i} - \sigma^2_{P',i})}\right)$$
$$Pr\left(\varepsilon_{1,i} > -x'_{1,i}[\beta_1 + \beta_2 \mathrm{I}(Active)] + \underbrace{\left(1 - \frac{2(\mu_{p',i} - \mu_{P,i})}{(\sigma^2_{P,i} - \sigma^2_{P',i})} - [\alpha_1 + \alpha_2 \mathrm{I}(Active)]\frac{2(2j_i+1)}{(\sigma^2_{P,i} - \sigma^2_{P',i})}\right)}_{Z}\right), \tag{5}$$

which translates into a probit model with the coefficient on (Z) equal to one instead of the typical probit normalization of the variance term. This procedure is quite similar to one of the methodologies employed by Cohen and Einav [2007].

The error terms corresponding to the distributions of logarithmic rate of return and relative risk aversion parameter are assumed to be independent of one another, $\varepsilon \perp \eta$, with both independent of the S&P 500 index return.

5.3 Investment Level Decision

With the investor's choice a discrete/continuous decision, we are also interested in understanding the factors that drive investment levels. However, given that we observe this information only for those of whom have invested, we must correct for sample selection/correlation between the discrete and continuous unobservables. If we were to regress $y_{2,i}$ on $x_{2,i}$, where $y_{2,i}$ is the level of investment, using only the observed values of y_2, it would generate inconsistent estimates of β_2 unless the errors of the investment (participation) decision and outcome equations were independent. We correct for any selection concerns with the use of a Heckman sample selection model. The correction for sample selection is slightly different than the usual procedure, as in our model we normalize the coefficient with respect to z to one. Consequently, we have to account for the variance in our correction procedure.

The participation equation from above is

$$y_1 = \begin{cases} 1 & \text{if } \gamma_i > Z \\ 0 & \text{if } \gamma_i \leq Z \end{cases}$$

and the outcome equation is

$$y_2 = \begin{cases} y_2^* & \text{if } \gamma_i > Z \\ - & \text{if } \gamma_i \leq Z \end{cases}$$

where $y_2^* = x'_{2,i}\psi_2 + \varepsilon_{2,i}$. The model specifies that the outcome variable is observed only when the investor invests with the company. Suppose the errors are jointly normally distributed and homoscedastic, with

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \sim \mathcal{N}\left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{matrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{matrix}\right].$$

From the bivariate normal distribution above, it implies the epsilons 1 and 2 are correlated, $\varepsilon_2 = \frac{\sigma_{12}}{\sigma_1^2}\varepsilon_1 + \xi$ where $\xi \sim \mathcal{N}[0, \sigma_2^2 - \sigma_{12}\frac{1}{\sigma_1^2}\sigma_{12}]$ is independent of ε_1.

Additionally, the conditional truncated mean of y_2 is

$$\begin{aligned} \mathbf{E}\left[y_2|\mathbf{x}, \rho < z\right] &= \mathbf{E}[\mathrm{x}'_2\psi_2 + \varepsilon_2|\mathrm{x}'_1[\beta_1 + \beta_2\mathrm{I(Active)}] + \varepsilon_1 > \mathrm{Z}] \\ &= x'_2\psi_2 + \mathbf{E}[\varepsilon_2|\varepsilon_1 > \mathrm{Z} - \mathrm{x}'_1[\beta_1 + \beta_2\mathrm{I(Active)}]] \\ &= x'_2\psi_2 + \mathbf{E}\left[\tfrac{\sigma_{12}}{\sigma_1^2}\varepsilon_1 + \xi|\varepsilon_1 > \mathrm{Z} - \mathrm{x}'_1[\beta_1 + \beta_2\mathrm{I(Active)}]\right] \\ &= x'_2\psi_2 + \tfrac{\sigma_{12}}{\sigma_1^2}\mathbf{E}[\varepsilon_1|\varepsilon_1 > \mathrm{Z} - \mathrm{x}'_1[\beta_1 + \beta_2\mathrm{I(Active)}]] \end{aligned}$$

and from the fact that the parameter of Z is normalized to one and not the variance of the error distribution

$$\begin{aligned} \mathbf{E}\left[y_2|\mathbf{x}, \rho < z\right] &= x'_2\psi_2 + \tfrac{\sigma_{12}}{\sigma_1^2}\sigma_1\mathbf{E}\left[\tfrac{\varepsilon_1}{\sigma_1}|\tfrac{\varepsilon_1}{\sigma_1} > \tfrac{\mathrm{Z} - \mathrm{x}'_1[\beta_1 + \beta_2\mathrm{I(Active)}]}{\sigma_1}\right] \\ &= x'_2\psi_2 + \tfrac{\sigma_{12}}{\sigma_1}\lambda\left(\tfrac{x'_1[\beta_1 + \beta_2\mathrm{I}(Active)] - Z}{\sigma_1}\right) \\ &= x'_2\psi_2 + \sigma_2\rho\lambda\left(\tfrac{x'_1[\beta_1 + \beta_2\mathrm{I}(Active)] - Z}{\sigma_1}\right) \end{aligned} \tag{6}$$

where $\lambda(\frac{x_1'[\beta_1+\beta_2 \mathrm{I}(Active)]-Z}{\sigma_1}) = \frac{\phi(\frac{x_1'[\beta_1+\beta_2 \mathrm{I}(Active)]-Z}{\sigma_1})}{\Phi(\frac{x_1'[\beta_1+\beta_2 \mathrm{I}(Active)]-Z}{\sigma_1})}$ is the inverse mills ratio, $\sigma_{12} = \sigma_1\sigma_2\rho$, and ρ is the correlation parameter. In order to determine if selection is a concern, we recover ρ and test whether it is statically different from zero by regressing the outcome variable on x_2 and $\lambda(\frac{x_1'[\beta_1+\beta_2 \mathrm{I}(Active)]-z}{\sigma_1})$. The parameter estimate for $\lambda(\frac{x_1'[\beta_1+\beta_2 \mathrm{I}(Active)]-Z}{\sigma_1})$ corresponds to $\sigma_2\rho$, and allows us to determine if ρ is zero. Or simply put, if $\sigma_2\rho$ is zero then selection is not a concern.

6 Identification

Angel investors face several decisions, from determining whether to invest, to deciding how much. Below, we discuss how the investment return and relative risk aversion distributions are identified using the variation in the data and generally how 2-step sample selection models are identified. But, before we do, it is important to discuss how we disentangling risk preferences from beliefs.

There are two approaches used in the literature to separate risk preferences from beliefs, but each requires making an assumption about preferences or beliefs. The first, and the one we use, is to assume that investors hold objective expectations. In the angel investment context, this translates into assuming investors know the objective return on investments. Once these "beliefs" are specified, the model takes them as given and focuses on identifying and estimating risk preferences. The second option is to assume that individuals are risk neutral and estimate investor subjective beliefs.

Our empirical model incorporates unobserved heterogeneity and, as a consequence, adds to the challenge in identifying model parameters. The mere presence of unobserved heterogeneity "implies that observationally equivalent people facing the same choice set, make difference choices" [Barseghyan et al., 2015]. Given this, to identify the investors' risk preferences, the researcher must observe how investors choose different options when facing a fixed menu, and then variation in the menu options across investors can be used to identify consumer risk preferences and the unobserved heterogeneity. Specifically, the CDF of the risk preference is pinned down by cross sectional variation in choice sets conditional on observed characteristics (demographics, experience and participation type).

Identification of the log normal distribution of angel returns is identified through the asset pricing model and is relatively straight forward to identify load factors given the availability of investment return data. For the log normal distribution of the S&P 500, we identify the location parameter and the variance of the log return from the assumption that investors use a 3-year rolling average of the log returns of the S&P 500. Thus, the location parameter of the log normal distribution for the S&P 500 index is estimated as $\mu_{r,0,t} = \frac{ln(1+R_{0,t-3})+...+ln(1+R_{0,t-1})}{3}$. The second moment is derived from the estimation of the location parameter and the variance of the log returns of the S&P 500. We also do not impose an assumption regarding the correlation of returns between the S&P 500 and angel ventures. Instead, we let the data inform us of this relationship–these two investment vehicles are correlated with each other and have a slight correlation parameter of -0.08985.

Identification of the non-pecuniary income parameter (α_1 and α_2) originates from the cross sectional variation in the differences in portfolio variances and a function of the number of outstanding ventures without a liquidity event. Given portfolio variance is an input, identification also relies on the ability to control for value added services and sorting effects in the asset return model. Moreover, the natural exclusion of the number of outstanding ventures from the risk preference function aids in the identification of the non-pecuniary effect. If the number of outstanding ventures entered into the risk preference function, we then would be unable to separate its effect from monetary utility.

Finally, we discuss what identification assumptions are needed to pin down the correlation between the investment decision and investment level errors. Given that our model is a variant of a bivariate sample selection model with normal errors, identification is achieved by a functional form assumption, as is usually the case. Of particular concern is multicollinearity. The strength of such is dependent upon how well the probit model can discriminate between participants and nonparticipants. In order for the model to discriminate between participants and nonparticipants, an exclusion restriction is required–our exclusion restrictions between the participation and investment level equations is that the number of co-investors and the years of relevant industry experience pertaining to the venture are restricted to only the investment level equation. With such, we are able to identify the correlation between ε_1 and ε_2. We motivate these exclusion restrictions through the fact that we do not explicitly observed the years of experience in the venture's industry for all potential investors and the fact that the number of co-investors is endogenous and therefore would be inappropriate to include in the investment selection model, without some correction as is the case here with the inclusion of the inverse mills ratio.

7 Results

Below we present the results of our model. We begin with the investor beliefs model, followed by the binary investment decision and conclude with the investment level model.

7.1 Investor Beliefs: Estimates

Estimates of the angel investment beliefs (returns) model are presented in Table 6. We present three models, i) CAPM, ii) Fama-French 3-factor model and iii) our model, which augments the 3-factor model, with non-traded entrepreneurial factors. The first model of CAPM finds that excess returns are an important risk factor with a loading of 1.88 and is statistically significant. Yet, the loading on the excess market factor decreases as the Fama-French or our entrepreneurial non-traded factors (with Fama-French) are included. When the Fama-French factors are included without the others, we find negative loadings for the book-to-market factor and size of the firm factor, which are indicative of a small growth firm. Furthermore, the growth potential associated with angel investment companies comprised much more of the total value of the firm than its publicly traded growth stock counterparts. We also present the results of Ewens et al. [2016] which studies venture capital returns from inside and outside financing in order to draw comparison against the returns of the venture capital market.

Next, we discuss our proposed model with the non-traded entrepreneurial factors. Like the Fama-French model, the loading associated with excess market returns is lower than in the CAPM case (1.33).[21] The estimated beta (1.33) indicates that angel investments are risky investments. The loading associated with the book-to-market and size factors remain negative and significantly different than zero. We further find that the non-traded factors, Kaufman Index and the 5-year success rate of startups, have loadings that are both statistically significantly different than zero, indicating the importance of incorporating non-traded factors when estimating entrepreneurial asset returns. Specifically, as the 5-year survival rate and Kaufman Index factors increase above their moving average, the associated returns increase. Finally, the standard deviation of the error term is roughly 0.38, indicating a lesser degree of variance in the unobserved component of the factor

[21] Note, the reported value does not pertain to the traditional β associated with CAPM as our model includes the logarithm of returns rather than levels. Thus, a conversion from log returns to levels is needed and given by $\beta = R_f \delta e^{\tau+\delta'\bar{\mathcal{F}}+\frac{1}{2}\delta'\sigma_F^2\delta+\frac{1}{2}\sigma^2}$,where $\bar{\mathcal{F}}$ are vector of factor means and σ_F^2 is the factor variance-covariance matrix. We report only the log parameterization of β as it is close to the level.

return model than when angel group fixed effects are not included (0.45). Similarly, the excess return associated with the model falls when fixed effects are not included (0.79) due the model pooling observations across groups rather than using within angel groups variation to determine the excess return.

[Insert Table 6 here]

7.2 Investment Decision

In Table 7, we present the parameter estimates from the investor choice model above (Model i) and a second model which does not account for non-pecuniary income (Model ii). The results illustrate how relative risk aversion is related to demographics, experience and investor type (passive, active). Most importantly, it highlights what characteristics entrepreneurs should consider when targeting angel investors for additional capital.

[Insert Table 7 here]

Given the motivations for investing include monetary and non-monetary incentives, angel investors are typically separated into two classifications, active and passive investors; both of which are found in angel groups. Active investors are motivated by not only financial returns (with and without the their value added services) but also with large non-pecuniary income returns; some angel investors may value being a part of the exciting development process of launching a new venture and/or the benefits from giving back (altruism), networking or tackling an intellectual challenge. Passive investors, on the other hand, are more interested in financial returns and the value investing in angel ventures brings through diversification of asset classes. These investors are able to leverage the benefits of angel groups differently from active investors and thus may exhibit differing investment patterns, risk preferences and non-pecuniary benefits. But, before doing so we discuss the demographic drivers of risk preference. First, women are found to be on average no more risk averse than men, a result that is inline with the existing psychology and behavioral economics literature Johnson and Powell [1994] when knowledge and experience is accounted for as is the case here. Next, we find significant differences in risk preference based upon the level of education. For instance, those who hold a Masters degree and are active are less risk averse than passive Masters or Bachelors degree holders. Additionally, passive PhDs are more risk averse than investors who hold a bachelors degree.

An important factor impacting an investor's risk preference is experience in angel investing. Yet, how experience impacts an investor's risk preference differs on whether the angel is a passive or active investor. For active investors, the number of years as an angel investor decreases risk aversion; for passive investors the opposite is found–more years of experience lead to a higher risk aversion. We also determine that the number of years of work experience in a large (500+ employee) firm affects risk preferences for active and passive investors alike and do not differ among types. All investors become more risk averse the longer they have worked in a large company. We conjecture that this result is due to employees observing their employer's culture toward innovation, particularly for those who have worked at a slow moving legacy company, which continually passes up new initiatives. Experience as an entrepreneur also leads active investors to be less risk averse with more years of experience where as with passive angels there is no effect. Lastly, we look to analyze how the number of angel investments made impacts risk preferences. Interestingly, the effect diverges for investor types. Active investors become less risk averse whereas passive investors their is no affect. We conjecture that this is do to active investors being engaged with the entrepreneur and are able to learn/observe the challenges a business must over come to become successful. On-the-other-hand, passive investors who are removed from any engagement with entrepreneurs, do not have the opportunities to discover the challenges firms face to become successful and therefore preferences do not change. The latter result, those pertaining to the passive investors, is similar to the findings from Meyer and Hutchinson [2001], who found that participants in an earthquake simulation failed to learn from the sparse occurrence of high-stakes choices.

As discussed above, the non-financial income portion of the investor's utility function is thought to be an important sources of income for active investors. Our model estimates of α_2 indicates that non–pecuniary income does indeed impact investor choice and is statistically different from zero.[22] Thus, *active investors do value non-pecuniary income* associated with being a part of the exciting development process of launching a new venture, networking benefits, an intellectual challenge, and for altruistic reasons, as we have controlled for the value added benefits of supporting firms through acting as a sounding board, monitoring, resource acquisition, and mentoring in the asset returns

[22] $\alpha_1$is found to be statistically insignificant

model via angel group fixed effects. Unfortunately, we are unable to identify gender differences associated with non-pecuniary sources of income due to the limited observations associated with active female investors. If we were in possession of data that had greater number of observation from women, we could test theory that predicts female active investors valuing non-pecuniary sources of income more than men as research in psychology find women to be more altruistic and have more pro-social behaviors [Fabes and Eisenberg, 1998].

The finding that active investors value non-pecuniary sources of income more than passive investors leads into an interesting question of which investor type, active or passive, is more risk averse? Are passive investors more risk averse because they are more interested in diversification of their asset portfolio or are active investors due to their ability to monitor ventures? Or does the ability to monitor investments lead these active investors to undertake more risky ventures indicating active angels are less risk averse than their passive counterparts. In order to answer this question, we employ the parameter estimates from Table 8 and the observed data to form risk preference by type. Our analysis indicates the median investor risk parameter is -1.39 with the medium passive and active investor risk parameters at -0.60 versus -1.79, respectively. Thus, the majority of angle investors are risk seeking with the median passive investor in our sample more risk averse than the medium active investor. In Figure 6, we provide the empirical density of the estimated relative risk aversion preference for each investor type to further illustrate the result. Finally, the mean estimated likelihood of investing for all angel types is 6.38% whereas the observed likelihood is 6.40%. Note, we also present results from model (ii) in which investors only value monetary utility. These results indicate that such a model underestimates investor risk aversion when non-pecuniary income is ignored (median investor risk preference of -1.95).

[Insert Figure 6 here]

7.3 Investment Levels

Below in Table 8, we present the results of our investment level analysis. Results are from models that i) correct for sample selection and ii) do not. We determine that the only factor that dictates the amount of investment in a venture is the number of co-investors with and without correcting for sample selection. This is a surprise finding as one would think that risk preferences would impact such a decision. However, if one analyzes how angel investments are made within an angel group, the result can be simply rationalized. Our results illustrate that risk preferences only impact the angel's decision whether to invest or not and not the level of investment. First, within an angel group, angel investors typically must invest a minimum amount each year to continue his/her involvement in the group. Most angel groups also have minimum levels of investments that must be made per deal. Thus, regardless of an investors risk preference, the optimal strategy for either type of investor is to diversify ones portfolio by investing the minimum level required over a larger number of deals. This is evident by Figure 3 and its large mass around $30,000. We also determine that the number of co-investors negatively impacts investment levels and industry experience does not. This former point is not surprising, as with angel investing most firms/entrepreneurs have a predetermined financing level that they seek, and once that amount is fullfilled the more investors join in financing the venture, the smaller the investment by each angel investor. Our investment level model also determines that industry experience has no statistical impact on investment levels. Some may assume that industry familiarity may entice investors to invest more, yet our results indicate that this not true. While the parameter estimate is positive, it is statistically insignificant at a 95% confidence level. Also, conditional on investing the average number of years experience an investor has in the invested venture industry is only 3.54 years, indicating that investors in our data may not specialize in industries that they have work experience in, in order to diversify their portfolio. One reason for this low number is that by banding together and forming angel groups, it "allows the [angels] to draw on each other's experience and expertise" and to get "input from others in the group before they decide whether to get involved" which is reflected in the capital asset pricing model through the inclusion of angel group fixed effects.[23] Lastly, the parameter that corrects for selection (lambda) is negative and statistically insignificant from zero, informing us that sample selection is not a concern; or more specifically, there is a no statistical correlation between the errors in the investment levels and participation equations. Next to these results in Table 9 are the results that do not correct for selection.

[Insert Table 8 here]

[23] https://www.investopedia.com/articles/personal-finance/060415/how-join-angel-investor-group.asp

8 Counterfactuals

8.1 Optimal Angel Investor

The results from the above analysis allow us to determine the optimal angel investor type. First we determine the risk preference of each investor type, active and passive, broken down by education level doing so at the observed means of the risk preference variables. In this exercise we find that the risk aversion associated with an active male investor at the mean investor characteristics is less risk averse than a passive investor. Additionally, an active male investor with an MBA (-1.99) is the least risk averse whereas a passive investor with an MBA (0.08) is the most. After identifying the most risk averse type, we move to analyze the impact each investor characteristic has on one's risk preference. We do so by calculating the partial effects associated with each variable for active MBA angel investors presented in Table 9 (again evaluated at the mean investor characteristics for each type). From such analysis, experience plays a vital role in determining the optimal angel investor for an entrepreneur to target. Our analysis highlights that entrepreneurs should target angel investors with extensive angel investment experience in the total number of angel investments made, the number of years the angel has been actively investing in angel ventures and has entrepreneurial experience. Finally, entrepreneurs should look for angels with limited number of years in a large company. In summary, our analysis indicates the ideal angel investor an entrepreneur should target is an active investor who holds an MBA and has extensive angel experience via the number of angel investments made, the number of years angel investing and years as an entrepreneur as this investor type has the lowest relative risk aversion preference.

[Insert Table 9 here]

8.2 The Impact of Non-pecuniary Income on Choice

With estimates of angel risk preferences, we run several counterfactuals to answer the following question: what is the impact of the non-pecuniary source of income on investor choice. We do so with two counterfactual exercises: 1) we assume active investor risk preferences remain constant and eliminate the non-pecuniary source of income to determine the impact on the likelihood of investing and 2) we search for the new portfolio mean return for each active angel investor so that the predicted likelihood from our model equates to the the newly formed simulated likelihood without non-pecuniary income, in order to put the change in likelihoods seen in counterfactual 1 in to a relative dollar measure.

In order to determine the impact that non-pecuniary income has on choice, we simulate investment decisions. We do so by simulating expected utility under the scenario where we "turn off" the non-pecuniary income for active investors. The expected utility of the active investor who holds portfolio P and invests in venture f and forms portfolio P' receives

$$E_{CF}\left[U_i(A_{P'}, \mathit{\Gamma}_{P'} = 0)\right] = K_i\Big(e^{(1-\gamma_i)\mu_{P',i}+\frac{1}{2}(1-\gamma_i)^2\sigma^2_{P',i}}\Big).$$

Investment in venture f is determined if the expected utility associated with portfolio P' is greater than without.

$$\text{Investment}_{\text{CF}} = 1, \text{ if } E\left[U_i(A_{P'}, \mathit{\Gamma}_{P'} = 0)\right] > E\left[U_i(A_P, \mathit{\Gamma}_P = 0)\right]$$

We then compare this investment decision to the scenario where non-pecuniary income is included as presented in the model section. The expected utility associated with portfolio P' with the non-pecuniary source of income is

$$E\left[U_i(A_{P'}, \mathit{\Gamma}_{P'})\right] = K_i\Big(e^{(1-\gamma_i)\mu_{P',i}+\frac{1}{2}(1-\gamma_i)^2\sigma^2_{P',i}+(\alpha_1+\alpha_2)(1-\gamma_i)(j_i+1)^2}\Big).$$

with the investment determined in a similar manner as above

$$\text{Investment} = 1, \text{ if } E\left[U_i(A_{P'}, \mathit{\Gamma}_{P'})\right] > E\left[U_i(A_P, \mathit{\Gamma}_P)\right].$$

After simulating investment decisions for all active investors, we determine the likelihood of investing with and without the non-pecuniary source of income. We present these results in Table 10 and determine the average likelihood of investing for an active angel investor in an angel venture would decrease roughly 6.92% from 3.47%.

With our second counterfactual exercise we determine that on average a 14.65% increase in the new portfolio's mean return is required to offset the loss of non-pecuniary income associated with counterfactual 1.

[Insert Table 10 here]

9 Limitations

We recognize that modeling and estimating von Neumann-Morgenstern utility functions with survey data may limit the generalizability of the results, but we believe, given the historic difficulty in obtaining independently verified angel investment data, return data, and data that includes *ALL* considered angel ventures, there is value in presenting our findings from what may be imperfect data rather than continuing to delay research in such an important area. Consequently, the conclusions drawn throughout our paper need to be understood in light of data and modeling limitations, of which we discuss below.

The first limitation is the use of survey data. With any survey data, the researcher needs to be cognizant of limitations that may lead to biased results (e.g. non-response, survivorship, and measurement error). For instance, the impact of non-response from survey "participants" is a reduction in the sample data size that leads to less precise estimates, but in severe cases it can also lead to a selective sample and surviorship bias. If only successful angel investors reported investment histories then the employed sample would not be representative of the angel population. If we assume that successful angels invest differently than non-successful angels, which results in unsuccessful angels abandoning angel investing altogether, then our estimator would be biased because the unsuccessful investors are no longer active and have not reported their failed investments. One possible method to mitigate this concern is to sample investors through angel groups, as it enables inactive investors to still report their historical investment activities. Although we cannot be certain that the AIPP sample is neither a selective sample nor includes survivorship bias, previous research from Wiltbank and Boeker [2007] indicates a lack of a significant difference in return on investments between high- and low-response-rate angel groups, reducing such concern.

The second data limitation is the fact that our constructed panel is formed from deals where at least one investor invested and are from only ventures that reached the investment decision stage. Thus, we do not see any ventures that were rejected during the screening or due diligence stage. The result of this data construction is also a selected sample. Yet, we are less concerned about this selection due to the process in which deals come in front of all members of an angel group. For example, Sand Hill Angels receives roughly 50 prospective deals each month and screen these 50 ventures down to 2-3 for individual angels to determine whether they should invest in. Specifically, screening for Sand Hill is done via a small collection of angels that form special interest groups at the benefit of all angel members (i.e. life sciences, semiconductors, etc.). Consequently, at the time of the funding stage the most risky investments have been screened away. Thus, the data we take to our model does not include ventures deemed excessively risky by the angel group.

The last limitation is the lack of forward looking consumers in our model. Dynamics we acknowledge are an important factor and may impact the estimated risk preferences. Without dynamics, the outside option for the angel investor is the return on the existing portfolio. Yet, with dynamic, an angel investor's outside option includes the option value of waiting until a future period to make an investment. Without this additional utility, an investor who rejects an investment is classified as having risk preferences that are too averse for the given investment, but in reality it maybe due to the fact the angel is waiting until next period to invest due to having more optimistic expectations of next period's state.

10 Conclusions

We examine angel investor risk preferences by building a model of investment decision making. In order to estimate an angel's risk preference, we employ a model of investor portfolio choice based upon microeconomic foundations. Our setting is characterized by a situation where angel investors are faced with large stakes and low probability of a very high return and not small or modest stakes. Specifically, we build a portfolio choice model for angel investors who maximize expected utility over monetary and non-monetary income, and estimate the model parameters using angel investment decision data. We determine that non-financial benefits play an important role for correctly modeling an angel investor's investment decision. Moreover, we analyze how risk preferences vary by individual characteristics and look to understand whether active or passive angel investors (with respect to how much an angel investor interacts with their portfolio of companies) are more risk averse.

The research we present above has important ramifications for entrepreneurs. Before our research, entrepreneurs and firm leadership had limited, if any, information concerning who and why they should target certain types of investors. Our analysis provides entrepreneurs with specific evidence about whom to target to maximize the likelihood that they will be successful in raising capital. Estimates of our model of portfolio choice determine that the median relative risk aversion preference parameter is -0.60 for passive investors versus -1.79 for active. In summary, our analysis indicates the ideal angel investor entrepreneurs should target is an active investor who holds an MBA and has extensive experience via the number of angel investments made, the number of years angel investing and in the number of years as an entrepreneur. This investor has the highest likelihood of investing. Non-pecuniary income also has a large effect on active investor choice behavior. We determine the likelihood of investing for these angel investors would decrease by roughly 6.92% without the non-monetary benefits they receive from actively engaging with entrepreneurs.

There are numerous directions for future research in this domain. Clearly, research that relaxes the assumption that individuals hold objective beliefs is fruitful. One might do so by employing methods that directly measure beliefs with survey data and then using this data with observed choices to identify risk preferences. With such a methodology, a researcher would estimate risk preferences without imposing a rational expectation assumption about outcomes. An additional avenue would be to determine how risk preferences moderate other related decisions. In general, understanding how risk preferences impact consumer decisions is an understudied area of empirical research and should be pursued in innovative domains to address new interesting substantive questions.

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Figure 1: Accredited Investors Distribution

Notes: The figure reports the distribution of net worth in 2010 for accredited investors.

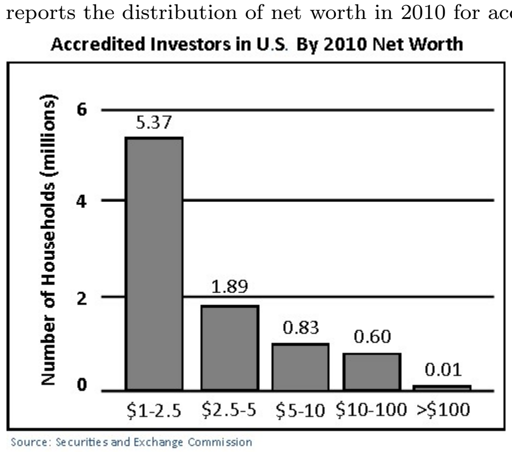
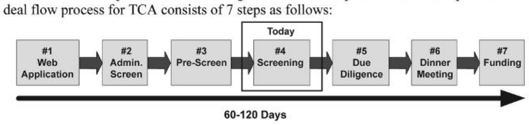


Figure 2: Screening Process Overview

Notes: The figure reports the typical deal flow process angel investment groups follow.

TCA Orange County Screening Overview

Welcome to the #1 Angel network in the US. We are pleased you are attending an Orange County screening session. The screening process is an important part of the TCA process. Typically, we have over 300 companies per year apply over the web for TCA funding. Approximately one third of these companies make it to the screening process which you are about to participate in. Although each year varies, we typically fund between 10 and 20 companies per year. TCA consists of 4 chapters, each facilitating the first three steps of the deal flow process a little differently. The overall deal flow process for TCA consists of 7 steps as follows:



1. **Web Application** – Entrepreneurs apply to TCA on the Internet. This process includes filling out a 4 page overview of their startup venture.

2. **Admin Screen** – TCA staff perform a quick screen on the application to insure it is within the target area for a TCA venture. For instance, we typically fund between $250,000 and $1 million. If a company is seeking outside this range, typically they are not moved forward to pre-screen.

3. **Pre-Screen** – In Orange County entrepreneurs present a brief overview of their company to 3-7 TCA members. This includes 5 minutes of presentation and 25 minutes of informal questions and discussion with the TCA members. At the conclusion of this session, the prospective company is moved to screening, or given feedback why they may not be a good fit for TCA.

4. **Screening** – Typically 3 companies present at a screening. This consists of 15 minutes of PowerPoint and 15 minutes of Q&A. After the Q&A, we ask the entrepreneurs to leave the room and we discuss the company in private (typically it takes 10-15 minutes). The entrepreneurs are invited back into the room, and a designated member provides quick feedback. Typically, the companies present at all 5 chapters. Therefore, it is possible for a company to get little interest at one chapter, but enough interest at another chapter that will allow it to move forward to due diligence. In Orange County we utilize a moderator to facilitate the sessions. This is intended to help balance questions for our members such that a member will not dominate the Q&A time. If you are a prospective member you are welcome to ask questions during the Q&A portion of the presentation.

5. **Due Diligence** – A due diligence team is formed based on the number of interested members who signed up during the screening. A deal lead steps forward and helps coordinate the due diligence activities. Due diligence consists of verifying representations by the venture, customers, agreements, references, backgrounds, etc. The results of the due diligence process are posted on the TCA website (members only section), and if the results are positive, the venture moves forward to dinner meetings.

6. **Dinner Meeting** – Companies that pass due diligence present at monthly dinner meetings at each chapter. This allows them to get in front of members who might not have seen them at screening or were involved in the due diligence process. This is the opportunity for the entrepreneurs to garner enough interest by members to secure funding.

7. **Funding** – Funding occurs after there has been enough interest generated through dinner meetings and internal communication from the entrepreneur and deal lead. Members invest in deals individually, thus only a small percentage of members need to participate for the venture to secure funding. Typically, the minimum investment amount $25,000.

 V1.2

Table 1: Summary Statistics: Investor

Notes: The table reports the characteristics of the main variables discussed in the empirical modeling section related to the different investor types (Active and Passive). The statistics are generated from the panel data set, unconditional of investing.

	Active (55.36%)				Passive (44.64%)			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
Wealth % in Angel Inv.	13.00	11.61	1	40	13.82	13.09	1	50
Total Lifetime Angel Investments	10.22	6.32	0	30	15.52	13.80	0	63
Total Angel Exits	2.72	3.32	0	19	6.19	8.45	0	40
Years at Large Firm	15.08	11.09	0	40	11.66	10.93	0	40
Years as Entrep.	16.15	10.21	0	34	13.79	9.56	0	34
Years Angel Investing	13.56	9.79	1	32	10.97	8.42	1	30
Male	0.85	0.35			0.92	0.26		
Bachelors	0.15	0.35			0.20	0.39		
JD	0.15	0.36			0.06	0.24		
Masters	0.50	0.50			0.61	0.48		
PhD	0.20	0.39			0.13	0.34		

Table 2: Summary Statistics: Investment

Notes: The table reports the characteristics of the main variables discussed in the empirical modeling section related to the investment angels make.

Variable	Mean/Percent	SD	Min	Max
Return Multiple	1.99	4.30	0	45.88
Ln(Investment Level)	10.31	0.75	8.51	12.61
# of Coinvestors	8.09	4.03	0	12
Years Industry Exper.	3.51	8.22	0	35
Seed	30.76%	-	-	-
Startup	44.61%	-	-	-
Early Growth	21.53%	-	-	-
Late Growth	1.53%	-	-	-
Turn Around	1.53%	-	-	-

Table 3: Summary Statistics: Investment (Industry)

Notes: The table reports the characteristics of the main variables discussed in the empirical modeling section related to the industry in which angels make investment in.

Industry	Percent	Cum.
Biotechnology	13.75	13.75
Business products and services	3.66	17.41
Computers and peripherals	0.65	18.06
Consumer products and services	10.41	28.48
Electronics / Instrumentation	1.87	30.35
Financial Services	1.22	31.57
Health Care Services	3.34	34.91
IT services	1.63	36.53
Industry / energy	0.57	37.1
Media & Entertainment	16.84	53.95
Medical devices and equipment	7.81	61.76
Other	15.38	77.14
Retail / distribution	6.35	83.48
Software	12.12	95.61
Telecommunications	4.39	100

Figure 3: Density: Ln(Investment Level)

Notes: The figure reports the distribution of log investment levels for all investments in which we observe and are included in our panel data set.

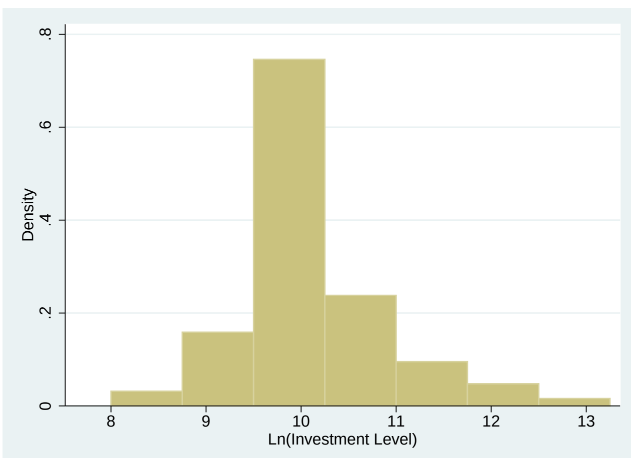


Figure 4: Density: Return Multiple

Notes: The figure reports the distribution of the return multiple for all investments in which we observe and are included in our panel data set.

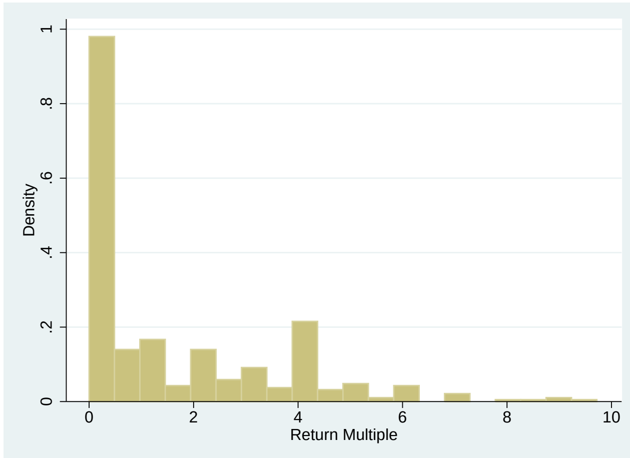


Table 4: Entrepreneurial Factors: Levels

Notes: The table reports the level characteristics of the additional factors discussed in the empirical modeling section related to investment returns. These factors are not used in estimation rather they are presented to illustrate the actual raw values found in the original source.

	Startup Growth	Kaufman Index	5y_Survival Rate
1998	3,956	0.09	46.54
1999	7,660	0.32	47.14
2000	23,914	0.33	48.08
2001	-3,261	0.52	48.47
2002	-12,147	0.05	46.96
2003	3,307	-0.52	46.03
2004	-8,656	-0.29	44.21
2005	26,038	0.06	43.37
2006	35,809	-0.26	42.91
2007	-11,900	0.28	43.2

Table 5: Entrepreneurial Factors: Level-3y_Moving Average

Notes: The table reports the characteristics of the additional factors discussed in the empirical modeling section related to investment returns and are used in the estimation of the Fama-French 3 factor model with additional entrepreneurial factors included. These measures are the difference between the level and three-year moving average.

	Startup Growth	Kaufman Index	5y_Survival Rate
1998	-19,275.67	-0.70	1.35
1999	-5,225.00	-0.24	1.58
2000	10,216.67	-0.07	1.83
2001	-15,104.33	0.27	1.22
2002	-21,584.67	-0.34	-0.94
2003	471.67	-0.82	-1.81
2004	-4,622.33	-0.31	-2.94
2005	31,870.00	0.31	-2.36
2006	28,912.67	-0.01	-1.63
2007	-29,630.33	0.44	-0.30

Figure 5: Log Portfolio Returns

Notes: The figure reports the distribution of the holding length adjusted log return of the constructed portfolios discussed in section 5.2. This figure is to aid in the visual inspection of a normal distribution. We also statistically test whether this distribution is normal using the Shapiro-Wilks test and determine that we cannot reject the null hypothesis that returns are normally distributed.

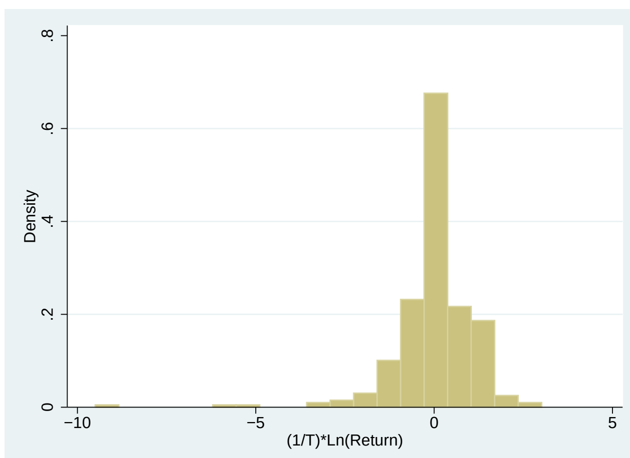


Table 6: Log Investment Returns

The table reports the log-CAPM estimates for the following model where $M_{fgt} = \log\left(\frac{A_{f,g,T}}{A_{f,g,t}}\right)$ is the gross multiple of a angel financing: $\log(M_{fgt\to T}) - \log\left(R^f_{t\to T}\right) = \tau_g + \beta_1(\log R^m_{t\to T} - \log R^f_{t\to T}) + \beta_2 \log SMB^f_{t\to T} + \beta_3 \log HML^f_{t\to T} + \beta_4 \log Kaufman^f_{t\to T} + \beta_5 \log StartGrowth^f_{t\to T} + \beta_6 \log Survival^f_{t\to T} + \eta_{f,g,t}$ where each term is weighted by $\sqrt{\ }$ T − t or the square root of the years to exit. The intercept τ_g does not represent a traditional CAPM α , however, the coefficient β does map to the traditional factor loads from a standard returns regression. $R^f_{t\to T}$ represents the non-periodic risk-free return (gross multiple) for the time period t to T. Similarly, for the market return ($R^m_{t\to T}$) , Fama-French factors and the non-traded entreprenuerial factors. Robust standard errors reported in parentheses. $*$, $**$ represent significance at the 10% and 5% level respectively. The VC Returns panel are results presented by Ewens et al. [2016].

	Angel Returns			VC Returns	
Variable	CAPM	Fama-French	Fama-French+Entre Factors	Outside Round (1)	Outside Round (2)
RmRf	1.888**	0.954**	1.331**	2.496**	2.412**
	(0.277)	(0.282)	(0.555)	(0.0732)	(0.1020)
SMB		-0.126**	-0.152*		-0.381
		(0.057)	(0.093)		(0.267)
HML		-0.165**	-0.095**		-0.0360
		(0.033)	(0.042)		(0.0606)
Kaufman Index			-0.277*		
			(0.147)		
Startup Growth			0.000		
			(0.000)		
5y_Survival Rate			0.051**		
			(0.0133)		
Intercept	-1.765**	-0.559*	-0.981*	-0.0848**	-0.0844**
	(0.305)	(0.316)	(0.553)	(0.0051)	(0.0220)

**indicates significant at 95%; *indicates significant at 90%; Angel Group FEs included

Table 7: Results: Relative Risk Aversion

The table reports the results of the investment threshold equation. We present two models: i) that accounts for non-pecuniary income and ii) that does not. A unit of observation is an angel investor venture decision pair. The sample is the discussed panel data set in Section 3.1. Parameter estimates are broken down by investor type (active and passive where passive is the deviation from the active parameter estimate). Characteristics include demographic and experience related. For demographics, Female is a dummy variable taking the value 1 if the investor is female and 0 if male. EDU(I[Masters]) is a dummy variable for whether the angel investor's highest degree is a masters degree. EDU(I[JD]) is a dummy variable for whether the investor's highest degree is a law degree. EDU(I[PhD])is a dummy variable for whether the investor's highest degree is a PhD degree. The total number of Angel investments is the number of angels investments the angel investor has made over his/her entire lifetime. Similarly, entrepreneurial experience is the total number of years the angel investor has as an entrepreuer. Years in a large firm is the number of years the angel has worked in a large firm where large is defined as with more than 500 employees. Years in angel investing is the total number of years participating in angel investing. Parameter signs have been adjusted to account for the negative sign in EQ (4), and education fixed effects are normalized to the Bachelor education level. Finally, parameters are unscaled to reflect estimated variance. Standard errors clustered at the angel group level. Clustered (by angel group) standard errors reported in parentheses. $*$, $**$ represent significance at the 10% and 5% level respectively.

	Probit Regression							
	(i)				(ii)			
Dep. var: 1 if invest	Passive		Active (Δ from Passive)		Passive		Active (Δ from Passive)	
Demographics	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Constant	-0.706**	0.301	0.492	0.467	-0.704**	0.313	-0.534	0.495
Female	0.106	0.222			0.028	0.200		
EDU(I[Masters])	0.800	0.613	-1.404*	0.820	0.683	0.620	-1.262	0.796
EDU (I[JD])	-0.208	0.195	0.223	0.356	-0.203	0.187	0.205	0.369
EDU*(I[PhD])	0.562**	0.293	-0.149	0.511	0.520*	0.270	-0.101	0.508
Experience Related								
Total # of Angel Investments	0.083*	0.0510	-0.216**	0.079	0.081	0.054	-0.223**	0.088
Total # of Angel Investments^2	-0.004**	0.002	0.005**	0.002	-0.004**	0.002	0.006**	0.002
Years as an Entrep.	-0.057*	0.033	0.127*	0.072	0.066	0.058	-0.116	0.070
Years as an Entrep.^2	0.001	0.001	-0.002	0.003	-0.001	0.002	0.001	0.003
Years in Large Firm	0.065**	0.020			0.066**	0.018		
Years in Large Firm^2	-0.003**	0.001			-0.003**	0.001		
Years in Angel Investing	0.250**	0.057	-0.352**	0.077	0.230**	0.058	-0.323**	0.077
Years in Angel Investing^2	-0.025**	0.004	0.025**	0.005	-0.023**	0.005	0.024**	0.005
Non-Monetary Utility								
α_1	-0.00001	0.00001						
α_2	0.00003*	0.00001						
Obs.			933				933	

Figure 6: Relative Risk Aversion

Notes: The figure reports the distribution of the estimated angel investor risk preferences smoothed using a Gaussian kernal with a bandwidth set at .55. The solid line is the distribution for all investors (active and passive) where as the dashed and dashed-dotted lines are the distributions for passive and active investors, respectively.

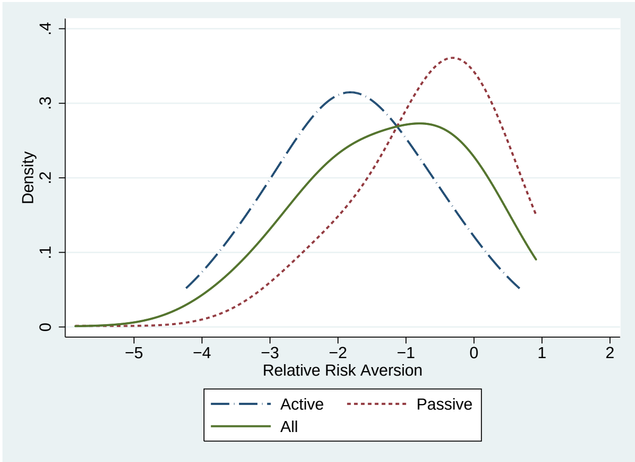


Table 8: Results: Log Investment Levels

The table reports the results of the investment level equation given the investment decision estimates found in model (i) in Table 7. We present two models: i) that corrects for selection bias and ii) that does not. A unit of observation is an angel investor venture investment pair. The sample consists of only observations in which we observe investments levels. Rho is the estimated relative risk aversion parameter estimate from Table 7 model (i). I(Passive) is a dummy variable if the angel is a passive angel investor. Female is a dummy variable taking the value 1 if the investor is female and 0 if male. The number of co-investors is the total number of co-investors who have invested in the venture. Industry experience is a continuous variable that specifies the total number of years of experience in the industry that the venture operates in. Lambda is the sample selection correction term. Standard errors clustered at the angel group level. Clustered (by angel group) standard errors reported in parentheses. $*$, $**$ represent significance at the 10% and 5% level respectively.

	Corrected for Selection		Not Corrected for Selection	
Variable	Coef.	SE	Coef.	SE
Constant	11.025**	0.712	10.667**	0.343
Rho	0.160	0.477	-0.144	0.127
# of Coinvestors	-0.067**	0.029	-0.071**	0.030
Industry Experience	0.021	0.014	0.021	0.014
Lambda	-1.159	1.739		
R^2	0.3064		0.2960	

Table 9: Results: Relative Risk Aversion Partial Effects

This table reports the pratial effects associated with model 1 presented in Table 8. Effects are calculated at the mean of the included variables for Active MBA angel investors.

Probit Regression: Partial Effects of Active Angels w/ an MBA	
	Active-MBA
Experience Related	Partial Effect
Total # of Angel Investments	-0.00190
Total # of Angel Investments^2	0.00002
Years as an Entrep.	-0.00081
Years as an Entrep.^2	0.00001
Years in Large Firm	0.00093
Years in Large Firm^2	-0.00004
Years in Angel Investing	-0.00146
Years in Angel Investing^2	0.00001

Table 10: Impact of Non-pecuniary Income on Choice

This table reports the results of our counterfactual exercise. Column 1 presents the results where active investor's non-pecuiary income is set to zero, whereas column 2 is where passive investors benefit from non-pecuniary income. The reported % change is across all repective angel types and is the percent difference between the simulated counterfactual and the observed data.

	CF-1: Active Investors
Model Prediction	3.47%
Counterfactual	3.23%
% Change	-6.92%