# Bite me! ABC's Shark Tank as a path to entrepreneurship

Baylee Smith
United States Navy

Angelino Viceisza
Spelman College

March 19, 2017

**Abstract**

Business pitch competitions provide early stage finance and mentoring for entrepreneurs. In this paper, we analyze data from possibly, the most public, high-stakes pitch competition in the US: ABC's Shark Tank. We construct a novel dataset comprising all entrepreneurs/firms that have aired between August 2009 (the show's inception) and May 2016 (the most recently completed Season 7) by collecting publicly available data from sources such as show episodes, social media, apps like Mattermark and Pretty-o-meter, and public registries. Our findings are as follows: (1) Funding on the show seems to relax an internal financial constraint, rather than signal the quality of the venture to potential outside investors; (2) to the extent that the latter is occurring, there is plausible evidence that the signaling effect works in an unexpected direction for women entrepreneurs–it may crowd out attention from potential investors; (3) while it is fairly clear that this pitch competition improves longer-run existence of firms, it has no significant impacts on innovation as measured by patent applications filed after the show; (4) there are no consistent differential impacts on racial/ethnic minorities. These findings complement existing literature on the impact of pitch competitions and (early) access to finance by exploiting a novel, high-stakes context that has gained the attention of millions of people (viewers) across the world.

*JEL Codes:* L26, O12, G30.

*Keywords:* entrepreneurship, pitch competition, angel-to-venture capital financing, Shark Tank.

# 1 Introduction

Entrepreneurship and innovation (E&I) are important for economic growth, and finance is an important element for enabling E&I (see for example Holtz-Eakin et al., 1994; Carpenter and Petersen, 2002; Clementi and Hopenhayn, 2006; Lofstrom et al., 2014, and the references within).[1] Pitch competitions are among a variety of approaches to providing finance; others (potentially overlapping) include venture capital, angel investment, incubators, and accelerators. To date, evidence from pitch competitions suggests that they (1) help entrepreneurs learn, thus increasing their likelihood of success (Howell, 2016; Robb and Yu, 2016) and (2) enable firms to buy more capital and hire more workers, with little impacts on business practices, networking, or mentoring (McKenzie, 2016).[2] Despite such evidence, it remains unclear whether pitch competitions are valuable because they lower financial barriers for winners or provide a signal of quality. Moreover, their impacts on women and minority owned businesses have not been widely studied.[3]

This paper attempts to fill these gaps in the literature by studying a unique and novel context–the reality TV show Shark Tank (`http://abc.go.com/shows/shark-tank`) which airs Fridays at 9 PM on ABC. Shark Tank is a pitch competition couched in a TV show that first aired on August 9, 2009. It is a derivative of other shows such as Tigers of Money (which first aired in Japan in 2001) and Dragon's Den (which first aired in the United Kingdom in 2005). The show's premise is one where entrepreneur-contestants pitch to a panel of five judges (also known as "sharks") who potentially make competing offers. It is a useful context to study the abovementioned issues because it is a prime example of a high-stakes pitch competition. In addition, while the show is edited, it airs nationwide, thus making quite some details of the entrepreneur-contestant, the pitch, and the bargaining process (specifically those that are crucial to the funding decision) widely observable to the general public, including potential outside investors.

Given Shark Tank's internal data are not available to the public, we construct a novel dataset comprising all entrepreneur-contestants/firms that have aired on the show from Season 1 to Season 7 ($N = 603$).[4] We collect/create a relatively wide range of variables by combining publicly available data from sources such as (1) show episodes, (2) the Shark Tank wikipedia page and blog, (3) social media such as Facebook and LinkedIn, (4) YouTube, (5) firm websites and related traffic (analytics) statistics, (6) Amazon, (7) apps such as Mattermark and Pretty-o-meter, (8) the Securities and Exchange Commission (SEC) company filings database (EDGAR), (9) the United States Patent and Trade Office (USPTO), and (10) state company registries. Using three post-show outcomes–existence one year after, existence between Fall 2015 and Fall 2016, and patent applications–we seek to assess the impact of getting an intention-to-fund ($ITF$). Since the deal made on the show is a "good-faith" offer that starts a proper due diligence process, we maintain this term throughout.

[1] An exception is Hurst and Lusardi (2004) who find entry into entrepreneurship to be unrelated to wealth over most of the wealth distribution.

[2] A related strand of literature explores determinants of successful pitches (e.g. Milovac and Sanchez-Burks, 2014; Wood Brooks et al., 2014; Poczter and Shapsis, 2016).

[3] For related literature on minority entrepreneurship more broadly, see for example Fairlie and Robb (2007), Bates and Bradford (2008), Chatterji and Seamans (2012) and the references within.

[4] The show is currently airing Season 8 and holding auditions for Season 9.

Our findings are as follows. First, a dummy for receiving an intention-to-fund on the show seems to correlate with post-Shark Tank existence in the short run, but not necessarily in the longer run. On the other hand, the amount associated with this good-faith deal (intention-to-fund) is significantly correlated with existence in both the short and the longer run. Further exploration of this effect using a variety of proxies for "finance" versus "quality" suggests that on average the intention-to-fund mainly relaxes a financial constraint. In fact, our findings allude to the fact that different sources of financing (in particular, prior self-investment and the intention-to-fund) are complementary. This is consistent with for example Cooper et al. (1994, who find that firm survival and growth are constrained by initial financial capital), Carpenter and Petersen (2002, who find that the growth of small firms is constrained by internal finance) and Lofstrom et al. (2014, who find that wealth levels predict entry into high-barrier industries).

Second, entrepreneur-contestant teams that have a greater proportion of women and receive a greater number of offers during the negotiation process are less likely to exist in the longer run (relative to teams with a comparable proportion of men and offers). Since we take the number of offers to be a proxy for "quality", we try to further understand the underlying mechanism. There is plausible evidence that outside investors who observe women doing better on the show (i.e. receiving more offers) are less likely to approach them relative to their male counterparts. This in turn could lead to such firms being less likely to exist in the longer run. There are of course other mechanisms that could be at play; however, our findings cannot rule out that doing better on the show may crowd out other potential investors. This mechanism is somewhat consistent with Poczter and Shapsis (2016) who also exploit the Shark Tank context, but to explore the determinants of success rates in financing. They find that women receive lower valuations and less capital relative to men and that this is partly because they initially ask for less. We of course exploit this same context to explore the impact mechanisms that ensue from receiving an intention-to-fund and as such, collect variables from a broader range of sources, including post-Shark Tank measures.

Finally, we find no robust heterogenous impacts with regard to race/ethnicity, which could be due to the small number of observations. Also, when we run the same analyses on post-Shark Tank patent applications, we find no significant impacts across the board.

Our findings have three policy implications. First, Shark Tank as a pitch competition mainly functions as an avenue towards complementary funding. Based on our data, it does not seem that this high-profile competition acts as a quality signal to other potential investors. Second, if at all, the signaling effect works in an unexpected direction for women entrepreneurs. So, to the extent that female contestants enter the tank in the hopes of reaching alternative sources of funding, they may need to be cautious. Finally, while this pitch competition has fairly clear implications for longer-run existence, it has no significant impacts on innovation (as measured by post-Shark Tank patent applications). This could very well be due to the fact that a substantial proportion of contestants already start with (provisional) patent applications.

The remainder of the paper proceeds as follows. Section 2 discusses some context and what is publicly known about the Shark Tank process. Section 3 explains the empirical strategy, some hypotheses, and data. Section 4 covers the main results. Finally, Section 5 concludes.

# 2 Shark Tank as a pitch competition

Details about Shark Tank's internal, behind-the-scenes process are restricted; as such, this section is mainly based on anecdotal evidence from shark interviews (with outlets such as Inc., Business Insider, and Entrepreneur Magazine) and facts observed during show episodes. Some of these details are relevant for how we analyze the data, so we return to them in Section 3.1.

Since its initial airing in 2009, Shark Tank has been quite popular. The show has counted an average of 6.72 million viewers in the US per season with a low of 4.81 in Season 1 and a high of 9.13 in Season 6. It is the most watched program on Friday nights in the 18- to 49-year-old demographic.[5] Shark Tank has also seen a steady number of applications/auditions via open casting calls organized by the show's producers at venues such as universities, incubators, co-working spaces, and hotels. According to Inc. Magazine, of the 45,000 people who applied to be on the show in 2014, less than one percent got the opportunity to pitch, making Shark Tank more selective than most elite US universities and their associated competitions.

By and large, the process leading up to and pitching on Shark Tank is as follows:

1. Hundreds of entrepreneurs complete an application (see `https://goo.gl/HojVyC`) and show up to give a brief pitch to members of the crew during the open casting calls announced at `https://goo.gl/rkXAF4`. The producers also recruit firms by monitoring crowdfunding sites like Kickstarter and attending trade shows. They keep favorites in mind as they narrow down the list for a particular season.

2. An entire season is shot in 15-17 days during the Summer to Fall. The sharks fly into Los Angeles several times and shoot marathon days in which approximately 20 entrepreneur-contestants pitch. Later, the segments are mixed and matched over multiple episodes; each of which lasts an hour and contains six pitches. Given episodes air anywhere from late August to mid May, there could be a time lag of a few weeks to nine months between production and airing.

3. The pitch/negotiation process goes from 30 minutes for bad ideas to 2.5 hours for others. A typical pitch lasts an hour, but is edited down to ten minutes to fit the episode. Everything that is aired is true; none of it is re-taped. However, the footage editors take out "unsexy" material such as the "nitty gritty" details on finances. Despite this, all elements that are crucial to the outcome (intention-to-fund) are included in the aired episode.

4. Entrepreneur-contestants face a panel of five judges that have been fairly stable over time, comprising three to four men (one of whom is African American) and one to two women. The sharks do not know the entrepreneur-contestants or products before they enter "the tank" such that the viewers learn about the firms along with them. A pitch consists of an introduction of the entrepreneur(s) and the concept/idea followed by an initial ask (amount and percent stake) and a negotiation process including questions

[5] The show's media impacts on entrepreneurship/innovation is the topic of a different paper by Robinson and Viceisza (2017), along the lines of the literature reviewed by DellaVigna and La Ferrara (2015).

and answers. The latter is intended to be a grilling session; hence the name "Shark Tank", since the judges–like sharks–are 'out for blood'.

5. During the negotiation process, interested sharks may compete for entrepreneur-contestants/firms or make joint offers. They may also retract offers at any given point if they are no longer interested. On the flip side, entrepreneur-contestants may pit sharks against each other or decline offers at any given time. The median number of offers and sharks making such offers is one, at a median valuation of $120,000 based on the authors' calculations.[6]

6. Entrepreneur-contestants are restricted from revealing any information about the end result after pitching on the show. Failure to do so is likely to lead to lawsuits.

7. Prior to 2013, Shark Tank (the producers) would get a percentage of the entrepreneur-contestant's business (5%) or profits (2%) forever in the future even if no deal was made. In 2013, Mark Cuban pushed for this clause to be removed, as it impacted the types of entrepreneurs who would audition for the show.

8. 60 to 80% of the deals made on the show actually lead to funding. The "handshake" after a deal is a "good faith" agreement that initiates a due diligence process. If everything checks out, the sharks see if the entrepreneur-contestants are still interested. So, the funding decision made on the show is an intention-to-fund.

9. About 20% of the pitches are not aired. The producers decide if there is enough "drama" in the unsuccessful pitches to warrant air time.

10. Sharks pitch "update" segments for future airing on the show based on the entrepreneur-contestants/firms they have decided to fund.

The above considered, it is clear that the Shark Tank pitching process is comparable to but also different from day-to-day competitions such as those discussed by Howell (2016). So, the pool of entrepreneurs under consideration is likely to be selected and we do not claim to report findings that are representative of pitch competitions across the US. Instead, we see the Shark Tank forum as a special case of a high-stakes pitch competition and this study seeks to tell a somewhat internally valid story on the impacts of funding in this context and the mechanisms by which these occur. We use data from all 603 pitches that aired between August 9, 2009 and May 20, 2016 across the first seven seasons and 151 episodes of Shark Tank.

[6] At the entrepreneur-contestant/firm level, this number is calculated by dividing the final amount offered/agreed to by the percent stake in the business. If no offer was made, this number takes the value zero. There are a few instances where the sharks ask for something that is different from a percent stake, e.g. $1 per unit sold. In such instances, we guesstimate the typical/average price for the unit of product under consideration and calculate the percent stake as the per-unit amount requested divided by the per-unit average price. Additional details are available in the Stata do file upon request.

# 3 Study design

## 3.1 Baseline empirical strategy

Our aim is to identify the impact of an intention-to-fund on three post-Shark Tank outcomes–existence one year after airing, existence between Fall 2015 and Fall 2016 and patent applications–using all pitches/entrepreneur-contestants/firms that have aired on the show from its initiation through May 2016. Given the context described in Section 2 and the fact that we do not have access to Shark Tank's internal data, particularly its selection criteria, a simple regression of the above outcomes on intention-to-fund is likely to suffer from selection on unobservables. While intention-to-fund would have ideally been randomly assigned for purposes of establishing causality, this was obviously not done since Shark Tank is a real-life competition couched in a TV show. So, our empirical strategy seeks to address the main threats to internal validity.

First, producers select which pitches should air and clearly do so not just based on the quality of the venture. They also care about the potential for good TV, since ratings drive the longevity of the show. In other words, the show needs some entrepreneur-contestants/firms to be guaranteed to fail (i.e. have $ITF$=0) and since sharks know nothing about the concepts prior to seeing them in the tank, producers will include some "doozies". For example, one of the sharks–Mark Cuban–has indicated that he 'loves the scams' or the people who 'do it just for the PR' (Business Insider, 2014, `https://goo.gl/jDx6Tg`).

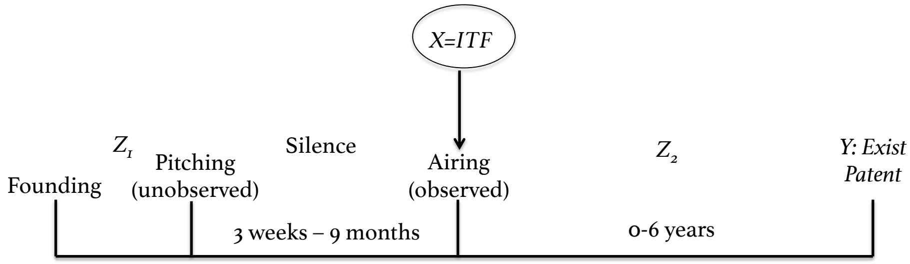
To mitigate concerns that this form of selection crowds in entrepreneur-contestants that were unlikely to get funded regardless of the pitch, we create a "bad idea" variable that takes the value one if the concept is particularly ridiculous and was clearly allowed to air for show appeal.[7] We then drop those firms from the sample, which leaves us with 584 pitches. Recalling from Section 2 that 20% of the unsuccessful pitches that were filmed are not aired to begin with (due to lack of show appeal), we believe that these two types of dropped/unobserved pitches make the (remaining) sample of entrepreneur-contestants/firms under consideration more homogeneous from the standpoint of their a priori likelihood of getting an intention-to-fund.

Second, as indicated in Section 2, the show's footage editors take out detailed discussions on finances. For example, sharks have revealed in interviews that "... some negotiations can go on for an hour or much longer, but the key moments are edited into palatable acts for television. Everything you see is true, none of it is re-taped, and the elements that are crucial to the outcome are included. But rather than drowning viewers in ... long minutes of going over sales numbers and distribution plans that don't amount to much, the editors compress events." This, at least anecdotally, suggests that the most relevant determinants from the standpoint of intention-to-fund are included in the aired segment.

To mitigate concerns that some important characteristics that help determine the intention-to-fund are observed by the sharks, but not by us, we rely on the following strategy.

[7]This variable was coded manually by research assistants who were instructed to carefully watch the episode/pitch and identify ridiculous ideas. Given such ideas were unlikely to be funded, they first filtered through the pitches that had not received an intention-to-fund. They subsequently worked their way through the remaining pitches. Their coding was further corroborated with keywords/phrases expressed on the Shark Tank blog, which typically summarizes highlights and public opinion regarding each episode/pitch.

Figure 1: Timeline of events consistent with Section 2




Consider the timeline in Figure 1. Any given entrepreneur-contestant/firm is observed by us during an aired episode, which is also when we learn the main "treatment" variable, *ITF*. However, prior to being observed by us, a firm is founded and pitches in the tank. If the intention-to-fund were randomized, we would expect entrepreneur-contestants/firms to be similar on pre-Shark Tank characteristics $Z_1$. Of course, the intention-to-fund is not randomized and accordingly, a potential concern is that the sharks observe some part of $Z_1$ that we do not and use that in making funding decisions. So, we (1) create as many $Z_1$ variables as possible from a wide range of data sources (see Section 3.3) and (2) test whether those are on average similar across the intention-to-fund. If entrepreneur-contestants/firms are indeed comparable on $Z_1$ variables observed by us, we feel that any impacts of intention-to-fund are less likely to be due to selection on unobservables.[8]

So, the above considered, our empirical strategy relies on (variants of) the following estimating equation:

$$Y = \beta_0 + \beta_{ITF} * ITF + \beta_{Z_1} * Z_1 + \delta_I + \delta_S + \delta_E + \varepsilon, \tag{1}$$

where $Y$ is a dummy for existence one year after airing (to reduce post-airing confounding factors) or a dummy for existence between Fall 2015 and Fall 2016 or a dummy for filing a post-Shark Tank patent application (depending on the specification); $ITF$ is a dummy for receiving/agreeing to a final intention-to-fund on the show; $Z_1$ is a set of pre-Shark Tank characteristics that are on average significantly different across $ITF$ (these are intended to control for observable differences across those who get an intention-to-fund or not); $\delta_I$, $\delta_S$, $\delta_E$ are industry, season, and episode fixed effects respectively; and $\varepsilon$ is a robust error term clustered at the episode level.[9]

We first estimate this equation as a linear probability model (LPM). Under the assumption that the $Z_1$ controls capture any remaining selection on unobservables, $\hat{\beta}_{ITF}$ should be a reasonable estimate for the true impact of receiving funding on the show. For robustness purposes, we extend the analysis by also estimating this effect via nearest neighbor matching (NNM) along the lines of Abadie and Imbens (2006) and Abadie and Imbens (2011). We match on the same set of $Z_1$ variables that are controlled for in equation 1. The potential gain from this approach is that the matching algorithm finds a more comparable set of firms to act as a control group for those firms that received an intention-to-fund(=1).

[8]This approach is analogous to balancing (baseline equivalence) tests conducted in experimental contexts.

[9]While the pitches are mixed/matched across episodes during editing, we use this unit/level of clustering regardless, as we have no better information on cohort effects due to lack of internal show data. In addition, this should help take care of any effects post-airing as a result of viewership.

### 3.2 Hypotheses and mechanisms

As mentioned in Section 1, our aim is to assess the type of constraint that an intention-to-fund (=1) relaxes. Regardless of the mechanism that is at play, however, we would expect $\hat{\beta}_{ITF} \geq 0$. If an intention-to-fund relaxes financial constraints (along the lines of Holtz-Eakin et al., 1994; Carpenter and Petersen, 2002; Clementi and Hopenhayn, 2006; Lofstrom et al., 2014, and the references within), it is expected that such firms are (weakly) more likely to exist or apply for patents after Shark Tank. On the other hand, if an intention-to-fund serves as a signal of quality, entrepreneur-contestants/firms who receive an intention-to-fund are also expected to receive greater attention, thus leading to a (weakly) greater likelihood of existence or patent applications. So, the aim of this section (and the remainder of our analysis) is to better pin down the mechanisms that are at play.

In so doing, we rely on an expanded version of equation 1:

$$Y = \beta_0 + \beta_{ITF} * ITF + \beta_{Z_1} * Z_1 + \beta_X * X + \beta_{ITF*X} * ITF * X + \delta_I + \delta_S + \delta_E + \varepsilon, \quad (2)$$

where all is defined as before, except that we introduce an additional set of covariates $X$ that act as proxies for the mechanisms that are at play. While we elaborate on the specific proxies in Section 4.3, it should be noted that $X$ will include components of $Z_1$ as well as post-Shark Tank characteristics $Z_2$ (recall Figure 1). Two immediate examples of $X$ variables that were also mentioned in Section 1 are the proportion of women and the proportion of racial/ethnic minorities on the pitching team. We estimate equation 2 via LPM, since NNM only allows for a binary treatment variable.

### 3.3 Data

Given we do not have internal show data, we combine publicly available data from a wide range of sources including (1) show episodes, (2) the Shark Tank wikipedia page and blog (primarily for cross-referencing), (3) social media such as Facebook and LinkedIn, (4) YouTube (e.g. views and likes at the pitch level), (5) firm websites and related traffic (analytics) statistics, (6) Amazon, (7) apps such as Mattermark (which seeks to track growth signals from all private tech, media and telecom companies) and Pretty-o-meter (which assesses beauty), (8) the Securities and Exchange Commission (SEC) company filings database (EDGAR) to distinguish between form D filings and initial public offerings, (9) the United States Patent and Trade Office (USPTO) for patent applications, and (10) company registries for the entrepreneur-contestant/firm's own state as well as the state of Delaware in particular, which Guzman and Stern (2016) have found to be correlated with future success.[10]

A complete list of variable definitions and sources is available from the authors upon request; however, below we highlight the most important variables for purposes of the analysis. The main outcome variables $Y$ are defined as follows:

1. *Exist*: A firm is assumed to exist when pitching on Shark Tank and thus exists between founding and pitching. The firm's year of founding is gathered from a combination of

[10]We also find that an intention-to-fund is significantly correlated with being registered in Delaware; however, since we do not have accurate data on the time stamp of the registration, we do not exploit this further in the analysis.

cross-referenced sources including (1) Hoover, Onesource, or Dun and Bradstreet (if available); (2) the entrepreneurs' social media pages such as LinkedIn, Facebook, and twitter; (3) state registries (in particular Delaware); and (4) manual web scraping through brute-force google searches (e.g. leading to relevant articles).
Post-Shark Tank existence is verified through the above sources combined with (1) the Shark Tank blog; (2) the firm's website and social media activity; (3) the firm's/product's representation on Amazon (as applicable); and (4) Mattermark (mm).
*Exist1after* takes the value 1 if the firm shows sign of life (according to the above cross-referenced sources) one year after airing on Shark Tank and 0 otherwise. *Exist* is the same except that the firm shows sign of life between Fall 2015 and Fall 2016.

2. *Post-Shark Tank patent applications*: Using publicly available data from USPTO, we track whether the product/concept(s) in question is associated with a related patent application and if so, for what time period. The time stamp is important, because Shark Tank inquires about patents upon application and one would expect several entrepreneur-contestants/firms pitching to have filed for a (provisional) patent. This variable takes the value 1 if a patent application exists and was filed after the firm aired on the show, and 0 otherwise.

The main explanatory and control variables are (others will be discussed as we progress through the analysis):

1. *ITF*: This variable takes the value 1 if the firm received a final intention-to-fund during the episode and 0 otherwise.

2. *ITF* amount: This variable is the total dollar amount agreed upon in the intention-to-fund divided by $100,000. The scaling is applied such that the magnitudes of the coefficients can be interpreted with some economic significance. It takes the value 0 when *ITF* is 0.

3. # pitching: The total number of entrepreneurs pitching during the episode.

4. Attractiveness: This is an average rating obtained by feeding the entrepreneurs' pictures (typically, still images from the episode) to two different beauty-rating apps.

5. Showed MVP: This variable takes the value 1 if the entrepreneur showed a minimum viable product (MVP; physical proof of concept) during the episode and 0 otherwise.

6. Demonstration: This variables takes the value 1 if the former variable is 1 or if the pitch included some other type of demonstration/illustration without a minimum viable product. It is 0 otherwise.

7. Pre-Shark Tank Patent: Similarly to post-Shark Tank patent, this variable takes the value 1 if the patent was obtained prior to airing on Shark Tank and 0 otherwise.

8. YouTube popularity: This variable is the total number of views that a given pitch has received on YouTube to date divided by 10,000 such that some interpretation can be attached to the associated coefficient. It is intended to proxy for a relative measure of viewership in absence of pitch-level Nielsen ratings, which are not freely available.

9. Industry: Since we do not have predetermined NAICS codes, we created the following broad classifications: apparel, children, entertainment, food, health, home, services, technology, and other. The industry fixed effects are dummies for these categories.

Finally, since these firms are typically privately held, we do not have accurate financial information for them. When available, these data tend to be for one time period and/or noisy because they are self-reported during the episode. As such, we do not analyze financials.

# 4 Results

## 4.1 Summary statistics and balancing on characteristics

We start with some basic summary statistics across several of the outcomes and covariates discussed previously (Table 1). 93% of firms exist one year after airing on the show while 89% still exist between Fall 2015 and Fall 2016. 10% of ventures file for a patent post-Shark Tank while 8% enter the tank with a patent application. 55% of entrepreneur-contestants get an intention-to-fund and the average amount is around $145,000. These intended deals emerge after an average of 1.43 total offers made by an average of 1.32 sharks. The average age of firms pitching on Shark Tank is 4.29 years. 95% of entrepreneur-contestants show a minimum viable product while on average 14% self-invest an average of $41,733.05. Additional characteristics are included in Table 1.

Next, we turn to the balancing exercise discussed in Section 3.1. Table 2 compares a wide range of pre-Shark Tank characteristics $Z_1$ across $ITF$. By and large, ECs/firms are comparable on many pre-characteristics. However, there are some significant differences. Specifically, the number of people pitching and their attractiveness are significant determinants of an intention-to-fund. Displaying a minimum viable product is also borderline significant. Yet, we believe these differences are sensible/expected.

First, a greater number of entrepreneur-contestants pitching for the same team is likely to be more effective because team members tend to (1) remedy each other's weaknessses (e.g. in a team of two, one person may have better "soft skills" while the other may be more "technical") and (2) be better equipped to handle the pressure faced from the sharks. This is also consistent with prior work that finds groups to be more rational (i.e. less subject to biases/cognitive limitations) than individuals (see for example Charness and Sutter, 2012).

Second, pitches by more attractive entrepreneur-contestants are more likely to be effective, given previous evidence by for example Milovac and Sanchez-Burks (2014) and Wood Brooks et al. (2014). These studies find that pitches delivered in more affective tone and by more attractive men tend to be more successful at convincing potential investors. This is also consistent with more general work on the beauty premium (see for example Rosenblat and Mobius, 2006).

Finally, we would expect that showing a minimum viable product positively impacts the intention-to-fund, as it clearly shows the sharks that there is some concrete proof of concept beyond 'just an idea'. With this being said, we note that the $p$-value associated with this test is 0.10, likely due to the fact that 93% of entrepreneur-contestants who did not get an intention-to-fund had displayed a minimum viable product. Indeed, on average 95% of the sample shows a minimum viable product.

Recalling the discussion in Section 3.1, we thus feel quite comfortable that the entrepreneur-contestants/firms in our sample are comparable on $Z_1$ and that any impacts of an intention-to-fund are less likely to be due to selection. To further mitigate such concerns, we control for these $Z_1$ characteristics when estimating LPM and match on them when conducting NNM (as discussed in relation to equation 1).

## 4.2 Main average impacts

Columns (1) through (4) of table 3 examine the average impact of an intention-to-fund on *Exist1after*, i.e. whether or not the firm exists one year after airing on Shark Tank. One of the main reasons for assessing impacts on this outcome variable is because it is less likely to be confounded by events that happen after the entrepreneur-contestant/firm airs on the show (i.e. $Z_2$ characteristics). So, it is a cleaner test of the impact of an intention-to-fund.

Columns (1) and (2) show the estimates for equation 1 via LPM and NNM respectively and thus control for/match on the unbalanced pre-Shark Tank $Z_1$ characteristics discussed in Section 4.1; notably, the number of entrepreneur-contestants pitching; their attractiveness; display of a minimum viable product; and a dummy for whether or not the firm is located in the state of Colorado. Entrepreneur-contestants/firms that receive an intention-to-fund are 8.6-8.7% more likely to exist a year after having appeared on Shark Tank.

Columns (3) and (4) maintain the same estimating equation, except that we now also control for/match on additional key variables; notably, the amount offered in the intention-to-fund; the total number of offers made throughout the pitch (as a first signal of quality); the firm's age when pitching on Shark Tank; and whether or not the entrepreneur-contestant/firm was featured as an update on Shark Tank or appeared more than once. While the NNM estimate persists at about 9%, the LPM estimate becomes insignificant. The point estimate is also much smaller at about 3-4%. With this being said, column (3) suggests that firms who receive a greater intention-to-fund amount are significantly more likely to exist one year out. We return to this in Section 4.3.

Columns (5) through (8) of table 3 examine the average impact of an intention-to-fund on *Exist*, i.e. whether or not the firm exists between Fall 2015 and Fall 2016. One of the benefits of this outcome variable (relative to *Exist1after*) is that it is defined for a larger sample size (since 2017 just started, we lose part of the sample when constructing *Exist1after*). With this being said, this is also one of its drawbacks, since the time period that has elapsed between airing and Fall 2015 to Fall 2016 can be significantly longer than one year. Accordingly, it can be argued that the intention-to-fund estimate is more likely to be confounded by $Z_2$ characteristics. To mitigate this concern, column (7) adds a measure of popularity constructed from YouTube views to date, under the assumption that this measure is likely to correlate with other important aspects such as sales and potential outside investments.

The LPM estimates are insignificant while the NNM estimates are significant in the range from 6.3-7.5%. As was the case for *Exist1after*, column (7) suggests that the amount of the intention-to-fund is highly associated with existence in the longer run also. In fact, the estimate seems to be much more significant than was the case in column (3). The popularity measure, however, does not seem to be significantly related to a firm's likelihood of existence in the longer run.

Finally, table 4 examines the average impact on post-Shark Tank patent applications. As before, columns (1) and (2) show estimates for equation 1 while (3)-(4) add the same set of covariates/matching variables as in table 3. None of the coefficients are significantly different from zero, suggesting that neither an intention-to-fund nor the associated amount seem to impact whether or not the entrepreneur-contestant/firm files a patent application after airing on the show. Perhaps this is not surprising, given approximately 7-8% of concepts enter the tank with a (provisional) patent application.

In summary, an intention-to-fund on Shark Tank seems to correlate with post-Shark Tank existence in the short run, but not necessarily in the long run. The amount associated with the good-faith deal on the other hand is significantly associated with existence both in the short and the longer run. The total number of offers extended throughout the negotiation process, which can be taken as a signal of quality of the venture, does not seem to affect a firm's existence, suggesting so far that the intention-to-fund primarily relaxes a financial constraint rather than serving as a signal to other potential investors.[11] The next section explores these mechanisms further.

### 4.3 Mechanisms

As discussed in Section 1, we would like to assess whether Shark Tank funding is meaningful because it lowers financial barriers ("finance") or serves a signal for quality ("quality"), which in turn may lead to additional investors. The previous section suggested that it is mainly about "finance"; however to pin down a more refined mechanism, we appeal to equation 2 and introduce three additional $X$ proxies: (1) a dummy for whether the entrepreneur-contestant self-invested, which we take as another proxy for "finance" together with the intention-to-fund amount; (2) the total number of sharks making offers throughout the negotiation process; and (3) a variable that measures the sharks' vibes during the negotiation.[12] The latter two variables proxy for "quality" together with the total number of offers throughout the pitch, as they are somewhat consistent with prior work by for example Kerr et al. (2011) on angel interest and quality of ventures.

Table 5 summarizes the estimates of equation 2. Columns (1)-(4) are for *Exist1after* while columns (5)-(9) are for *Exist.* It is pretty clear that the "finance" proxies dominate the

[11] Using publicly available data from EDGAR, we also tracked whether the firm in question filed with the SEC. It turns out that 5.82% of the firms in our sample (i.e. 34 firms) appear in EDGAR; however, only 1 of these 34 firms (i.e. 0.17% of the sample) underwent a true initial public offering. The remainder filed for so-called form D, which privately held companies raising capital are required to file with the SEC to declare exempt offering of securities. Moreover, form-D filings tend to be for investments in small, growing companies by venture capital and angel investors. Since we see this as an automatic by-product of appearing on/getting funding from the sharks, we did not use the data from SEC/EDGAR to construct an initial-public-offering dummy. Accordingly, we also end up not using this as an outcome, since it has too little variation to be meaningful.

[12] This variable was coded manually by research assistants who were instructed to carefully watch the episode/pitch and identify keywords/phrases as explained next. The variable is constructed by summing the following across all sharks on the panel: For any given shark, the sub variable takes the value 1 if a shark uses terms such as "I get a *good vibe* from you", -1 if s/he says "I get a *bad vibe* from you", and zero if s/he express *no vibes* verbally (i.e. indifference). The sub variables were further corroborated with keywords/phrases expressed on the Shark Tank blog, which typically summarizes highlights from each episode/pitch.

"quality" proxies. Specifically, the amount of the intention-to-fund remains highly significant while the intention-to-fund itself is not. Moreover, those who self-invested are more likely to exist in the longer run if they also got an intention-to-fund; meanwhile in absence of an intention-to-fund, entrepreneur-contestants who self-invested are less likely to survive. This suggests that different sources of financing (i.e. self-investment and the intention-to-fund) are complementary in this context.

This is consistent with for example Cooper et al. (1994, who find that firm survival and growth are constrained by initial financial capital), Carpenter and Petersen (2002, who find that the growth of small firms is constrained by internal finance) and Lofstrom et al. (2014, who find that wealth levels predict entry into high-barrier industries). Due to data limitations, we are unable to exploit industry- and education-specific barriers along the lines of some of these papers.[13] However, given a fairly substantial body of literature on financial capital constraints as barriers to entrepreneurship, we feel comfortable making this claim.

The same analysis performed on post-Shark Tank patent applications leads to no significant impacts, for either "finance" or "quality" proxies (see table 6). So, overall Shark Tank funding seems to mainly relax financial constraints, in turn complementing prior self investment by the entrepreneur-contestant(s). This seems to increase the firm's likelihood of existence in the longer run, but has no impact on post-Shark Tank patent applications.

### 4.4 Heterogeneous impact by gender and race

Finally, we seek to assess the impact of Shark Tank as a pitch competition on teams with different gender and racial/ethnic compositions. Prior to doing so, it makes sense to assess whether teams with a greater proportion of women are associated with a different set of characteristics than those with less. Similarly, are racially/ethnically more diverse teams different on other characteristics from teams that are less diverse?

So, we first run a regression of the proportion of women pitching on the full set of $Z_1$ characteristics in table 2 and the following $Z_2$ characteristics: intention-to-fund, the amount of the intention-to-fund, the total number of offers during the negotiation, years of schooling, and an overconfidence measure.[14] This regression, which is not included but available upon request, shows that (1) larger teams tend to be associated with a higher proportion of women (suggesting that women are less likely to pitch or work alone) and (2) the higher the proportion of women, (a) the more likely it is that the team shows a minimum viable product and (b) the lower the number of offers they receive. These results are consistent with Poczter and Shapsis (2016) who find, for the Shark Tank context, that women receive lower valuations and less capital to finance their ventures relative to men. Further, female teams receive less funding because they initially ask for significantly lower valuations.

[13] Anecdotally, we note that entrepreneur-contestants who get an intention-to-fund are not significantly different from those who do not on education and industry. In addition, firms who have more educated entrepreneur-contestants are no more likely to exist, be it in the short or the longer run.

[14] The latter variable is the difference between (1) the entrepreneur's (perceived) valuation based on the initial ask during the episode and (2) the shark's (perceived) valuation based on the final intention-to-fund amount and stake, divided by $1,000,000. The shark's valuation is assumed to be 0 when the intention-to-fund itself (and thus the associated amount) is 0. The scaling is necessary to interpret the magnitude (economic significance) of the coefficient on this variable.

Next, we run a regression of the proportion of minorities/non-White entrepreneur-contestants (i.e. Black/ African American, Latino/Hispanic, and Asian) on the same set of characteristics as above. This regression, which also is not included but available upon request, shows that higher intention-to-fund amounts are associated with less racially diverse teams. In other words, teams with more minorities are offered lower amounts.

In order to assess whether Shark Tank has a differential impact on women and racial/ethnic minorities (based on the main outcomes of interest), we add these proportions to the fullest specifications from table 3 (see columns 3 and 7) and table 4 (see column 3) and also their interactions with the key "finance" and "signal" proxies; i.e. intention-to-fund, the associated amount, and total number of offers throughout the negotiation. We first introduce these interactions piecewise (see columns 1-3, 5-7, and 9-11 of table 7) and then combine them all in one specification (see columns 4, 8, and 12 of the same table).

As before, there seem to be no gender- or race-specific effects for post-Shark Tank patent applications. However, the amount of the intention-to-fund continues to play a significant role in determining both short- and longer-run existence. In one of the specifications (column 4), there is a hint that more racially diverse teams that are offered larger intention-to-fund amounts, are less likely to exist in the short run. However, since this effect is insignificant when interacted in isolation (column 2), we do not deem it worthy of detailed discussion.

Perhaps more noticeably is the result that teams with higher proportions of women that also receive more offers, are less likely to exist in the longer run (relative to teams with comparable proportions of men and offers). Recalling that gender diversity is negatively correlated with the number of offers to start with, we check whether there is common support among the distributions of offers across the proportion of women (men) and find that to be the case. Further recalling that we take the number of offers to be a proxy for "quality", and in light of Poczter and Shapsis (2016), we wonder what mechanism could be at play here. Specifically, could it be that observing higher-quality women (i.e. those receiving more offers) crowds out other investors? There are several reasons why this may occur. First, it seems women typically receive fewer/worse offers in other (more general) contexts. If that is the case here, potential investors watching the show will be increasingly less likely to approach women who received more offers. Second, more offers may be perceived as "having too much confidence or being too good", which society tends to receive differently from women.

Given the vast number of covariates (relative to the number of observations) included at this stage, it is difficult to continue exploring refined mechanisms, for example by adding third-order interactions or gender-disaggregated regressions. To get an intuitive feel for the potential mechanism that is at play, we run a separate regression of gender on some proxies for "quality/outside interest". This regression is quite heuristic and by no means definitive or causal. Table 8 shows the coefficients of the proportion of women on the pitching team regressed on (1) YouTube popularity to date (in 10,000); (2) overconfidence (as defined before in millions); and (3) whether the entrepreneur-contestant/firm had a Kickstarter campaign at any given point since founding. Indeed, the signs are consistent with a story in which women entrepreneurs get less attention than their male counterparts.

First, women have received less views to date on YouTube. Second, women tend to be less (over)confident, which is consistent with Poczter and Shapsis (2016) as well as behavioral work on gender differences in preferences and decisionmaking (see Croson and Gneezy, 2009, and the references within for examples). Finally, women are also less likely to have had a

Kickstarter campaign since the firm's founding. So, while other mechanisms could certainly be at play, it is also plausible that outside investors who observe women doing better on the show (i.e. receiving more offers) approach them less (relative to their male counterparts), thus impacting firm existence in the longer run.

# 5 Conclusions and discussion

We construct a novel dataset comprising all entrepreneurs/firms that have appeared on the ABC show Shark Tank (a reality TV based pitch competition) between its initial airing in August 2009 to May 2016 (Seasons 1-7). We document several findings. First, an intention-to-fund on the show seems to correlate with post-Shark Tank existence in the short run, but not necessarily in the longer run. The amount associated with the good-faith deal on the other hand is significantly associated with existence in both the short and the longer run. Further exploration using a variety of proxies for "finance" versus "quality" suggests that on average the intention-to-fund mainly relaxes a financial constraint. In fact, our findings suggest that different sources of financing (i.e. self-investment and the intention-to-fund) are complementary in this context. This is consistent with for example Cooper et al. (1994, who find that firm survival and growth are constrained by initial financial capital), Carpenter and Petersen (2002, who find that the growth of small firms is constrained by internal finance) and Lofstrom et al. (2014, who find that wealth levels predict entry into high-barrier industries).

Second, entrepreneur-contestant teams that have a greater proportion of women and receive a greater number of offers during the negotiation process are less likely to survive in the longer run (relative to teams with comparable proportions of males and offers). Since we take the number of offers as a proxy for "quality", we crudely explore this further. Somewhat consistent with Poczter and Shapsis (2016), there is plausible evidence that outside investors who observe women doing better on the show (i.e. receiving more offers) are less likely to approach them relative to their male counterparts. This in turn could lead to such firms being less likely to exist in the longer run. There are likely confounding mechanisms at play; however, our findings cannot rule out that women doing better on the show may crowd out outside potential investors.

Finally, we find no robust heterogenous impacts with regard to race/ethnicity, but this could be due to the relatively small number of observations. Moreover, when we perform the above analyses on post-Shark Tank patent applications, we find no significant impacts.

Our findings thus have three policy implications. First, Shark Tank as a pitch competition mainly functions as an avenue towards complementary funding. Based on our data, it does not seem that this high-profile competition acts as a quality signal to other potential investors. Second, if at all, the signaling effect works in an unexpected direction for women entrepreneurs. So, to the extent that female contestants enter the tank in the hopes of reaching alternative sources of funding, they may want to be cautious. Finally, while this pitch competition has fairly clear implications for longer-run existence of the firm, it has no significant impacts on innovation (as measured by post-Shark Tank patent applications). This could very well be due to the fact that a substantial proportion of contestants already start with (provisional) patent applications.

# 6 Acknowledgments

We thank audiences at the 2017 American Economic Association Meetings, Duke I&E (Fuqua), GA Tech (Scheller), and the Kauffman Foundation Workshop "Seeking New Insights and Potential Sources of New Entrepreneurial Growth: Minority Entrepreneurship" for useful comments. We also thank Peter Arcidiacono, Tim Bates, William Bradford, Aaron Chatterji, Andrew Dillon, Eric Edmonds, Erica Field, Fred Finan, Robert Garlick, Ruth Vargas Hill, Yael Hochberg, Joe Hotz, Sari Kerr, Eduardo Maruyama, Manju Puri, EJ Reedy, Howie Rhee, Alicia Robb, David Robinson, Rodney Sampson, Rob Seamans, Juan Carlos Suárez Serrato, Joel Sobel, Wilbert van der Klaauw, and two anonymous referees for meaningful suggestions. Viceisza is particularly grateful to the Economics Department at Duke University where much of this work was completed. We also thank Abiana Adamson, Kendyl Curry, Easlynn Lee, Rayna Thornton, and Kadija Yilla for assistance with collecting the data and Camille Black and MoNeka Young for reviewing last-minute drafts of the manuscript. Any errors are those of the authors.


# References


Abadie, A. and G. W. Imbens (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica 74*(1), 235–267.

Abadie, A. and G. W. Imbens (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics 29*(1), 1–11.

Bates, T. and W. D. Bradford (2008). Venture-capital investment in minority business. *Journal of Money, Credit and Banking 40*(2-3), 489–504.

Carpenter, R. E. and B. C. Petersen (2002). Is the growth of small firms constrained by internal finance? *Review of Economics and Statistics 84*, 298–309.

Charness, G. and M. Sutter (2012, April). Groups make better self-interested decisions. *Journal of Economic Perspectives 26*(3), 157–76.

Chatterji, A. K. and R. C. Seamans (2012). Entrepreneurial finance, credit cards, and race. *Journal of Financial Economics 106*(1), 182 – 195.

Clementi, G. L. and H. A. Hopenhayn (2006). A theory of financing constraints and firm dynamics. *The Quarterly Journal of Economics 121*(1), 229–265.

Cooper, A. C., F. Gimeno-Gascon, and C. Y. Woo (1994). Initial human and financial capital as predictors of new venture performance. *Journal of Business Venturing 9*(5), 371 – 395.

Croson, R. and U. Gneezy (2009, June). Gender differences in preferences. *Journal of Economic Literature 47*(2), 448–74.

DellaVigna, S. and E. La Ferrara (2015). Economic and social impacts of the media. In S. Anderson, J. Waldfogel, and D. Stromberg (Eds.), *Handbook of Media and Economics*, Volume 1A.

Fairlie, R. W. and A. M. Robb (2007). Why are black-owned businesses less successful than white-owned businesses? The role of families, inheritances, and business human capital. *Journal of Labor Economics 25*(2), 289–323.

Guzman, J. and S. Stern (2016, March). The state of american entrepreneurship: New estimates of the quantity and quality of entrepreneurship for 15 us states, 1988-2014. Working Paper 22095, National Bureau of Economic Research.

Holtz-Eakin, D., D. Joulfaian, and H. S. Rosen (1994). Sticking it out: Entrepreneurial survival and liquidity constraints. *Journal of Political Economy 102*(1), 53–75.

Howell, S. (2016). Learning and success in entrepreneurship. Working paper, New York University.

Hurst, E. and A. Lusardi (2004, April). Liquidity Constraints, Household Wealth, and Entrepreneurship. *Journal of Political Economy 112*(2), 319–347.

Kerr, W. R., J. Lerner, and A. Schoar (2011). The consequences of entrepreneurial finance: Evidence from angel financings. *Review of Financial Studies*.

Lofstrom, M., T. Bates, and S. C. Parker (2014). Why are some people more likely to become small-businesses owners than others: Entrepreneurship entry and industry-specific barriers. *Journal of Business Venturing 29*(2), 232–251.

McKenzie, D. (2016). Identifying and spurring high-growth entrepreneurship: Experimental evidence from a business plan competition. Bread working paper 462.

Milovac, M. and J. Sanchez-Burks (2014). Positivity makes for poor pitches: Affective tone conveyed by entrepreneurs shapes support for creative ideas. *Academy of Management Proceedings 2014*(1).

Poczter, S. and M. Shapsis (2016). Know your worth: Angel financing of female entrepreneurial ventures. Working paper.

Robb, A. and S. Yu (2016). How does feedback impact entrepreneurial performance? Working paper, University of California, Berkeley.

Robinson, D. and A. C. G. Viceisza (2017). See and ye shall be: The impact of ABC's Shark Tank on entrepreneurship and innovation. In progress.

Rosenblat, T. and M. Mobius (2006). Why beauty matters. *American Economic Review 96*, 222–235.

Wood Brooks, A., L. Huang, S. W. Kearney, and F. E. Murray (2014). Investors prefer entrepreneurial ventures pitched by attractive men. *Proceedings of the National Academy of Sciences 111*, 4427–4431.

# A Tables

Table 1: Summary statistics

| Variable | N | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| *Exist1after* | 521 | 0.93 | 0.26 | 0 | 1 |
| *Exist* | 584 | 0.89 | 0.32 | 0 | 1 |
| post-Shark Tank patent | 584 | 0.10 | 0.31 | 0 | 1 |
| intention-to-fund (*ITF*) | 584 | 0.55 | 0.50 | 0 | 1 |
| *ITF* amount (in $100,000) | 584 | 1.45 | 3.46 | 0 | 50 |
| # offers throughout pitch | 584 | 1.43 | 1.64 | 0 | 11 |
| # sharks making *ITFs* | 584 | 1.32 | 1.35 | 0 | 5 |
| # pitching | 584 | 1.48 | 0.59 | 1 | 6 |
| proportion pitching women | 584 | 0.33 | 0.43 | 0 | 1 |
| proportion pitching non-white | 584 | 0.14 | 0.33 | 0 | 1 |
| attractiveness (beauty apps) | 584 | 0.75 | 0.09 | 0.47 | 0.97 |
| firm age on Shark Tank | 566 | 4.29 | 4.35 | 0 | 39 |
| showed MVP (1=yes) | 584 | 0.95 | 0.23 | 0 | 1 |
| demonstration (1=yes) | 584 | 0.96 | 0.19 | 0 | 1 |
| pre-Shark Tank patent | 584 | 0.08 | 0.27 | 0 | 1 |
| self investment (1=yes) | 584 | 0.14 | 0.35 | 0 | 1 |
| amount self investment | 584 | 41,733.05 | 26,6045.50 | 0 | 4,000,000 |
| sharks' vibes | 584 | 0.04 | 0.95 | -5 | 5 |
| Kickstarter funding (1=yes) | 584 | 0.10 | 0.30 | 0 | 1 |
| overconfidence (in millions) | 583 | 1.17 | 6.38 | -117.33 | 30 |
| Youtube popularity to date (in 10,000) | 560 | 0.35 | 0.98 | 0.002 | 9.51 |

Table 2: Balance of pre-characteristics $Z_1$ across $ITF$ (No versus Yes)

| Pre-characteristics | N | All | No | Yes | P-value diff. |
|---|---|---|---|---|---|
| # pitching | 584.00 | 1.48 | 1.40 | 1.55 | 0.00 |
| proportion pitching women | 584.00 | 0.33 | 0.31 | 0.35 | 0.31 |
| proportion pitching non-white | 584.00 | 0.14 | 0.13 | 0.16 | 0.34 |
| proportion pitching black | 584.00 | 0.08 | 0.08 | 0.07 | 0.69 |
| proportion pitching hispanic | 584.00 | 0.02 | 0.02 | 0.02 | 0.44 |
| attractiveness (beauty apps) | 584.00 | 0.75 | 0.74 | 0.76 | 0.01 |
| firm age on Shark Tank | 566.00 | 4.29 | 4.59 | 4.04 | 0.14 |
| industry | 584.00 | 5.71 | 5.77 | 5.66 | 0.67 |
| showed MVP (1=yes) | 584.00 | 0.95 | 0.93 | 0.96 | 0.10 |
| demonstration (1=yes) | 584.00 | 0.96 | 0.95 | 0.97 | 0.19 |
| pre-Shark Tank patent | 584.00 | 0.08 | 0.07 | 0.08 | 0.45 |
| self investment (1=yes) | 584.00 | 0.14 | 0.12 | 0.16 | 0.14 |
| amount self investment | 584.00 | 41,733.05 | 44,064.15 | 39,796.55 | 0.85 |
| entrepreneur's valuation (ask) | 584.00 | 2,416,941.72 | 2,495,944.63 | 2,351,312.35 | 0.68 |
| California[a] | 569.00 | 0.28 | 0.26 | 0.30 | 0.31 |
| Colorado | 569.00 | 0.03 | 0.04 | 0.02 | 0.09 |
| Florida | 569.00 | 0.06 | 0.04 | 0.07 | 0.12 |
| Georgia | 569.00 | 0.03 | 0.02 | 0.04 | 0.22 |
| Illinois | 569.00 | 0.04 | 0.03 | 0.05 | 0.43 |
| North Carolina | 569.00 | 0.03 | 0.03 | 0.02 | 0.25 |
| New York | 569.00 | 0.09 | 0.10 | 0.08 | 0.48 |
| Oregon | 569.00 | 0.03 | 0.03 | 0.03 | 0.89 |
| Pennsylvania | 569.00 | 0.03 | 0.02 | 0.03 | 0.52 |
| Texas | 569.00 | 0.08 | 0.08 | 0.09 | 0.69 |
| Utah | 569.00 | 0.04 | 0.03 | 0.05 | 0.19 |
| Washington | 569.00 | 0.02 | 0.02 | 0.02 | 0.54 |

p-values in last column are for two-tailed t-tests. All variables are in principle pre-determined.

[a]This is a dummy for being located in California, as are the other state variables.

Table 3: Impact of *ITF* on *Existence* outcomes

| | *Exist1after* (1)-(4) | | | | *Exist* (5)-(8) | | | |
|---|---|---|---|---|---|---|---|---|
| | LPM | NNM | LPM | NNM | LPM | NNM | LPM | NNM |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| intent-to-fund (*ITF*) | 0.086 | 0.087 | 0.035 | 0.092 | 0.031 | 0.063 | -0.021 | 0.075 |
| | (0.033)*** | (0.027)*** | (0.048) | (0.025)*** | (0.041) | (0.026)** | (0.062) | (0.029)*** |
| *ITF* amount (in $100,000) | | | 0.007 | | | | 0.010 | |
| | | | (0.003)* | | | | (0.004)*** | |
| # offers throughout pitch | | | 0.012 | | | | 0.013 | |
| | | | (0.013) | | | | (0.017) | |
| Youtube popularity to date (in 10,000) | | | | | | | 0.008 | |
| | | | | | | | (0.012) | |
| $R^2$ | 0.28 | | 0.29 | | 0.32 | | 0.33 | |
| $N$ | 515 | 515 | 512 | 512 | 569 | 569 | 534 | 534 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at episode level in parentheses.
Included in all specifications (not shown): industry, season, and episode fixed effects,
# pitching, attractiveness, showed MVP, a dummy for being located in Colorado.
Additional controls/matching variables in columns (3)-(4) and (7)-(8):
firm age when on Shark Tank, whether the entrepreneur-contestant/firm appeared twice on Shark Tank,
whether the entrepreneur-contestant/firm was featured as an update.

Table 4: Impact of *ITF* on post-Shark Tank patent applications

| | LPM | NNM | LPM | NNM |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| intent-to-fund (*ITF*) | -0.011 | -0.026 | -0.039 | -0.032 |
| | (0.025) | (0.045) | (0.031) | (0.038) |
| *ITF* amount (in $100,000) | | | 0.002 | |
| | | | (0.003) | |
| # offers throughout pitch | | | 0.007 | |
| | | | (0.011) | |
| Youtube popularity to date (in 10,000) | | | 0.005 | |
| | | | (0.012) | |
| $R^2$ | 0.56 | | 0.60 | |
| $N$ | 569 | 569 | 534 | 534 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robust standard errors clustered at episode level in parentheses.

Included in all specifications (not shown):

industry, season, and episode fixed effects,

# pitching, attractiveness, showed MVP,

a dummy for being located in Colorado,

whether the entrepreneur-contestant/firm appeared twice on Shark Tank,

whether the entrepreneur-contestant/firm was featured as an update.

Additional controls/matching variables in columns (3)-(4):

firm age when on Shark Tank, whether there is a pre-Shark Tank patent application.

Table 5: Mechanisms of *ITF* on *Existence* outcomes (LPM)

| | *Exist1after* (1)-(4) | | | | *Exist* (5)-(9) | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| intent-to-fund (*ITF*) | 0.015 | 0.078 | 0.036 | 0.017 | -0.047 | -0.002 | -0.021 | -0.024 | -0.054 |
| | (0.052) | (0.045)* | (0.048) | (0.052) | (0.063) | (0.058) | (0.061) | (0.062) | (0.063) |
| *ITF* amount (in $100,000) | 0.007 | 0.007 | 0.007 | 0.007 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 |
| | (0.003)** | (0.004)* | (0.003)* | (0.003)* | (0.004)** | (0.004)** | (0.004)** | (0.004)*** | (0.004)** |
| # offers throughout pitch | 0.011 | | 0.013 | 0.012 | 0.012 | | 0.014 | 0.013 | 0.012 |
| | (0.013) | | (0.013) | (0.014) | (0.017) | | (0.017) | (0.017) | (0.017) |
| self investment (1=yes) | -0.109 | | | -0.108 | -0.254 | | | | -0.262 |
| | (0.077) | | | (0.077) | (0.114)** | | | | (0.113)** |
| *ITF**self investment | 0.137 | | | 0.135 | 0.240 | | | | 0.243 |
| | (0.095) | | | (0.095) | (0.131)* | | | | (0.130)* |
| # sharks making *ITFs* | | -0.010 | | | | 0.004 | | | |
| | | (0.017) | | | | (0.020) | | | |
| sharks' vibes | | | 0.012 | 0.012 | | | 0.020 | | 0.021 |
| | | | (0.026) | (0.026) | | | (0.033) | | (0.031) |
| *ITF**sharks' vibes | | | -0.035 | -0.034 | | | -0.048 | | -0.052 |
| | | | (0.036) | (0.035) | | | (0.048) | | (0.048) |
| Youtube popularity to date (in 10,000) | | | | | 0.009 | 0.008 | 0.009 | -0.007 | -0.032 |
| | | | | | (0.013) | (0.012) | (0.012) | (0.099) | (0.099) |
| *ITF**Youtube popularity | | | | | | | | 0.015 | 0.045 |
| | | | | | | | | (0.099) | (0.100) |
| $R^2$ | 0.30 | 0.29 | 0.29 | 0.30 | 0.35 | 0.33 | 0.33 | 0.33 | 0.35 |
| $N$ | 512 | 512 | 512 | 512 | 534 | 534 | 534 | 534 | 534 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at episode level in parentheses.
Included in all specifications (not shown): industry, season, and episode fixed effects,
# pitching, attractiveness, showed MVP, a dummy for being located in Colorado,
firm age when on Shark Tank, whether the entrepreneur-contestant/firm appeared twice on Shark Tank,
whether the entrepreneur-contestant/firm was featured as an update.

Table 6: Mechanisms of *ITF* on post-Shark Tank patent applications (LPM)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| intent-to-fund (*ITF*) | -0.039 | -0.033 | -0.038 | -0.036 | -0.034 |
| | (0.032) | (0.033) | (0.031) | (0.032) | (0.034) |
| *ITF* amount (in $100,000) | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| # offers throughout pitch | 0.007 | | 0.008 | 0.008 | 0.008 |
| | (0.011) | | (0.011) | (0.011) | (0.011) |
| self investment (1=yes) | -0.009 | | | | -0.007 |
| | (0.060) | | | | (0.060) |
| *ITF**self investment | 0.003 | | | | 0.001 |
| | (0.075) | | | | (0.076) |
| Youtube popularity to date (in 10,000) | 0.005 | 0.006 | 0.006 | 0.025 | 0.022 |
| | (0.012) | (0.012) | (0.013) | (0.025) | (0.024) |
| # sharks making *ITFs* | | 0.005 | | | |
| | | (0.015) | | | |
| sharks' vibes | | | -0.001 | | -0.001 |
| | | | (0.008) | | (0.008) |
| *ITF**sharks' vibes | | | -0.009 | | -0.008 |
| | | | (0.021) | | (0.021) |
| *ITF**Youtube popularity | | | | -0.021 | -0.018 |
| | | | | (0.026) | (0.025) |
| $R^2$ | 0.60 | 0.60 | 0.60 | 0.60 | 0.60 |
| $N$ | 534 | 534 | 534 | 534 | 534 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robust standard errors clustered at episode level in parentheses.

Included in all specifications (not shown):

industry, season, and episode fixed effects,

# pitching, attractiveness, showed MVP,

a dummy for being located in Colorado,

whether the entrepreneur-contestant/firm appeared twice on Shark Tank,

whether the entrepreneur-contestant/firm was featured as an update.

Additional controls/matching variables in columns (3)-(4):

firm age when on Shark Tank, whether there is a pre-Shark Tank patent application.

Table 7: Heterogeneous impact of *ITF* by gender & race on *Existence* outcomes & post-Shark Tank patent applications (LPM)

| | *Exist1after* (1)-(4) | | | | *Exist* (5)-(8) | | | | post-Shark Tank patent (9)-(12) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| intent-to-fund (*ITF*) | 0.040 | 0.044 | 0.045 | 0.027 | 0.009 | -0.015 | -0.009 | -0.025 | -0.013 | -0.033 | -0.033 | -0.030 |
| | (0.058) | (0.049) | (0.049) | (0.058) | (0.076) | (0.062) | (0.061) | (0.079) | (0.042) | (0.031) | (0.032) | (0.042) |
| *ITF* amount (in $100,000) | 0.006 | 0.006 | 0.006 | 0.006 | 0.009 | 0.010 | 0.009 | 0.008 | 0.002 | 0.004 | 0.002 | 0.004 |
| | (0.003)* | (0.004)* | (0.003)* | (0.004)* | (0.004)*** | (0.004)** | (0.004)*** | (0.004)** | (0.003) | (0.003) | (0.003) | (0.003) |
| # offers throughout pitch | 0.009 | 0.009 | 0.013 | 0.017 | 0.011 | 0.011 | 0.027 | 0.031 | 0.007 | 0.008 | 0.013 | 0.011 |
| | (0.013) | (0.013) | (0.015) | (0.014) | (0.017) | (0.017) | (0.019) | (0.020) | (0.011) | (0.011) | (0.011) | (0.012) |
| proportion # pitching women | -0.064 | -0.070 | -0.034 | -0.055 | 0.010 | -0.041 | 0.046 | 0.030 | 0.005 | -0.007 | 0.004 | 0.005 |
| | (0.064) | (0.042)* | (0.056) | (0.066) | (0.068) | (0.043) | (0.059) | (0.070) | (0.032) | (0.028) | (0.029) | (0.033) |
| *ITF**proportion women | 0.012 | | | 0.058 | -0.088 | | | 0.041 | -0.047 | | | 0.005 |
| | (0.070) | | | (0.094) | (0.089) | | | (0.120) | (0.061) | | | (0.070) |
| *ITF* amount*proportion women | | 0.008 | | 0.011 | | -0.000 | | 0.013 | | -0.014 | | -0.012 |
| | | (0.009) | | (0.009) | | (0.011) | | (0.011) | | (0.009) | | (0.010) |
| # offers*proportion women | | | -0.017 | -0.038 | | | -0.063 | -0.082 | | | -0.019 | -0.013 |
| | | | (0.025) | (0.031) | | | (0.030)** | (0.039)** | | | (0.024) | (0.027) |
| proportion # pitching non-white | 0.013 | 0.029 | 0.005 | 0.010 | 0.021 | 0.044 | 0.032 | 0.029 | 0.023 | 0.015 | 0.014 | 0.020 |
| | (0.091) | (0.051) | (0.072) | (0.093) | (0.109) | (0.067) | (0.081) | (0.111) | (0.071) | (0.041) | (0.059) | (0.074) |
| *ITF**proportion non-white | -0.011 | | | 0.012 | 0.033 | | | 0.027 | -0.042 | | | -0.022 |
| | (0.107) | | | (0.123) | (0.133) | | | (0.165) | (0.080) | | | (0.083) |
| *ITF* amount*proportion non-white | | -0.018 | | -0.027 | | 0.002 | | -0.005 | | -0.017 | | -0.017 |
| | | (0.013) | | (0.013)** | | (0.016) | | (0.023) | | (0.012) | | (0.014) |
| # offers*proportion non-white | | | -0.001 | 0.014 | | | 0.006 | 0.004 | | | -0.009 | 0.005 |
| | | | (0.025) | (0.025) | | | (0.030) | (0.031) | | | (0.023) | (0.024) |
| Youtube popularity to date (in 10,000) | | | | | 0.005 | 0.006 | 0.003 | 0.003 | 0.004 | 0.005 | 0.004 | 0.004 |
| | | | | | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.012) | (0.012) | (0.012) |
| $R^2$ | 0.30 | 0.30 | 0.30 | 0.30 | 0.33 | 0.33 | 0.34 | 0.34 | 0.60 | 0.61 | 0.61 | 0.61 |
| $N$ | 512 | 512 | 512 | 512 | 534 | 534 | 534 | 534 | 534 | 534 | 534 | 534 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at episode level in parentheses.
Included in all specifications (not shown): industry, season, and episode fixed effects,
# pitching, attractiveness, showed MVP, a dummy for being located in Colorado,
firm age when on Shark Tank, whether the entrepreneur-contestant/firm appeared twice on Shark Tank,
whether the entrepreneur-contestant/firm was featured as an update.

Table 8: Select correlates of gender associated with quality/outside interest (LPM)

| | Proportion of women on the pitching team |
|---|---|
| Youtube popularity to date (in 10,000) | -0.027 |
| | (0.015)* |
| overconfidence (in millions) | -0.010 |
| | (0.004)*** |
| Kickstarter funding (1=yes) | -0.121 |
| | (0.054)** |
| Constant | 0.365 |
| | (0.021)*** |
| $R^2$ | 0.02 |
| $N$ | 559 |

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robust standard errors in parentheses.