Exploring Angel Investor Impact: Diving into the Shark Tank!

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KEY FINDINGS

- A close examination of the seed level investments of Shark Tank Angel Investors suggests that they do not have the ability to pick winners on average. To the extent that these celebrity investors are no less capable than typical angel investors, seed-stage investors may consider a strategy of investing less capital across more ventures (e.g., throwing darts) to enhance the opportunity of success.
- We found only weak and inconsistent connections between angel investor characteristics (e.g., reputation, experience, and network) and the performance of their investments; however, the reputation of the Shark Tank venue did appear to have a positive impact on the new ventures receiving investment. Thus, entrepreneurs may wish to consider the reputation of the venue of their presentations at least as much as the characteristics of the investors in the audience.
- While Shark Tank Angel Investors do not appear to be able to pick winners, their individual characteristics do appear to influence their likelihood to make investment offers and to ultimately close deals. Therefore, entrepreneurs seeking early-stage investment may wish to consider investor characteristics even though those characteristics are not directly linked to venture performance.

ABSTRACT

This article explores the investment impact and performance of a unique group of angel investors: those featured on the television show *Shark Tank*. It explores the relationship between the investors' individual characteristics such as experience, reputation, and network, with their investments' performance and attributes. The authors find evidence that investor and deal characteristics matter for predicting whether an investor is more or less likely to make offers and close deals. However, on average, Sharks do not have the ability to select outperforming companies, where investment performance is measured by the survival and website traffic of the start-up companies. They found the reputational impact of Shark Tank as a venue is significant. While these Shark investors are not typical of the vast majority of angel investors, the authors identify fundamental insights that may be of value to understanding the much larger and less famous angel investor community and the entrepreneurial firms they finance.

The angel investment process has long been one of the least transparent transactions in business. Deals were struck with little public access or scrutiny—until popular shows like Shark Tank brought this important element of entrepreneurial finance to an enthusiastic public audience in 2009. Thanks to the mainstreaming of the angel investment process in this entertaining format, entrepreneurs and potential investors can learn from the discussion of equity funding, valuations, and growth strategies in illiquid, high-risk, but potentially high-return, ventures. However, does Shark Tank accurately reflect the angel investment process? In short, the answer is no.

Shark Tank is made to entertain a TV audience. But is there anything we can learn from this glamorized version of entrepreneurial finance? Maybe. At least we think so. Certainly, the investors of Shark Tank are not your typical angel investors. But they do some of the things most angel investors do. They evaluate new ventures, estimate the value of new ventures, and commit their own capital to some of the ventures they view. While the disparities between Shark Tank and conventional angel investor forums are clear, so is the transparency of the investment process, however glamorized it is.

In this article, we examine an exhaustive list of Shark Tank investments and seek to understand their impact from both the short-term and long-term perspective. While we readily acknowledge the limitations of this sample as a proxy for typical angel investments, we hope to reveal some fundamental insights into angel investment characteristics that could have some value to entrepreneurs and their more likely less famous financial backers.

While much research has been devoted to exploring the impact of venture capital firms on the innovative and entrepreneurial processes of global business (Sahlman 1990; Lerner 1995; Gompers and Lerner 2004), comparatively less research has been directed at the pre-cursor angel investor segment (e.g., Boulton et al. 2019; Poczter and Shapes 2018; Bonini et al. 2018; Capizzi 2015; Hellmann and Thiele 2015; Huang and Pearce 2015; and Brush et al. 2012) even though angel group investments have been found to contribute similarly to innovation rates as VC investments (Dutta and Folta 2016). This may be due to the less public and less systematic nature of individual angel investing compared to organizational venture capital investing, making access to data and its analysis more challenging.

However, the impact and relevance of the angel investor segment has increased in recent years, as traditional venture capital funding has tended to emphasize later stage investing with larger rounds of capital, to which brand new ventures may have neither the need nor the access. For example, while 2020 was a record year for venture capital investments, it was later stage investments that grew most significantly while the number of seed stage investments fell in Q4 2020 (see PitchBook NVCA Venture Monitor Data Q4 2020). This bifurcation in the funding environment points to the importance of angel financing to new entrepreneurs. Angel investment, while much smaller than venture capital firm investment, still registered $4.3 billion in 2019 (Angel Resource Institute 2019).

Mason (2008) defines angel investors as "high net worth individuals who invest their own money, along with their time and expertise, directly in unquoted companies in which they have no family connection, in the hope of financial gain." While skill is often credited for successful early-stage firm investing (Kaplan and Schoar 2005; Korteweg and Sorensen 2017), observing these skills in practice is rare.

Thanks to the rise of publicly observable angel investors, access to angel investor thinking and investing strategies has entered the public domain with a splash. Widely watched shows such as Dragons Den and Shark Tank have allowed the public, not just researchers and professional investors, a glimpse of the angel investor process. Again, these shows are not representative of typical angel investment forums; they are edited for TV to increase ratings and time-delayed for audience viewing, and the investment decisions seen by the audience are non-binding, with some of the investments not coming to fruition. However, given their role in providing a portal to the traditionally obscure angel investment process to a wide audience, we sought to understand if any aspects of these shows corresponded to what we know of traditional angel investing. While open to public viewing, precise data from these angel investors shows are still difficult to collect, code, and analyze. Over time, we have been able to develop a proprietary data set of angel investment decisions from Shark Tank and data related to the performance of the startups. That has enabled us to explore and unearth some aspects of angel investor characteristics and performance.

Our findings on Shark Tank are counter-intuitive in that we find only weak and inconsistent evidence that the Shark characteristics we measured (e.g., reputation, experience, and network) affect the performance of their company investments. Furthermore, we found that Sharks do not have the ability to select outperforming companies on average. In this respect, our results lend credence to the "throwing darts" approach to angel investing, as early-stage investments simply have too many unknowns. Given this limitation to early investing, we reason that more but smaller investments across seed-stage new ventures may be the best approach. We do find evidence that investor characteristics matter for predicting whether an investor is more likely to make offers and close deals and for the characteristics of those deals. Taken together, our results suggest that in the realm of angel investing, the attractiveness of a potential investor as a partner, and the angel's ability to make deals, both alone and with others, are more important than angel investors' ability to pick winners.

We also found that the reputational impact of Shark Tank as a venue for angel investing is significant. Appearing on Shark Tank significantly improves company website traffic. This may be relevant to the brand value of more typical angel groups and forums. Thus, throwing darts in a well-respected angel investor venue may be just as good as a diligent selection of a small set of companies. Interestingly to this point, we find that the most popular and experienced Sharks make more deals per appearance on the show. While these Shark investors are not typical of the vast majority of angel investors, we attempt to identify fundamental insights from this research that may be of value to understanding the much larger and less famous angel investor community and the entrepreneurial firms they finance.

In the following sections, we describe the existing literature on angel investor performance and review our approach to determining performance among our sample of Shark Tank angel investors. The remainder of the article is organized as follows: The first section discusses the extant research on angel investing and the theoretical perspective that helped frame our research and hypotheses. The second section discusses our data and methodology. The third and fourth sections review our analysis and results, the fifth section discusses our results in light of the other research in angel investing, and the sixth concludes the paper.

SELECT PRIOR RESEARCH ON ANGEL INVESTORS

While early-stage financiers or angel investors are very important in the growth and success of nascent companies, there is little data on them. One of the more recent studies to analyze a detailed data set on angel investing found that ventures funded by two angel groups had an increased likelihood of success as measured by improved survival and exits (among other indicators) (see Kerr et al. 2011). Even this study, though, had to rely on very esoteric metrics to judge company performance as detailed financial data were not available.

A more recent study (Smith and Viceisza 2018) that was focused on the impact of Shark Tank Angels' intention to fund an enterprise concluded that entrepreneurs on the show who received an intention to fund from one or more of the Shark Tank Investors were more likely (about 8.5%) to have their ventures still existing one year after appearing on the show than those who did not receive an intention to fund.

They also found that higher amounts of funding increased the likelihood of the existence of the ventures in both the short term and longer term (greater than a year). Not dissimilar to a Shark Tank model of collaborative investing, Wood et al. (2020) asserted that angel investing has moved from individual angel investments to deals based on networks of angel investors.

Capizzi (2015) examined the returns of Italian Angel Investors, and using an econometric analysis found a U-shape return between experience and internal rate of return (IRR). The study also found a correlation between shorter holding periods of the investment (less than three years) and lower IRR, and a higher rejection rate of entrepreneur proposals and higher IRR. In summary, Capizzi (2015) essentially found that angel investors with moderate experience, who are highly selective, and who hold their investments for more than three years tend to have higher performance as measured by IRR.

Studies on angel investing as discussed above led us to explore certain characteristics of Sharks to assess their relevance in this interesting albeit unrepresentative sample of angel investors. We sought to examine the experience of angel investors as well as the reputational effects at an individual and organizational level, and the cross-industry connectivity effects. We looked at these characteristics in part through the lens of what appeared to us to be relevant theoretical frameworks, namely prior knowledge (angel investor experience), resource base view (Shark reputation), and strength of ties (cross-industry connectivity of Sharks). We also examined the question of whether the Sharks could construct outperforming portfolios. We developed several hypotheses to examine these questions:

Hypothesis 1a: *Companies receiving an investment from angels with more experience perform better.*

Hypothesis 1b: *Companies receiving an investment from angels with more recognition or reputation perform better.*

Hypothesis 1c: *Companies receiving investments from angels with a more diverse network across multiple industries perform better.*

Hypothesis 1d: *Companies receiving an investment from angels investing together in a syndicate enlarge their weak tie connections and perform better.*

Hypothesis 2: *Companies that receive an investment from angel investors perform better than those that do not receive an investment.*

Hypothesis 3: *Certain angel investors have the ability to select winning companies consistently.*

DATA

The data for this study includes every presentation aired on Shark Tank between August 2009 and April 2019.[1]

[1] For more info see https://abc.go.com/shows/shark-tank. Over time, the actual judges or Sharks on the show have changed, but the principal Sharks include billionaire Mark Cuban, owner and chairman of AXS TV and outspoken owner of the Dallas Mavericks; real estate mogul Barbara Corcoran; "Queen of QVC" Lori Greiner; technology innovator Robert Herjavec; fashion and branding expert Daymond John; and venture capitalist Kevin O'Leary (a.k.a. Mr. Wonderful). It is believed that each Shark earns $50,000 per episode.

Many details of the presentations were collected, including the type of company, product, how much the company requested in funding, whether or not they received an offer, counter-offers made, whether they accepted the offers, deal terms, and other details.[2] The data were collected by watching all Shark Tank episodes and coding all pertinent information, using the Shark Tank website, and by searching the Internet for other information on the companies that appeared on the show. The deal results and financing terms were recorded in our dataset.[3]

To measure the short-term market awareness and long-term performance of startups on Shark Tank, we acquired company web visit data for both desktop and mobile web visits since August 2015. This measure encompasses not only the fact that a company has not gone bankrupt but also the popularity of the business on its online platform. We sourced data from SimilarWeb, which uses a variety of methods to collect data and accurately measure the web traffic of websites.[4] The software uses machine learning, modeling, and estimations that are of a similar caliber to Google Analytics. The data, collected on a monthly basis, are available from August 2015 to the end of our sample period. Our study sample covers the period from August 2015 to April 2019.

We use short-term website traffic data as an indicator of market awareness and long-term website traffic data as an indicator of company performance.[5] Although website traffic data is not a perfect proxy for financial success, it seems to be an indication of it in the longer term. For example, on a 20/20 episode, the Sharks described DoorBot (a.k.a. Ring) and Bombas as two of the most successful companies to appear on Shark Tank (https://abc.com/shows/2020/episode-guide/2020-02/26-shark-tank-greatest-of-all-time). One can see from Exhibit 1 that their website traffic growth is much higher than the average website traffic growth of other companies appearing on Shark Tank.

We considered other potential measures of long-term performance (profits, ROI, additional rounds of funding, patent applications/grants, etc.), but after considering the limitations of each measure we chose website traffic data as the best consistent proxy of company performance. For example, as most firms remained private, profits and ROI data were rarely available. Furthermore, successful fast-growth companies are often unprofitable for years as they build market share.[6] While additional funding

[2]Prior to 2013, companies that participated on Shark Tank were required to enter into a binding agreement with Finnmax LLC. That is, Shark Tank's production company. In the agreement, Finnmax LLC, Sony Pictures Television Inc. and American Broadcasting Companies, Inc. (hereinafter referred to as Shark Tank Entities) choose to receive (or choose not to) the following: (1) receive a 2% royalty of the operating profits of the company, or (2) receive warrants that give Shark Tank Entities or their designees a 5% equity interest in the company. In 2013, Shark Tank investor Mark Cuban provided the lawyers in Shark Tank an ultimatum to remove the clause, or he would abandon the show. Ultimately, the clause was removed retroactively and every contestant who had participated on the show since the first season of Shark Tank was relieved of the commitment. However, the exact details of these arrangements remain undisclosed.

[3]According to a Forbes survey of 237 companies, 73% of deals had a different deal than the deal made on TV. We attempted to confirm alterations to reported deal terms, but were unable to do so across the large range of deals. However, we found no evidence that any changes to deal terms were done in anything but a random manner across all deals and so would not have a significant impact on the analysis of original deals overall.

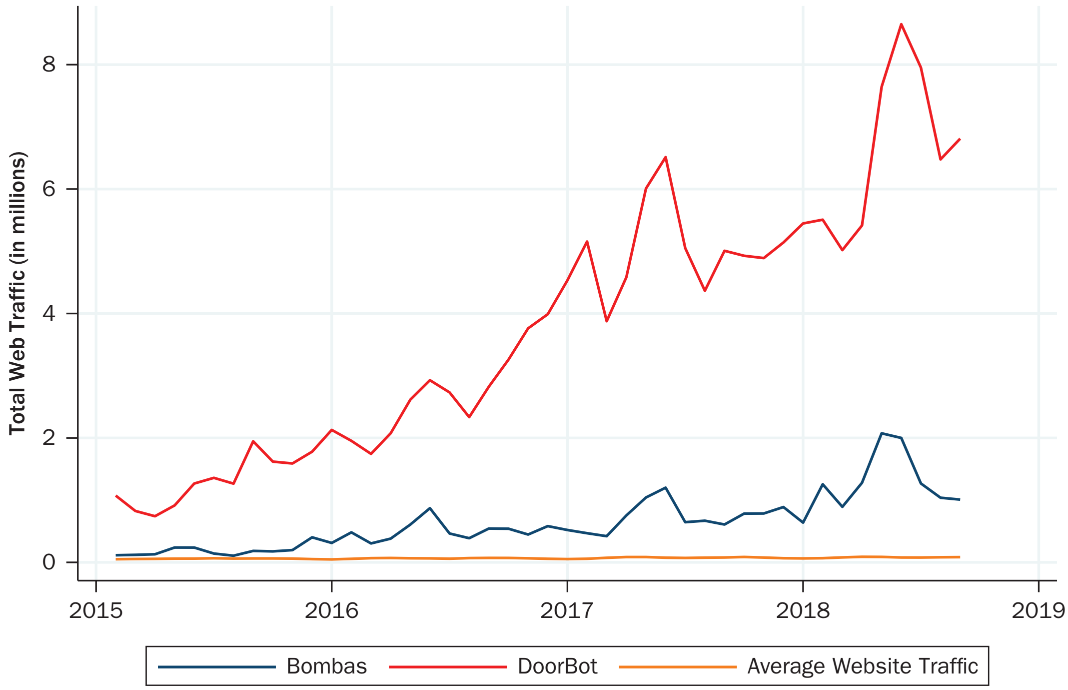
[4]Their website describes their methodology. For more information, see https://www.similarweb.com/.

[5]We are not the only study to use website traffic growth as a proxy for angel company success (Kerr et al. 2011).

[6]We obtained financial information for some of Shark Tank companies from Privco. Privco is an online financial data company that collects and makes available financial data on private companies. We attempted to extract as much financial data as possible, ultimately collecting data on 56 out of a total of 873 Shark Tank companies. Much of this data was not very useful and so we ultimately did not use it for our analysis.

EXHIBIT 1

Website Traffic Growth of Two Successful Shark Tank Companies



NOTE: This exhibit shows the website traffic growth of Bombas and DoorBot (a.k.a. Ring) compared with the average website traffic growth of all companies on Shark Tank.

rounds could be perceived as a measure of performance, they do not necessarily correlate with performance, as some firms may not need additional funding, and others may raise funding due to necessity or lower than expected operating cash flow. Patent applications/grants also are not a viable proxy for performance as most firms have limited associated patentable technology, and patents among those that do may not prove commercially valuable. Finally, as indicated previously, website traffic (alongside other indicators) has been used as a measure of performance (Kerr et al. 2011) and market value (Graham et al. 2002) in earlier empirical studies. Given these practical and methodological limitations of other potential measures of performance, we remained consistent with website traffic as an indicator of market awareness in the short term and company performance over the long term in our study.

Exhibit 2 contains summary statistics about Shark offers over the history of the show. We included statistics over the full range of investing from 2009 to 2019 but did not include special deals (e.g., those including royalties, debt, or other special terms) as they were not included in the analysis in the rest of this paper.[7] It's clear from the data that the most prominent and stable Sharks are Kevin O'Leary, Mark Cuban, Robert Herjavec, Lori Greiner, Daymond John, and Barbara Corcoran. Among them, the highest frequency of offers, 32% of all presentations, has been made by Kevin O'Leary (aka Mr. Wonderful). His deal rate is the lowest of the group, suggesting that he makes very aggressive offers or that companies do not choose him.

The highest percentage of accepted deals occur with Mark Cuban at 87%. Cuban also has invested the most money, a total of $30.1 million. His single largest investment was $2 million. The largest deal on Shark Tank, valued at $25 million,

[7] In Appendix A, we describe an interesting way to convert royalty payments into equity-equivalent amounts. Doing this for debt and other special deals was not as easy and hence why we decided to exclude these deals from the analysis in this paper.

EXHIBIT 2

Statistics about Shark Offers by Shark

Sharks	Show Times	No. Offer	No. Deal	Total Inv.	Largest Inv.	Largest Deal	Male	Male Dev.
Kevin O'Leary	754	32.10	18.60	9,689	2,500	25,000	63.22	4.57
Mark Cuban	710	20.99	87.25	30,112	2,000	15,000	61.74	–0.02
Robert Herjavec	704	24.86	42.29	22,946	5,000	12,000	65.71	9.07
Lori Greiner	583	24.36	72.54	18,038	1,000	12,000	52.11	–5.34
Daymond John	538	27.88	50.00	14,595	3,000	6,000	56.67	–1.54
Barbara Cocoran	444	25.45	56.64	7,183	600	3,000	49.56	–10.40
Kevin Harrington	74	17.57	69.23	945	250	1,000	53.85	–8.06
Chris Sacca	33	33.33	54.55	1,270	300	12,000	45.45	–14.81
Rohan Oza	20	40.00	50.00	2,750	1,250	10,000	50.00	–7.50
Sara Blakely	17	23.53	50.00	475	350	1,400	25.00	–28.85
Bethenny Frankel	14	50.00	71.43	850	350	1,750	57.14	–1.82
Alex Rodriguez	14	35.71	40.00	575	500	8,333	40.00	–30.00
Richard Branson	8	37.50	100.00	375	250	1,250	0.00	–
Nick Woodman	8	62.50	60.00	360	175	1,200	60.00	3.57
Matt Higgins	8	25.00	100.00	200	100	909	50.00	14.29
Jamie Siminoff	7	28.57	100.00	1,250	750	4,000	100.00	20.00
Charles Barkley	7	14.29	100.00	50	50	100	100.00	0.00
Ashton Kutcher	7	14.29	100.00	50	50	500	100.00	28.57
Jeff Foxworthy	6	50.00	66.67	500	400	2,000	33.33	0.00
John Paul Dejoria	4	50.00	100.00	90	50	200	50.00	0.00
Troy Carter	4	50.00	50.00	50	50	333	50.00	–16.67
Alli Webb	3	33.33	100.00	150	150	750	100.00	0.00
Steve Tisch	3	66.67	50.00	125	125	1,250	50.00	0.00
Sharks Statistics by Gender								
Male Sharks	–	26.72	46.98	86,266	5,000	25,000	61.39	–
Female Sharks	–	25.05	65.04	26,360	1,000	12,000	50.38	–

NOTES: This exhibit shows the deal statistics of all Sharks who appeared on the show between August 8, 2009, and April 7, 2019. There were 84 special deals that involved debt, royalties, or some other arrangement other than straight equity. These special deals were eliminated from the summary statistics because they were not used in the later analysis. Shark Tank Show Times indicate the number of pitches a Shark received while appearing on the show (note: the first 13 episodes had five pitches per episode while the rest of the seasons had four). No. Offer is the percentage of offers extended by the Shark out of total Show Times. No. Deal is the percentage of Shark offers accepted by the entrepreneurs. Total Inv. is the total dollar amount (in thousands) invested by the Shark. The Largest Inv. is the largest single investment (in thousands) made by a Shark. Largest Deal is the implied valuation of the highest valued company from any single deal that a Shark completed. Male is the percentage of offers made to solely male entrepreneurs out of the total Show Times. Male Dev. is the percentage of offers a Shark extends to male entrepreneurs minus the percentage of male entrepreneurs they have seen. The percentage of offers the Shark extends to men is a ratio of offers to men compared to offers to men or women but not both. The percentage of men a Shark sees is a ratio of male entrepreneurs who pitched their company to the Shark compared to male or female entrepreneurs but not both. Shark statistics by gender summarizes the data based on Shark gender. Male Sharks is a compilation of the statistics of all males that participated as investors on the show. Female Sharks groups the statistics of all the females that participated as investors on the show.

was with Kevin O'Leary.[8] It was for ZIPZ Wine, which came into the Tank asking for $2.5 million for a 10% equity stake. We also can see that male and female Sharks make about the same percentage of offers (27% vs. 25%), yet the female Sharks land more deals, 65% vs. 47%.

Exhibit 3 contains summary statistics about the main Sharks on Shark Tank.[9] O'Leary appeared on 754 episodes, followed by Cuban at 710 and Herjavec at 704. Herjavec and Cuban made the highest average investments per company, $310,000

[8] In our sample period, there was a larger deal for $66.6 million, but it was a special deal involving debt as well as equity with Vengo Labs.

[9] As before, we do not include special deals.

and $232,000 respectively. The average deal size (i.e., valuation of the company) varies by Shark. Cuban had the highest average valuation at $1,735,000, while John and Corcoran invested in companies with the lowest average valuation, $807,000 and $607,000 respectively.[10] Many deals had more than one shark. For example, 65% of Cuban's deals involved another shark.[11]

While it is not possible to conclude definitively from this simple summary data, it appears that when comparing female offers to female deals, female entrepreneurs are more likely to accept deals from female Sharks and male entrepreneurs to accept deals from male Sharks. This is consistent with the findings of Boulton et al. (2019) who also reviewed investment decisions by members of Shark Tank, with a focus on the personal characteristics of the investors and the entrepreneurs. Finally, we show the distribution of Shark investments by industry.[12] Greiner clearly has a preference for Consumer Durables and Apparel, with 62% of her deals in that sector.

EMPIRICAL ANALYSIS

One of the main curiosities of the analysis of Shark Tank as a boost for entrepreneurs is whether or not the investment by a Shark improves the company's probability of success or market awareness. One way to determine that is to do an event type of analysis, where we look at the website traffic prior to and after the airing of every company that made a pitch. While this is not a precise indicator, as the show is filmed months before its actual airing, the airing of the show does have an impact in terms of marketing awareness. Exhibit 4 shows the event analysis of all companies that aired on Shark Tank from the period February 2016 to May 2018.[13] It is very clear from the graph that there is a "Shark Tank effect" on website traffic. The increased market awareness aspect occurs whether or not the company was funded by a Shark. This can be seen in the spike in average traffic regardless of whether a deal is made.

Our initial look at the data indicates that the value of pitching on Shark Tank, at least in the short term, is most closely related to the institution of Shark Tank and the exposure it provides rather than to the actual investment by a Shark Tank angel investor. Exhibit 4 also shows that the substantial increase in web traffic common to both deal and no-deal firms is limited to the month of the airing of a company's pitch on the show (in month 0). We find it reasonable that appearing on the show would generate a short-term increase in website traffic growth by increasing market awareness in the month of airing.[14]

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[10] Although we did not consider companies with special deals, if you add these companies, then the largest average valuation came from O'Leary's investments.

[11] The data also indicate that female Sharks tend to fund female entrepreneurs more than would occur from a simple, no-bias probabilistic sense. We find no such deviation for the male Sharks. One of the guest Sharks, Blakely, has publicly stated that she prefers to promote females (Rhone 2019).

[12] Sectors were mapped as best possible to GICS sectors.

[13] This figure tracks a subset of 247 companies aggregated by examining the air-dates from February of 2016 to May of 2018 (inclusive). The data was limited to this subset given that we wanted to include only the companies for which we had a complete monthly web traffic history ranging from 6 months before they appeared on Shark Tank and up to 8 months after. Companies were grouped by the month during which they aired on the show and were separated by whether they got a deal or not. The graph shows the cumulative web traffic growth across this subset, tracking the averages at monthly intervals starting 6 months before they were featured on the show to 8 months after, with 0 representing the month in which the show was aired. By scaling the set of all companies relative to their air date month, the average web traffic growth can be measured and accrued in monthly intervals on an axis that depicts the change in the average web traffic growth (in percentage terms) for these companies.

[14] Note that while Exhibit 4 shows that web traffic remains very stable on average for some months after show airing, especially for deal firms, there is variation at the firm level in monthly web traffic in this period, and average web traffic does vary month to month, just by a relatively small amount compared to other months.

Measurement of Short-Term Deal Effect

The main goal of our research was to gain some insights from this very unique sample of angel investors. While clearly not representative of typical angel groups, we did hope to identify any effects Shark investments might create. Our first step was to investigate the short-term impact of getting a deal before turning to the impact of investor characteristics on deal performance. We also investigated the long-term impact of deals across investor characteristics. Following this, we investigated whether investor characteristics make getting a deal more or less likely, and finally we measure the impact of investor characteristics on the likelihood of making offers, and the equity share and amounts invested by the Sharks. For all these investigations, we dropped "special deal" companies with debt or royalties attached in order to make the analysis of equity stake more precise.

Overall short-term deal impact. To test for the short-term effect of getting a deal, we use an event study around the airing of the show in which the company appeared. We categorized month $t-3$ to month $t-1$ as the estimation window because we observe similar and consistent growth rates of web traffic for deal and no deal firms in this pre-event window (see Exhibit 4), where month t is the month when the company's pitch was aired on Shark Tank. Exhibit 4 also shows a substantial impact of appearing on the show on web traffic across both deal and no-deal firms in the month the show airs; we posit this represents a pure market awareness effect. For this reason, we exclude month t from the data used in our estimations to ensure that the Shark Tank effect does not obscure our investigation of the impact of getting a deal. In further

EXHIBIT 3
Deal Summary Statistics for the Main Sharks

	Daymond J.	Kevin O.	Lori G.	Mark C.	Robert H.	Barbara C.
Panel A: Shark Deals Summary Statistics						
Shark Tank Show Times	538	754	583	710	704	444
Percentage Show Times (%)	68.19	95.32	73.70	89.76	89.00	56.13
# of Offers	150	242	142	149	175	113
# of Deals	75	45	103	130	74	64
Average Capital Investment	195	215	175	232	310	112
Maximum.	3,000	2,500	1,000	2,000	5,000	600
Minimum.	20	33	20	0	20	13
Average Deal Size	807	1,643	1,431	1,735	1,701	607
Maximum	6,000	25,000	12,000	15,000	12,000	3,000
Minimum	63	70	60	76	100	91
Average Equity Stake	0.28	0.20	0.20	0.19	0.18	0.26
Maximum	1.00	0.50	0.65	1.00	0.50	0.55
Minimum	0.04	0.04	0.03	0.03	0.04	0.05
Acceptance Criterion	0.59	0.67	0.81	0.72	0.72	0.61
Shark Co-Investment	23.00	24.00	45.00	65.00	32.00	24.00
# of Special Deals	0.00	0.00	0.00	0.00	0.00	0.00
Male Entrepreneurs Offers (%)	56.67	63.22	52.11	61.74	65.71	49.56
Female Entrepreneurs Offers (%)	24.67	22.73	28.87	26.17	17.71	37.17
Both Genders Entrepreneurs Offers (%)	18.67	14.05	19.01	12.08	16.57	13.27
Male Entrepreneurs Deals (%)	50.67	66.67	48.54	61.54	64.86	43.75
Female Entrepreneurs Deals (%)	28.00	17.78	33.98	26.92	20.27	42.19
Both Genders Entrepreneurs Deals (%)	21.33	15.56	17.48	11.54	14.86	14.06

(continued)

EXHIBIT 3 *(continued)*

Deal Summary Statistics for the Main Sharks

	Daymond J.	Kevin O.	Lori G.	Mark C.	Robert H.	Barbara C.
Panel B: Shark Deals across Industries						
Automobiles & Components	0.00	0.00	0.00	1.54	1.35	0.00
Commercial Services & Supplies	0.00	0.00	0.00	0.00	1.35	0.00
Consumer Durables & Apparel	42.67	31.11	62.14	36.15	39.19	32.81
Consumer Services	5.33	6.67	3.88	6.92	6.76	6.25
Diversified Financials	0.00	4.44	0.00	0.77	1.35	0.00
Food & Staples Retailing	0.00	0.00	0.97	0.00	1.35	0.00
Food, Beverage, & Tobacco	16.00	15.56	12.62	19.23	10.81	32.81
Health Care Equipment & Services	0.00	4.44	4.85	4.62	2.70	9.38
Household & Personal Products	26.67	8.89	7.77	10.77	17.57	17.19
Media	2.67	4.44	0.00	5.38	2.70	1.56
Retailing	0.00	0.00	0.00	0.00	0.00	0.00
Software & Services	5.33	17.78	6.80	10.77	10.81	0.00
Technology Hardware & Equipment	1.33	6.67	0.97	3.85	4.05	0.00

NOTES: This exhibit shows deal statistics for the main Sharks who were featured more consistently on the show between August 8, 2009, and April 7, 2019. There were 84 special deals that involved debt, royalties, or some other arrangement other than straight equity. These special deals were eliminated from the summary statistics since they are not used in the later analysis. Shark Tank Show Times indicate the number of pitches a Shark received while appearing on the show (note: the first 13 episodes had five pitches per episode while the rest of the seasons have four pitches per episode). Percentage Show Times is the number of pitches a Shark received while appearing on the show divided by the total number of pitches between August 8, 2009, and April 7, 2019. # of Offers is the total number of offers extended by the Shark during all appearances on the show. # of Deals is total number of deals made by the Shark with any entrepreneurs during all appearances on the show. Capital Investment refers to the quantity (in thousands of dollars) that was invested by each Shark. Average Deal Size refers to the implied valuation (in thousands of dollars) of the companies that struck a deal. Equity Stake refers to the percentage of stake in the company the Shark now holds. Acceptance Criterion compares the average equity offered by entrepreneurs to the average equity stake Sharks end up receiving for deals where the requested amount by the entrepreneurs is equal to the established deal amount with the Shark(s). Shark Co-Investment refers to the number of deals in which two or more Sharks shared the deal. # of Special Deals is the number of deals that were not equity-only deals. We deleted these (set to 0) as they were not used in later analysis. Male Entrepreneurs Offers is the percentage of offers extended to only males, Female Entrepreneurs Offers is the percentage of offers extended to only females, and Both Genders Entrepreneurs Offers refers to the percentage of offers that were extended to both male and female entrepreneurs that presented on the same pitch. Male Entrepreneurs Deals is the percentage of deals made with only males, Female Entrepreneurs Deals is the percentage of deals made with only females and Both Genders Entrepreneurs Deals refers to the percentage of deals that were made with both male and female entrepreneurs who presented on the same pitch. Panel B shows the percentage of deals made by a Shark by GICS sector.

specifications, we include month t in the data and separately control for its impact on web traffic. We investigate the short-term impact of deals on web traffic from months $t+1$ to $t+3$ as well as $t+1$ to $t+6$, excluding the Shark Tank effect in month t.

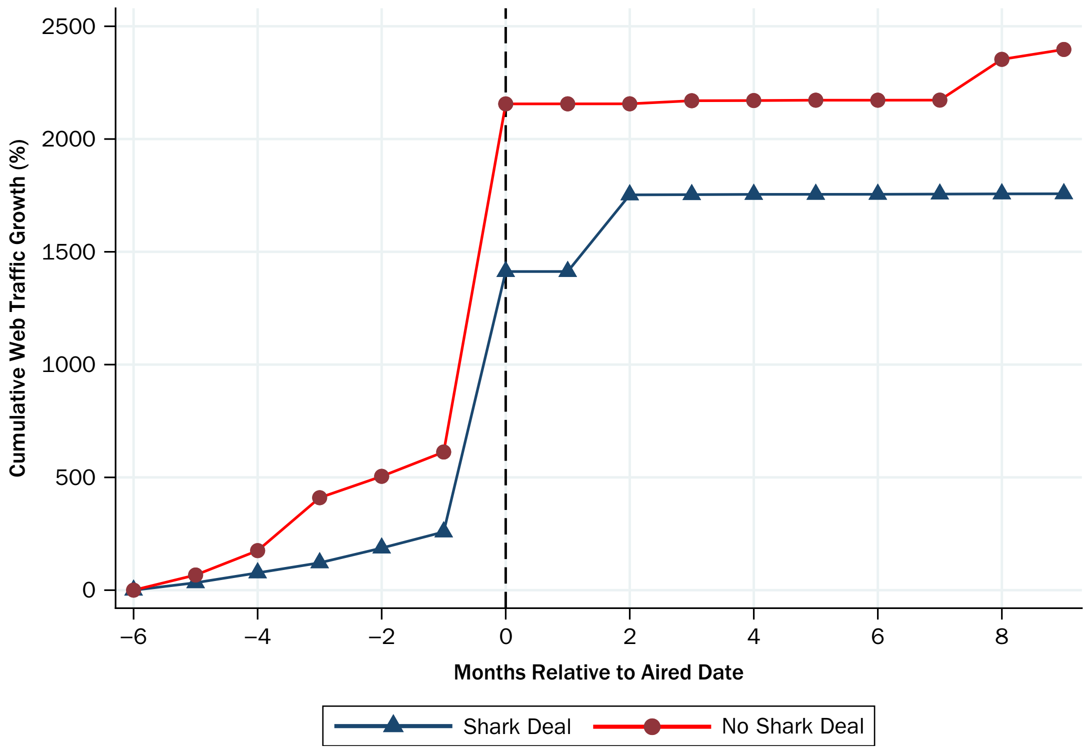
We estimated the following regression,

$$WSTG_{it} = \beta_0 + \beta_1 D_i + \beta_2 SM_{it} + \beta_3 (SM_{it} \cdot D_i) + \beta_4 P_{it} + \beta_5 (D_i \cdot P_{it}) + S_i + \epsilon_{it} \qquad (1)$$

where $WSTG_{it}$ is the website traffic growth of company i in month t, D_i is a dummy variable that takes on a value 1 if the company received a deal from the Sharks and a value of 0 otherwise, SM_{it} is a dummy variable that takes on a value of 1 the month a company appears on the show and 0 otherwise, P_{it} is a dummy variable taking on a value of 1 in the post event window of $t+1$ to $t+3$ or $t+1$ to $t+6$ and taking a value of zero otherwise, S_i is a GICS sector fixed effect, and ϵ_{it} is an error term. We employ robust standard errors.

EXHIBIT 4

Average Website Traffic Before and After Appearance on Shark Tank



NOTES: This exhibit tracks a subset of 247 companies aggregated by examining the airdates from February of 2016 to May of 2018 (inclusive), which limits the data to include only companies for which we had a complete monthly web traffic history ranging from six months before to eight months after they appeared on Shark Tank. Companies were grouped by the month during which they aired on the show and were separated by whether or not they got a deal. The exhibit shows the cumulative web traffic growth across this subset, tracking the averages at monthly intervals from six months before they are featured on the show to eight months after, with 0 representing the month in which the show was aired. By scaling the set of all companies relative to their air date month, we could measure and accrue the average web traffic growth in monthly intervals on an axis that depicts their change in the average web traffic growth (in percentage terms).

Columns 1 and 3 of Exhibit 5 show estimates from the event study where the month a firm appears on the show is excluded from the data for the $t + 1$ to $t + 3$ and $t + 1$ to $t + 6$ post-event windows, respectively. Columns 2 and 4 of Exhibit 5 show estimates from the event study where the month a firm appears on the show is included in the data and its effect on web traffic is controlled for separately for deal and no-deal firms for the $t + 1$ to $t + 3$ and $t + 1$ to $t + 6$ post-event windows, respectively. The results confirm that the month a company's pitch airs (SHOW MONTH) is associated with a significant increase in web traffic growth for both deal and no-deal firms, and there is no significant difference in this effect across deal and no-deal firms (SHOW MONTH*DEAL).[15]

We do find that deal firms realized relatively higher web traffic growth than no-deal firms (DEAL*POST) in months $t + 1$ to $t + 3$ and $t + 1$ to $t + 6$. While this differential is not statistically significant at standard significance levels, it is significant at the 15% level. This finding is consistent across post-event windows and our treatment of month t. In summary, appearing on Shark Tank in and of itself seems to have a

[15] Because firms that get a deal do not have a statistically different performance than no deal firms when the show airs, our hypothesis is that any impact of a Shark's investment must come in the months after a pitch airs.

EXHIBIT 5

The Impact of Making a Deal on Short-Term Website Traffic

Estimation Period	$T-3$ to $T+3$		$T-3$ to $T+6$	
Treatment of Show Month	**Ex. Month**	**Inc. Month**	**Ex. Month**	**Inc. Month**
Variable	**(1)**	**(2)**	**(3)**	**(4)**
DEAL	–98.9147	–102.0183	–94.3508	–96.9797
	(–1.2213)	(–1.2461)	(–1.2356)	(–1.2599)
POST	–141.1**	–141.1**	–143**	–143**
	(–2.037)	(–2.006)	(–2.11)	(–2.095)
DEAL*POST	194.2	194.2	139.6	139.6
	(1.472)	(1.455)	(1.563)	(1.552)
SHOW MONTH		1398**		1398**
		(2.198)		(2.197)
SHOW MONTH*DEAL		–304		–304
		(–0.3588)		(–0.3589)
Constant	73.43	–70.45	97.45	–5.671
	(0.7634)	(–0.4543)	(1.172)	(–0.0466)
R-sqr	0.0160	0.0270	0.0115	0.0305
Obs	1248	1456	1872	2080
Sector Fixed Effects	Y	Y	Y	Y

NOTES: This exhibit shows the effect of getting a deal on Shark Tank on companies' web traffic. The key variable of interest is DEAL*POST. DEAL is whether the company receives a deal on the show or not, POST indicates the post-airing $t+1$ to $t+3$ or $t+1$ to $t+6$ window. SHOW MONTH is a dummy variable indicating the month a firm's pitch aired. "Ex. Month" and "Inc. Month" indicate that the sample excludes or includes the month the show aired (month t), respectively. The data examined in these regressions only include shows that aired between February 2016 and May 2018, in order to include only companies for which we had a complete monthly web traffic history ranging from before and after appearing on the Shark Tank. The results of this exhibit are based on an event study including data on companies' web traffic from three months prior to appearing on Shark Tank up to six months after. We employ robust standard errors and include GICS sector fixed effects in each specification. The *t*-stats of coefficients are listed directly under the parameter estimates in parentheses. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

clear, dominant, and positive effect on short-term firm performance, while getting a deal seems to be associated with a marginally detectable positive effect on short-term firm performance.

We extended this event study analysis to other aspects of the Shark Tank investor characteristics that we tested as described in the following sections.

Experience and reputation effects. We found some evidence that getting a deal on Shark Tank has a positive short-term effect on firm performance. Our next objective was to investigate whether investor characteristics matter for the short-term success of their deals.[16] It is important to note that this investigation conditions on the occurrence of a deal rather than accounting for the joint impact of investor characteristics on deal performance and whether an investor makes a deal. For clarity in the interpretation of the results, we first isolate the impact of investor characteristics on deal performance and subsequently investigate the impact of investor characteristics on the likelihood that a deal is made.

[16] We focused on comparing deal vs. no-deal firms because we find it more informative than further looking at whether no-deal firms received an offer and what this implies. While a deal represents a clear meeting of the minds between the firm and the investor, a lack of offers or offers that are rejected can be interpreted in many different ways. For example, Sharks sometimes make ridiculous offers to companies they do not think are very good, and firms may reject these. On the other hand rejecting an offer may be a sign the firm has private information that its valuation is higher than implied by the investor's offer.

Hypothesis 1a examines the impact of angel investors' experience as it relates to their investment success. As a proxy for experience we compared the number of deals each investor made on Shark Tank prior to the investment in the current company.[17] To test Hypothesis 1a, we used the same type of regression as in Exhibit 5 Column 3, using the $t - 3$ to $t + 6$ estimation period and excluding the month of show airing.[18] We restricted our attention to deal firms only, included a variable for the experience of the Sharks, and estimated the following regression:

$$WSTG_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 (EXPERIENCE_{it} \cdot P_{it}) + S_i + \epsilon_{it} \quad (2)$$

where $WSTG_{it}$ is the website traffic growth of company i in month t, $EXPERIENCE_{it}$ represents the Shark's experience at the time of the deal based on deals made previously on Shark Tank, P_{it} is a dummy variable taking on a value of 1 in the post event window of $t + 1$ to $t + 6$ and a value of zero otherwise, S_i is a GICS sector fixed effect, and ϵ_{it} is an error term. We employed robust standard errors. We did not include the variable $EXPERIENCE_{it}$ itself in our reported regressions because we were restricting the sample to firms that made a deal, and there is no theoretical reason the experience of the Shark that makes a deal should be associated with the pre-deal web traffic of the company with which the Shark makes a deal later. Nevertheless, we have repeated the regression controlling for $EXPERIENCE_{it}$ and found qualitatively the same results.

The results, shown in Column 1 of Exhibit 6, show a negative sign and no significant effect of experience on website traffic growth. Thus, at least as a short-term phenomenon, the experience of the Shark does not result in higher website traffic.

Hypothesis 1b examines the reputation effect of Shark Tank investors. This test is built upon the perspective of a resource base view where reputation (e.g., celebrity) is a resource that has the properties of being valuable, rare, hard to copy, and hard to substitute for (Barney 1991; Wernerfelt 1984; Conner 1991). One problem with this test is that there are very few observations. We collected the number of Twitter, Instagram, and Facebook followers of each Shark, which makes for one observation per Shark as of April 2019. Thus, in reality, we only have a total of 23 observations.[19]

We estimate a similar regression as before, including an interaction dummy of the popularity of the shark:

$$WSTG_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 (SHARKPOP_{it} \cdot P_{it}) + S_i + \epsilon_{it} \quad (3)$$

where $WSTG_{it}$ is the website traffic growth of company i and in month t; $SHARKPOP_{it}$ represents the Shark's popularity and is the number of Twitter followers, Instagram followers, etc. in millions; P_{it} is a dummy variable taking on a value of 1 in the post-event window of $t + 1$ to $t + 6$ and zero otherwise; S_i is a GICS sector fixed effect; and ϵ_{it} is an error term. We employ robust standard errors.

Specification 2 of Exhibit 6 shows the results of Shark popularity on website traffic, where there is no significant effect. Thus, for Hypothesis 1b (reputation effect of individual Shark Tank investor) we do not find a statistical significance in the

[17] We considered other measures of experience, such as the age of each Shark, number of years in business, etc., but reasoned that experience investing in similar type deals is the experience most applicable to investing in new potential deals (Capizzi 2015).

[18] We found qualitatively the same results as those we describe below using the other three columns of Exhibit 3 as a baseline.

[19] While we expect that appearing on Shark Tank probably does impact each Shark's social media followership, we believe the relative reputation of each Shark, however it was attained, still is a factor worth considering with relation to investor impact.

EXHIBIT 6

The Impact of Shark Characteristics on Short-Term Website Traffic for Deal Firms

Variable	(1)	(2)	(3)	(4)	(5)
POST	81.9958	39.4207	88.2504	119.1083	369.3125
	(0.5926)	(0.3884)	(0.5890)	(0.6626)	(0.8847)
EXPERIENCE*POST	–1.286				–2.349
	(–1.05)				(–1.053)
SHARKPOP*POST		–5.6290			3.0018
		(–0.9527)			(1.151)
HHI*POST			–327		–412.6
			(–0.9788)		(–1.016)
SHARKNUM*POST				–95.22	–96.26
				(–0.9751)	(–1.003)
Constant	–13.55	30.32	15.51	–15.12	–44.56
	(–0.2434)	(1.603)	(0.5235)	(–0.2678)	(–0.5454)
R-sqr	0.0351	0.0354	0.0353	0.0359	0.0371
Obs	1035	1035	1035	1035	1035
Sector Fixed Effects	Y	Y	Y	Y	Y

NOTES: This exhibit shows the effect of Shark characteristics on companies' web traffic for companies that made a deal. The month *t* that a company appears on the show is excluded from the sample. The key variables of interest are EXPERIENCE*POST, SHARK-POP*POST, HHI*POST, and SHARKNUM*POST. POST indicates the post-airing month $t + 1$ to month $t + 6$ window. EXPERIENCE represents the number of deals on Shark Tank each investor made prior to the investment in the current company. SHARKPOP is a measure of the reputations of the Sharks as noted by the size of their following on Twitter, Instagram, and Facebook in millions. HHI is the deal diversity of the Shark's prior investments at the time of the deal ranging from 0 (complete diversity) to 1 (no diversity). SHARKNUM is the number of Sharks that make the deal. The data examined in these regressions includes only shows that aired between February 2016 and May 2018. The data were limited to this subset to include only companies for which we had a complete monthly web traffic history ranging from before and after appearing on the Shark Tank. The results of this exhibit are based on a regression including data on companies' web traffic from three months prior to appearing on Shark Tank to six months after. We employ robust standard errors and include GICS sector fixed effects in each specification. The *t*-stat of coefficients are listed directly under the parameter estimates in parenthesis. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

short run. This finding is somewhat surprising and runs counter to the prescription of the Resource Base View.

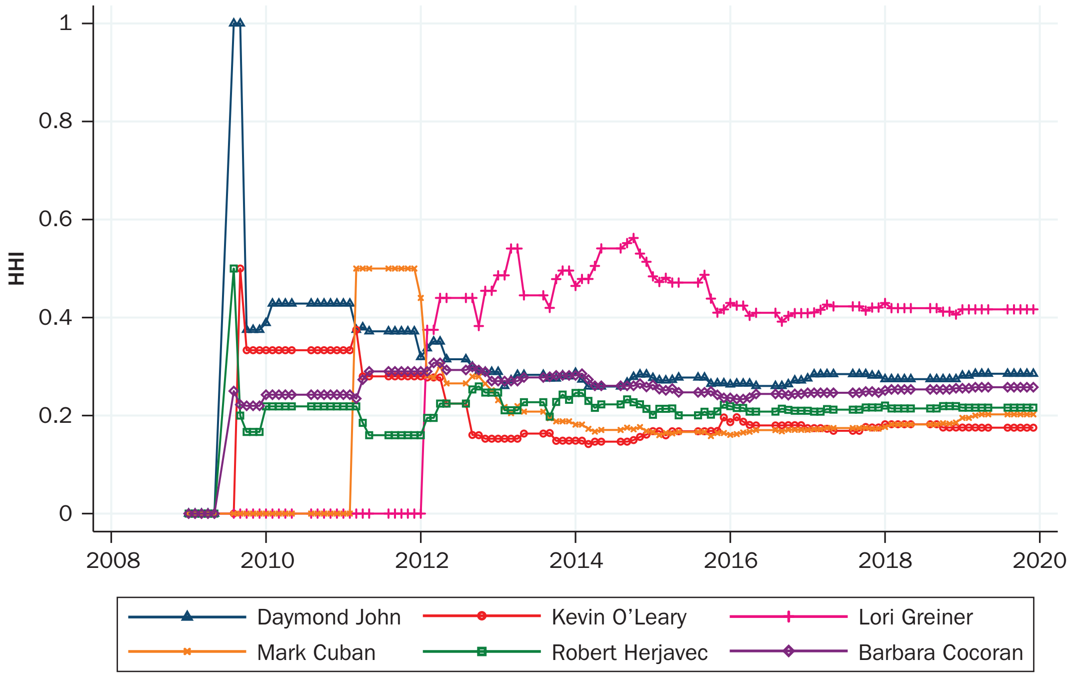
Industry concentration effect. Next, we wanted to test whether or not a Shark's network connections across industries might be able to help companies become more successful (Hypothesis 1c). This test relies on the perspective of Strength of Weak Ties (Granovetter 1973; Ding et al. 2014), which predicts that greater opportunities come from the establishment of an increasing number of contacts across varying industries. In order to measure this, we use the actual historical investments of each Shark in his or her portfolio and measure a Herfindahl index of the industry concentration of the portfolio of companies.[20] If this is true, then we would expect a lower HHI to have a great impact on the future success of the companies.

Exhibit 7 shows how the main Sharks' industry diversification index changed over time. The highest value for this index is 1, where a Shark is very poorly industry diversified, while a Shark closer to zero is more industry diversified. Other than

[20] We actually use the normalized Herfindahl-Hirschman Index (HHI). We adapted the measure to determine how concentrated Sharks' portfolios are based on the GICS sector of companies in which they invested on the show. We calculated an HHI measure on a monthly basis to capture how each Shark's portfolio concentration changed over time. Thus, Sharks who have investments in more industries will have a lower HHI, whereas Sharks with investments only in a few industries will have a higher HHI.

EXHIBIT 7

Industry Diversity of Shark Investments



NOTES: This exhibit shows the normalized Herfindahl-Hirsh Index of industry diversification of individual Shark investments according to GICS codes. A higher value indicates less industry diversity, while a lower value indicates less concentration.

at the beginning of the show, the HHI for each shark stayed pretty constant.[21] Greiner had the highest industry diversity index.

In order to examine the short-term industry concentration effect, we estimated the following regression,

$$WSTG_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 (HHI_{it} \cdot P_{it}) + S_i + \epsilon_{it} \tag{4}$$

where $WSTG_{it}$ is the website traffic growth of company i and in month t, HHI_{it} is the average *HHI* in a multi-person deal and the *HHI* of the shark in a single deal based on all deals up until that episode aired, P_{it} is a dummy variable taking on a value of 1 in the post-event window of $t+1$ to $t+6$ and zero otherwise, S_i is a GICS sector fixed effect, and ϵ_{it} is an error term. We employed robust standard errors.

The results, in specification 3 of Exhibit 6, show that HHI has a negative sign, but an insignificant coefficient on website traffic growth over the event period. Thus, we found that Shark Tank investors with a greater breadth of investing across multiple industries did not have a statistically significant higher impact on a company's website traffic growth.

Syndicate investing. Next, we wanted to explore whether Sharks are more successful as a group than alone (Hypothesis 1d). In order to do this, we introduced a variable measuring the total number of Sharks involved in a particular deal.[22] Exhibit 8 shows the distribution of deals made on Shark Tank by how many Sharks

[21] This could potentially provide a very small sample size. That is, to the extent that a Shark's portfolio doesn't change much over time, we really have very few data points for the analysis.

[22] This is a test that more Sharks lead to more success for a company and that customers react to this syndicate in a strong fashion.

EXHIBIT 8

The Distribution of Shark Deals by Number of Sharks

Number of Sharks	Number of Deals	Percent of All Deals
0	384	43.89
1	359	41.03
2	110	12.57
3	16	1.83
4	2	0.23
5	4	0.46

NOTE: This exhibit shows the number of deals and percentage of deals that involved zero to five sharks over the period 2009 to 2019.

were on the deal. Of all the deals, 44% did not receive any funding (i.e., zero Sharks), 41% were funded by one shark, 13% were funded by 2 Sharks, and only 2.5% were funded by three or more Sharks.

In order to test for the impact of the number of Sharks on a deal, we estimated the following regression,

$$WSTG_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 (SHARKNUM_{it} \cdot P_{it}) + S_i + \epsilon_{it} \quad (5)$$

where $WSTG_{it}$ is the website traffic growth of company i and in month t, $SHARKNUM_{it}$ is the number of Sharks on any given deal, P_{it} is a dummy variable taking on a value of 1 in the post event window of $t+1$ to $t+6$ and zero otherwise, S_i is a GICS sector fixed effect, and ϵ_{it} is an error term. We employ robust standard errors.

The results in specification 4 of Exhibit 6 show a negative sign, but are statistically insignificant as to the effect of the number of Sharks on a deal. Thus, we find no statistically significant support for the notion that syndication enhances a deal structure by spreading risk across a number of investors in the short term (Hypothesis 1d).

Specification 5 of Exhibit 6 confirms that we continue to find no significant effect of investor characteristics on short-term web traffic for companies that made a deal when controlling for the full set of investor characteristics.[23]

Measurement of Long-Term Angel Impact

Our previous analyses calculated the impact of Shark Tank appearances, deals, and Shark characteristics on company performance as measured by website traffic. In this section, we examine the long-term impact on firms that appeared on Shark Tank. In some respects, this is the most important analysis, since it allows more time to pass between the appearance on the Shark Tank and the measurement of the success of the firm. This is especially key given the substantial short-term impact of appearing on the show.[24] We used website traffic and the existence or non-existence of the company as our proxy for success. For website traffic, we measured success up to three years after a company's appearance on the Shark Tank, and we measured existence or non-existence from the beginning of the show, giving us as much as 10 years of data for certain firms.

We thus chose only companies with at least three years of data since their appearance on the Shark Tank. We then ran regressions using two dependent variables, the cumulative website traffic since appearing on Shark Tank (CWT) and whether the company existed or did not exist at the end of our sample period. One benefit of using the existence dummy variable is that we were able to examine the performance of companies over a longer time period as well as analyze a greater set of companies. That is, we had more time to analyze the effect of the Shark Tank, whereas, with website traffic data, we only had a three-year window.

[23] Also note that we find qualitatively the same results for all specifications in Exhibit 6 when we repeat the regressions employing the other specifications in Exhibit 5 as the baseline and when including the investor characteristics themselves in the regressions.

[24] While we took steps to control for the effect of appearing on the show including excluding the month a company appears on the show and separately controlling for this effect, looking at the long term is another way to ensure our results are not biased by the short-term effect of appearing on the show.

We estimated the following equations:

$$CWT_{t,T} = \beta_0 + \beta_1 DEAL_t + \Gamma \mathbf{Z}_t + TREND_t + S_i + \epsilon_t \quad (6)$$

$$E_{t,T} = \beta_0 + \beta_1 DEAL_t + \Gamma \mathbf{Z}_t + TREND_t + S_i + \epsilon_t \quad (7)$$

where $CWT_{t,T}$ is the cumulative website traffic for that company since appearing on Shark Tank, $E_{t,T}$ is a 1 if the company still exists and a 0 if the company no longer exists, $DEAL_t$ is 1 for companies that received a deal with Shark Tank and 0 otherwise, S_i is a GICS sector fixed effect, and TREND is a time trend. $\mathbf{Z}_t$ are a series of variables we are interested in testing, including the percentage of equity that the Sharks obtained during the deal (EQSTAKE); the popularity of the Shark (SHARKPOP) based on Twitter, Instagram, and Facebook followers in millions; the industry diversity effect (HHI); the number of Sharks on the deal (SHARKNUM); and the experience of the Sharks (EXPERIENCE).[25]

Following our approach to investigating short-term performance, specification 1 for each dependent variable uses a sample including both deal and no-deal firms, while specifications 2 to 6 restrict the sample to deal firms. This approach again allowed us to separately investigate the impact of getting a deal on firm performance and the impact of investor characteristics given a deal on firm performance. We show the results in Exhibit 9.

We find for long-term website traffic growth, that getting a deal does not have an impact and that investor characteristics do not have an impact given a deal. However, when considering companies' existence or non-existence as the dependent variable, certain variables are statistically significant. Specifically, getting a deal on Shark Tank improves the likelihood of the company's existence in the future (Hypothesis 2). However, we find that the higher the equity stake of the Sharks and greater experience of the Sharks, the less likely a company will exist in the future.

The results for experience are somewhat surprising and run counter to Hypothesis 1a.[26] The relationship between a higher equity ownership by Sharks and a lower likelihood of company existence is also somewhat surprising. Here we can only speculate that either higher investor ownership resulting in lower founder ownership may result in lower motivation by the founder and thus a lower likelihood of company survival. While we show no causal link, this may be an area that warrants further research, as the implications to investor ownership objectives and relative valuations could be meaningful to entrepreneurial success or failure. Finally, more Sharks being involved in a deal is associated with a higher likelihood of existence in the future (Hypothesis 1d), statistically significant at the 10% level.

Investor Characteristics and Deal Likelihood

We found some evidence that getting a deal on Shark Tank has a positive short-term effect on firm performance, no significant evidence that investor characteristics affect the short-term performance of deals that were made, and some evidence that investor and deal characteristics affect the long-term performance of deals that were made. However, it is important to note that investor characteristics also may be predictors of whether an investor makes a deal, either alone or as part of a syndicate. To investigate how investor characteristics may affect the likelihood that the investor

[25] We considered running the Cox proportional-hazards regression as an alternative test; however, given the data available, the Logit regression provided for the most reliable results.

[26] It is plausible that our results are related to the U-shaped impact of experience on performance found by Capizzi 2015. For example, our sample of Sharks may be further on in their careers and in this range, Capizzi finds that greater experience reduces performance.

EXHIBIT 9

The "Long-Term" Impact of Shark Tank Appearance

	CWTt, T						Exists or Not					
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
DEAL	–488.8400						0.6526**					
	(–0.4722)						(2.2178)					
TREND	58.6	50.71	50.9	59.04	56.56	53.03	–0.0226***	–0.0157**	–0.0207***	–0.0526***	–0.0217***	–0.024***
	(0.9483)	(0.7085)	(0.7083)	(0.8017)	(0.757)	(0.7484)	(–4.721)	(–2.152)	(–2.834)	(–3.056)	(–2.82)	(–3.145)
EQSTAKE		–634.1						–2.891**				
		(–0.1767)						(–2.255)				
SHARKPOP			–15.4						0.0240			
			(–0.2977)						(0.689)			
EXPERIENCE				9.743						–0.0386**		
				(0.5036)						(–2.147)		
HHI					2262						2.952	
					(0.455)						(1.156)	
SHARKNUM						–637.6						0.8686*
						(–0.5343)						(1.754)
Constant	–617.8	–837.8	–723.5	–1573	–1829	–357.6	2.848***	4.615***	4.093***	7.623***	3.635***	3.297**
	(–0.1168)	(–0.5789)	(–0.3886)	(–0.8105)	(–0.7086)	(–0.1697)	(2.839)	(4.448)	(3.971)	(3.936)	(2.865)	(2.485)
R-sqr	0.0712	0.0850	0.0851	0.0858	0.0861	0.0874						
Pseudo R-sqr							0.1110	0.1066	0.0811	0.1079	0.0914	0.0984
Obs	208	115	115	115	115	115	706	362	362	362	362	362
Sector Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

NOTES: This exhibit shows the effects of receiving a deal on Shark Tank on companies' website traffic and on their existence. The exhibit also shows the impact of investor characteristics on companies' website traffic and on their existence given that the company makes a deal. The key variables of interest are DEAL, TREND, EQSTAKE, SHARKPOP, EXPERIENCE, HHI, and SHARKNUM. DEAL is whether the company receives a deal on the show or not, TREND is a time variable to capture any effects of time passing on cumulative website traffic growth, EQSTAKE is the percentage of equity obtained by the Shark on the deal. SHARKPOP is the popularity as measured by Twitter, Instagram, and Facebook followers in millions. HHI is the deal diversity of the Shark's prior investments at the time of the deal, ranging from 0 (complete diversity) to 1 (no diversity). SHARKNUM is the number of Sharks who make the deal. The "Exists or Not" are logit regressions given that this is a dummy variable that intends to capture whether the company's website still exists. For these regressions, the entire dataset was used, whereas for the web traffic regressions, the data were restricted to companies that appeared on the show between February 2016 and May 2018. For each dependent variable, specification 1 uses a sample including both deal and no-deal firms while specifications 2–6 restrict the sample to deal firms. The *t*-stats of coefficients are listed directly under the parameter estimates in parparentheses, *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

makes a deal, we estimated a multinomial logit model that uses investor characteristics to predict whether the investor makes a deal. We separately used samples of shows that aired between February 2016 and May 2018 to show the results for the same set of companies for which we had a complete monthly web traffic history, and shows that aired from August 2009 to April 2019 to show the results for all of the shows in our data. Our samples treated each appearance of a Shark at a company's pitch as a data point, thereby creating between four and six data points for each pitch, depending on how many Sharks appeared for the pitch.[27]

We estimated the following multinomial logit model,

$$D_{it} = \beta_0 + \beta_1 EXPERIENCE_{it} + \beta_2 SHARKPOP_{it} + \beta_3 HHI_{it} + \epsilon_{it} \tag{8}$$

where D_{it} is a variable that takes on a value 1 if SHARK i made a deal at the pitch at time t alone, a value of 2 if SHARK i made a deal at the pitch at time t with at least one other Shark, and a value of 0 otherwise. $EXPERIENCE_{it}$ represents the Shark's experience at the time of the pitch based on deals made previously on Shark Tank. $SHARKPOP_{it}$ represents the Shark's popularity and is the number of Twitter followers, Instagram followers, etc. in millions. HHI_{it} is the HHI of the Shark at the time of the pitch and ϵ_{it} is an error term.[28]

The results in Exhibit 10 show evidence that Shark characteristics matter for whether Sharks make a deal and whether they do so alone or as part of a syndicate. Specifically, we see some evidence that more experienced Sharks are more likely to make deals, both alone and with other Sharks, relative to not making a deal. In particular, we see strong evidence (at the 1% level in both specifications for the full sample of shows) that more experienced Sharks are more likely to make deals alone relative to not making a deal.[29] We find strong evidence at the 5% level at least across specifications and samples that more popular Sharks are more likely to make deals as part of a syndicate relative to not making a deal. Finally, we find strong evidence at the 1% level across samples and specifications that investors with less diverse prior deals (higher HHI) are more likely to make deals as part of a syndicate, relative to not making a deal.

To summarize our results so far, we found some evidence that getting a deal improves firm performance in the short and the long term, no evidence that shark characteristics matter for short-term performance for deal firms, and some evidence that firms making deals with less experienced Sharks and Sharks forming part of a syndicate have improved long-term performance. However, these results are generally inconsistent across specifications and are marginally statistically significant. We found evidence that more experienced Sharks are more likely to make deals, and that more popular and less diversified Sharks are more likely to make deals as part of a syndicate. Therefore, Shark characteristics seem more important for predicting whether they close deals than for predicting deal performance.

Investor Characteristics and Other Outcomes

Thus far, we have investigated how Shark characteristics impact the likelihood of making a deal as well as the performance of firms with which the Sharks made a deal. To gain further insights, we investigate how Shark characteristics affect three outcomes: the likelihood a Shark makes an offer (either alone or as part of an offer

[27] This differs from what we have done previously, which treated each pitch as a data point and aggregated across Shark characteristics when multiple Sharks made a deal.

[28] We exclude sector fixed effects in this model because there is insufficient data to estimate the model with fixed effects.

[29] Note that in a multinomial logit model, coefficients on a variable for each set of outcomes are interpreted relative to the omitted outcome, in this case not making a deal.

EXHIBIT 10

The Impact of Shark Characteristics on Deal Occurrence and Deal Syndicates

	February 2016–May 2018				Aug 2009–April 2019			
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Solo Deal								
EXPERIENCE	0.0081*			0.0079	0.008***			0.0078***
	(1.813)			(0.8483)	(4.229)			(3.472)
SHARKPOP		0.0201		–0.0071		0.0472***		0.0224
		(0.7529)		(–0.1212)		(3.675)		(1.299)
HHI			–1.23*	–0.8434			0.5631*	0.8873***
			(–1.725)	(–1.067)			(1.898)	(2.759)
Constant	–2.859***	–2.436***	–2.014***	–2.592***	–2.781***	–2.648***	–2.612***	–3.126***
	(–9.076)	(–14.37)	(–9.324)	(–5.033)	(–26.7)	(–31.65)	(–24.41)	(–21.13)
Syndicate Deal								
EXPERIENCE	0.0066			0.0117	0.0001			–0.0014
	(0.9384)			(1.623)	(0.0562)			(–0.5358)
SHARKPOP		0.0984***		0.0647**		0.075***		0.068***
		(4.244)		(2.388)		(5.504)		(4.485)
HHI			1.908***	2.428**			1.322***	1.024***
			(3.331)	(2.572)			(4.164)	(2.725)
Constant	–3.112***	–3.243***	–3.288***	–4.565***	–2.666***	–3***	–3.063***	–3.223***
	(–6.49)	(–17.45)	(–13.91)	(–6.596)	(–22.2)	(–31.5)	(–25.04)	(–17.75)
Pseudo R-sqr	0.0044	0.0168	0.0113	0.0277	0.0042	0.0089	0.0041	0.0149
Obs	1066	1066	1066	1066	3970	3970	3970	3970

NOTES: This exhibit shows the effect of Shark characteristics on the likelihood a Shark makes a deal alone or with other Sharks. Each observation is the appearance of a Shark for a pitch. The key variables of interest are EXPERIENCE, SHARKPOP, and HHI. EXPERIENCE represents the number of deals each investor made on Shark Tank prior to the appearance for the current pitch. SHARKPOP is a measure of the reputation of a Shark as noted by the size of its following on Twitter, Instagram, and Facebook in millions. HHI is the deal diversity of the Shark's prior investments at the time of appearance on the current pitch, ranging from 0 (complete diversity) to 1 (no diversity). The data examined in these regressions include shows that aired between February 2016 and May 2018 in the first set of four specifications, to show the results for the same set of companies for which we had a complete monthly web traffic history ranging from before and after appearing on the Shark Tank. The second set of four specifications includes all shows from August 2009 to April 2019. We employ robust standard errors in each specification. The *t*-stat of coefficients is listed directly under the parameter estimates in parenthesis. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

syndicate), the size of the investment given a deal, and the equity stake given a deal. Since these investigations do not utilize our website traffic data, our sample is not restricted and includes each pitch that was made on the show from August 2009 to April 2019.

We estimated the following multinomial logit model predicting whether Sharks makes offers,

$$O_{it} = \beta_0 + \beta_1 EXPERIENCE_{it} + \beta_2 SHARKPOP_{it} + \beta_3 HHI_{it} + \epsilon_{it} \quad (9)$$

where O_{it} is a variable that takes on a value 1 if SHARK *i* made an offer at the pitch at time *t* alone, a value of 2 if SHARK *i* made an offer at the pitch at time *t* with at least one other Shark, and a value of 0 otherwise. $EXPERIENCE_{it}$ represents the Shark's experience at the time of the pitch based on deals made previously on Shark Tank; $SHARKPOP_{it}$ represents the Shark's popularity and is the number of Twitter followers, Instagram followers, etc. in millions; HHI_{it} is the *HHI* of the Shark at the time of the pitch; and ϵ_{it} is an error term.[30]

[30] We exclude sector fixed effects in this model because there is insufficient data to estimate the model with fixed effects.

EXHIBIT 11

The Impact of Shark Characteristics on Offers and Offer Syndicates

Variable	(1)	(2)	(3)	(4)
Solo Offer				
EXPERIENCE	0.0008			0.0039
	(0.3528)			(1.197)
SHARKPOP		–0.0367*		–0.051*
		(–1.702)		(–1.812)
HHI			–0.2365	–0.0047
			(–0.5077)	(–0.0096)
Constant	–2.807***	–2.627***	–2.706**	–2.721***
	(–22.9)	(–24.02)	(–17.83)	(–13.94)
Syndicate Offer				
EXPERIENCE	–0.002			–0.0003
	(–1.499)			(–0.1839)
SHARKPOP		–0.0256**		–0.0253**
		(–2.312)		(–2.043)
HHI			0.2053	0.2434
			(0.8637)	(0.9941)
Constant	–1.152***	–1.127***	–1.289***	–1.187***
	(–18)	(–19.6)	(–16.21)	(–11.3)
Pseudo R-sqr	0.0005	0.0016	0.0002	0.0022
Obs	3970	3970	3970	3970

NOTES: This exhibit shows the effect of Shark characteristics on the likelihood a Shark makes an offer alone or with other Sharks. Each observation is the appearance of a Shark for a pitch. The key variables of interest are EXPERIENCE, SHARKPOP, and HHI. EXPERIENCE represents the number of deals on Shark Tank each investor made prior to appearance for the current pitch. SHARKPOP is a measure of the reputation of a Shark as noted by the size of the following on Twitter, Instagram, and Facebook in millions. HHI is the deal diversity of the Shark's prior investments at the time of appearance for the current pitch, ranging from 0 (complete diversity) to 1 (no diversity). The data examined in these regressions only include all shows that aired between August 2009 to April 2019. We employ robust standard errors in each specification. The *t*-stat of coefficients is listed directly under the parameter estimates in parenthesis. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

The results in Exhibit 11 show evidence that Shark characteristics matter for whether Sharks make an offer and whether they do so alone vs. as part of an offer syndicate. Interestingly, experience and HHI do not show a consistent and significant effect on whether a Shark makes offers. Exhibit 11 shows consistent and significant evidence that more popular Sharks are less likely to make offers.

We next explored how Shark characteristics affect the size of a Shark's investment given a deal, and their equity stake given a deal. We again utilized every pitch that was made on the show from August 2009 to April 2019. We estimated the following regressions over these outcomes,

$$\begin{aligned} EQSTAKE_{it} &= \beta_0 + \beta_1 EXPERIENCE_{it} + \beta_2 SHARKPOP_{it} + \beta_3 HHI_{it} \\ &\quad + \beta_4 SHARKNUM_{it} + S_i + \epsilon_{it} \end{aligned} \tag{10}$$

$$INV_{it} = \beta_0 + \beta_1 EXPERIENCE_{it} + \beta_2 SHARKPOP_{it} + \beta_3 HHI_{it} + \beta_4 SHARKNUM_{it} + S_i + \epsilon_{it} \tag{11}$$

where $EQSTAKE_{it}$ is a variable that measures the percentage stake in the company taken by SHARK *i* at the pitch at time *t*; INV_{it} is a variable that measures the dollar amount invested in the company by SHARK *i* at the pitch at time *t* in thousands of dollars; $EXPERIENCE_{it}$ represents the Shark's experience at the time of the pitch based on deals made previously on Shark Tank; $SHARKPOP_{it}$ represents the Shark's

EXHIBIT 12

The Impact of Shark Characteristics on Equity Stake and Invested Amount

	Equity Stake					Invested Amount				
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
EXPERIENCE	–0.0005***				–0.0009***	1.0884***				1.1077**
	(–3.2303)				(–4.7888)	(3.1219)				(2.3784)
SHARKPOP		–0.0034***			–0.0006		–3.469			–5.895
		(–3.013)			(–0.4835)		(–0.8318)			(–1.195)
HHI			–0.0338		–0.085***			–120.8**		–32.19
			(–1.206)		(–3.003)			(–2.003)		(–.5456)
SHARKNUM				–0.0678***	–0.0718***				–7117***	–64.29***
				(–12.01)	(–12.65)				(–5.939)	(–5.471)
Constant	0.2511***	0.253***	0.2669***	0.3857***	0.4384***	97.82***	103.1***	160.4***	242.3***	247.6***
	(769.9)	(173.7)	(19.05)	(34.13)	(23.21)	(140.3)	(26.86)	(5.321)	(10.11)	(5.872)
R-sqr	0.0720	0.0686	0.0581	0.2176	0.2561	0.1154	0.1074	0.1091	0.1317	0.1383
Obs	537	537	537	537	537	537	537	537	537	537
Sector Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

NOTES: This exhibit shows the effect of Shark characteristics on the equity stake of a Shark (as a percentage of the company) and the invested amount of a Shark in thousands of dollars. Each observation is the appearance of a Shark for a pitch. The key variables of interest are EXPERIENCE, SHARKPOP, and HHI. EXPERIENCE represents the number of deals each investor made on Shark Tank prior to appearance for the current pitch. SHARKPOP is a measure of the reputation of a Shark as noted by the size of following on Twitter, Instagram, and Facebook in millions. HHI is the deal diversity of the Shark's prior investments at the time of appearance for the current pitch, ranging from 0 (complete diversity) to 1 (no diversity). SHARKNUM indicates the total number of Sharks on the deal. The data examined in these regressions include all shows that aired from August 2009 to April 2019. We include sector fixed effects and employ robust standard errors in each specification. The *t*-stat of coefficients is listed directly under the parameter estimates in parenthesis. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

popularity and is the number of Twitter followers, Instagram followers, etc. in millions; HHI_{it} is the HHI of the Shark at the time of the pitch; $SHARKNUM_{it}$ is the number of Sharks on the deal at the pitch at time t including investor I; S_i is a GICS sector fixed effect; and ϵ_{it} is an error term.

The results in Exhibit 12 show evidence that Sharks' characteristics are important in predicting their equity stake and amount invested if they do make a deal. More experienced investors tend to take lower equity stakes and invest larger amounts, and these results are statistically significant at the 1% level across specifications. We do not find significant and consistent evidence that more popular Sharks tend to take different equity stakes or invest different amounts. We find that less diversified Sharks tend to take significantly lower equity stakes but not that they invest different amounts once we control for other regressors. Finally, having a larger number of Sharks on a deal is significantly associated with a lower equity stake and a lower invested amount for the individual Sharks who make a deal.[31]

We summarize our results on the impact of Shark characteristics on offers, deals, equity stakes, and invested amounts in Exhibit 13. The exhibit shows the sign and significance of the coefficients for all specifications using the full sample of shows from the prior three Exhibits. It shows that greater Shark experience is significantly and consistently associated with an increased likelihood of making a deal alone vs. not making a deal, and a lower equity stake and higher amount invested if a deal is made.

The fact that more experienced Sharks are no more likely to make offers, but are more likely to make solo deals, suggests a number of possibilities, including: 1) that these Sharks have gained more prowess at making offers that are likely to be accepted or at negotiating deals, 2) that they simply make more attractive offers,

[31] While the number of Sharks is an important control in these regressions, it is not terribly informative in and of itself.

EXHIBIT 13

Summary of the Impact of Shark Characteristics on Offers, Deals, Equity Stake, and Invested Amount

Outcome	Solo Offer	Syndicate Offer	Solo Deal	Syndicate Deal	Equity Stake	Invested Amount
Variable						
EXPERIENCE	+, +	–, –	+***, +***	+, –	–***, –***	+***, +**
SHARKPOP	–*, –*	–**, –**	+***, +	+***, +***	–***, –	–, –
HHI	–, –	+, +	+*, +***	+***, +***	–, –***	–**, –

NOTES: This exhiibit summarizes the results of the prior three tables for the full sample of shows. The first sign (+ or –) indicates the sign of the coefficient when the variable is controlled for alone, and the second sign when it is included with the other variables in the model. *, **, *** indicate statistical significance at the 10%, 5% and 1% level respectively.

or 3) that they are less in need of other investors' capital and ability. The additional fact that more experienced Sharks tend to invest more and take lower equity stakes in their deals suggests that they tend to make relatively attractive offers.

Exhibit 13 shows that higher Shark popularity is significantly and consistently associated with a decreased likelihood of making offers either alone or with other Sharks, and an increased likelihood of making syndicate deals. The fact that more popular Sharks make fewer offers and yet get more deals, especially in syndicates, may indicate that the popularity of Sharks is attractive to firms, that more popular Sharks make more attractive offers, or that the more popular Sharks recognize the value of syndication and have formed a shadow syndicate of some kind. The additional findings that more popular Sharks don't take systematically different equity stakes or invest different amounts supports the idea that their popularity is attractive to firms, leading to higher offer conversion rates. This goes against the idea that more popular Sharks make relatively attractive offers.

Finally, Exhibit 13 shows that lower Shark diversification is significantly and consistently associated with an increased likelihood of solo and syndicate deals. The fact that less diversified Sharks are no more likely to make offers but are more likely to make deals, especially as part of a syndicate, may indicate that less diversified Sharks leverage their trusted colleagues' abilities to select and negotiate investments.

Performance of Sharks

Another area that has been of keen interest in the financial and entrepreneurial worlds is whether or not angel investors can pick winners. Some angel investors, notably Ron Conway, believe it is better to throw lots of darts and the likely home runs will make up for all the losers. Others believe it takes dedication and skill to do the right due diligence to find the winners. In this section, we use our data on Shark Tank to examine the issue. Ideally, we would have liked to use more financial criteria for this evaluation, including the profits of the company, the return on the actual investment, and other measures directly related to the monetary gain on the investment.[32] Unfortunately, we could not obtain enough of these numbers, as most of the ventures are still privately held. So for all of our performance evaluations, we use website traffic as a proxy.

Basic performance. Exhibit 14 shows some basic summary statistics about the companies to which the Sharks did and did not make offers, along with

[32] For example, Ring, a company rejected by the Sharks, was bought by Amazon for $1 billion. In line with most of the marketing approach of our paper, the CEO of Ring credited the free publicity from the show with helping boost sales, getting the company back on track. "Nothing will ever supersede Shark Tank," he said. "We'd have been gone." He eventually returned as a guest judge on the Tank.

EXHIBIT 14
Shark Success (Offers)

	Offers						No Offers						
Shark	N_O	**Amount ($)**	**Equity SA**	**GCWTG**	**CCWTG**	**Exist (%)**	N_{NO}	**Amount ($)**	**Equity SA**	**GCWTG**	**CCWTG**	**Exist (%)**	**CWTG W – L**
Kevin O'Leary	134	330,149	10.52	4.46	–39.91	0.99	186	282,226	14.28	17.07	2,896.52	0.96	–12.61
Mark Cuban	76	297,303	11.69	29.07	–54.19	0.99	284	307,567	12.70	8.54	2,054.31	0.97	20.53
Robert Herjavec	71	277,662	11.18	13.26	–38.01	1.00	212	297,783	13.49	14.84	2,629.59	0.97	–1.59
Lori Greiner	95	314,684	12.28	25.40	–63.10	0.99	257	292,603	12.57	9.31	2,218.00	0.97	16.09
Daymond John	61	261,639	12.47	5.14	–63.15	1.00	115	320,426	12.85	6.31	4,662.18	0.95	–1.18
Barbara Cocoran	45	212,222	12.28	8.06	–50.11	1.00	119	359,790	12.94	5.97	–57.93	0.97	2.08
Chris Sacca	13	217,308	7.00	2.52	–45.36	1.00	27	512,963	9.89	2.32	–51.89	0.93	0.21
Rohan Oza	8	487,500	11.13	17.95	–0.04	1.00	16	346,875	8.28	18.91	–8.68	0.94	–0.96
Sara Blakely	7	240,714	13.04	8.26	–69.62	1.00	13	280,000	11.73	11.46	30.29	0.85	–3.20
Bethenny Frankel	6	241,667	13.58	6.39	–48.12	1.00	10	316,000	11.80	5.53	–61.84	1.00	0.86
Alex Rodriguez	8	306,250	10.63	16.40	–61.38	1.00	8	271,875	10.25	5.68	–43.55	1.00	10.72
Richard Branson	5	227,000	11.50	6.89	–78.79	1.00	3	400,000	10.00	20.93	16.33	1.00	–14.04
Matt Higgins	2	800,000	20.00	18.85	–67.10	1.00	2	300,000	10.00	0.38	–91.80	1.00	18.48
Jamie Siminoff	1	100,000	20.00	0.00	–83.10	1.00	3	568,333	8.33	2.58	–32.32	1.00	–2.58
Charles Barkley	3	150,000	10.33	–12.75	–87.34	1.00	5	375,000	9.40	430.45	4.45	1.00	–443.20
Ashton Kutcher	2	200,000	17.50	–2.85	–83.29	1.00	6	516,667	8.93	2.82	–85.02	1.00	–5.67
Troy Carter	2	165,000	15.00	0.61	–92.38	1.00	2	225,000	15.00	1.66	–89.42	1.00	–1.05
Sharks Statistics by Gender													
Male Sharks	386	293,832	13.00	7.66	–61.08	0.99	869	363,440	11.80	40.96	912.36	0.97	–33.30
Female Sharks	153	252,322	12.80	12.03	–57.74	0.99	399	312,098	12.26	8.07	532.13	0.97	3.96
Sharks Statistics by Group of Six Main Sharks													
Main Sharks	482	282,277	11.74	14.23	–51.41	0.99	196	310,066	13.14	10.34	2,400.45	5.81	3.89

NOTES: This exhibit shows relevant descriptive variables and measures of success for companies to which Sharks did or did not make offers, based on whether they were on the show. Given that the website traffic data was used, we restricted the sample to companies that aired on Shark Tank between August 2015 and February 2019. The amount indicated is the average amount requested by the companies to which sharks made or did not make an offer, and equity is the average equity offered in return. GCWTG is the geometric mean of the monthly web traffic growth, and CCWTG is the cumulative monthly web traffic growth of all the companies in the shark portfolio within the category and time period described. Shark Statistics by Gender groups Sharks by gender and summarizes the results. The Main Sharks grouping includes Kevin O'Leary, Mark Cuban, Robert Herjavec, Lori Greiner, Daymond John, and Barbara Cocoran.

details about the equity stake and the amount requested, and the subsequent website traffic growth of these companies. GCWTG is the geometric mean of the website traffic growth of all companies in which they invested. Following our approach from the event study, we do not include the month of the show's appearance; we count growth only after that month. We also have CWTG, which is the cumulative website traffic growth of all companies from when they appeared on Shark Tank to the end of the sample period.[33] Amount is the average amount of funds requested by those companies.

The final column is the CWTG W-L of companies to which the Sharks made offers minus those to which they did not make offers. A positive number indicates they can "pick" good companies; a negative indicates they cannot. There is a caveat, however. Sometimes, Sharks make ridiculous offers to companies they do not think are very good. So, to get a different picture of their general ability to pick or not pick, we also show Exhibit 15, which contains the performance of the Sharks on companies with which they made deals. All other variables are similar to the offer Exhibit. When we look at deals actually made, we find that Mark Cuban, Matt Higgins, and Alex Rodriguez had the highest winner-minus-loser website growth.

Portfolio performance. Next we created portfolios of companies consisting of companies to which the Sharks made offers, signaling that they were a good pick, and companies to which they did not make offers. We split those companies into two groups for the month in which they appeared on Shark Tank. We also did this for companies with which they made a deal vs. companies with which they did not.

In month $t + 1$, the month following the month of company presentations, we calculated the growth rate in website traffic for every company that presented to the Sharks or made a deal with a Shark in the previous month. Call this $g(i, t, t + 1)$. This represents the growth in website traffic of company i, from t to $t + 1$. We then computed the equal-weighted portfolio for offers and no offers (deals and no deals) for that Shark. Thus, if the Shark made offers to 4 companies in month t and did not offer to 10 companies, the portfolios would be $WTG_{\text{Offers}}(t+1) = 1/4\sum_i g(i, t, t+1)$ and the $WTG_{\text{No Offers}}(t + 1) = 1/10\sum_i g(i, t, t + 1)$. The difference between these two portfolios ($WTG_{\text{Offers}} - WTG_{\text{No Offers}}$) is one way to measure whether Sharks are able to choose winning companies.

The following month when new companies presented on the show, $t + 1$, we split the new companies into offers and no offers (or deals/no deals). Suppose in month $t + 1$, for the same Shark, there are 12 new companies, and he makes an offer to 2 of those, but not the other 10. Then, we add these companies to their existing portfolio. Thus, for the period $t + 1$ to $t + 2$, the "return" of the portfolio of companies would be $WTG_{\text{Offers}}(t + 2) = 1/6\sum_i g(i, t + 1, t + 2)$, where these are company growth rates from $t + 1$ to $t + 2$. $WTG_{\text{No Offers}}(t + 2) = 1/20\sum_i g(i, t + 1, t + 2)$. In other words, the "return" from $t + 1$ to $t + 2$ is the entire portfolio of offers and no offers to that date, equally weighted, but only for the month in which the companies were in the Shark's portfolio. We continued this process each month for both offers and no offers (deals and no deals) until the end of the sample period.

At that point, we computed, for every Shark, a monthly series of "returns" for the offer portfolio, the no-offer portfolio, the deal portfolio, and the no-deal portfolio. We then took the time series averages of each, and the difference between offers and no-offers and deals and no-deals, and computed t-statistics on whether the return difference was significantly different from zero. The results of this portfolio analysis are shown in Exhibit 16 for the main Sharks on the show.

The important columns are column 5 and column 8. Column 5 shows the difference in average portfolio returns for the offer and no-offer portfolios, and column 8

[33] Unfortunately, this measure will weight different lengths of time the same.

EXHIBIT 15

Shark Success (Deals)

	Deals						No Deals						
Shark	N_O	**Amount ($)**	**Equity SA**	**GCWTG**	**CCWTG**	**Exist (%)**	N_{NO}	**Amount ($)**	**Equity SA**	**GCWTG**	**CCWTG**	**Exist (%)**	**CWTG W – L**
Kevin O'Leary	33	313,030	11.27	4.55	–20.45	1.00	287	301,059	12.87	13.10	1,971.47	0.97	–8.55
Mark Cuban	69	300,870	12.06	31.28	–54.90	0.99	291	306,474	12.59	8.41	2,011.28	0.97	22.87
Robert Herjavec	29	258,586	10.67	9.26	–5.84	1.00	254	296,634	13.17	15.08	2,225.65	0.98	–5.82
Lori Greiner	75	318,933	12.97	6.26	–67.24	0.99	277	293,047	12.36	14.95	2,039.11	0.97	–8.69
Daymond John	27	199,259	14.44	8.50	–76.20	1.00	149	318,315	12.41	5.50	3,712.31	0.96	3.00
Barbara Cocoran	25	180,000	13.24	4.71	–77.39	1.00	139	344,353	12.67	6.79	–52.65	0.98	–2.07
Chris Sacca	8	218,750	6.25	0.94	–24.55	1.00	32	466,406	9.63	2.72	–55.44	0.94	–1.78
Rohan Oza	4	712,500	8.75	8.00	–32.92	1.00	20	330,000	9.32	20.54	–0.36	0.95	–12.54
Sara Blakely	4	293,750	12.81	9.66	–74.22	1.00	16	259,375	12.03	10.85	17.59	0.88	–1.19
Bethenny Frankel	3	250,000	18.00	6.66	–44.92	1.00	13	296,923	11.19	5.71	–58.68	1.00	0.94
Alex Rodriguez	5	190,000	11.00	19.07	–66.91	1.00	11	334,091	10.18	6.69	–44.55	1.00	12.38
Richard Branson	3	145,000	13.33	8.67	–77.27	1.00	5	380,000	9.50	14.24	–22.63	1.00	–5.57
Matt Higgins	2	800,000	20.00	18.85	–67.10	1.00	2	300,000	10.00	0.38	–91.80	1.00	18.48
Jamie Siminoff	1	100,000	20.00	0.00	–83.10	1.00	3	568,333	8.33	2.58	–32.32	1.00	–2.58
Charles Barkley	3	150,000	10.33	–12.75	–87.34	1.00	5	375,000	9.40	430.45	4.45	1.00	–443.20
Ashton Kutcher	2	200,000	17.50	–2.85	–83.29	1.00	6	516,667	8.93	2.82	–85.02	1.00	–5.67
Troy Carter	1	250,000	10.00	–0.96	–93.74	1.00	3	176,667	16.67	1.93	–90.22	1.00	–2.89
Sharks Statistics by Gender													
Male Sharks	187	295,230	12.74	7.12	–59.51	0.99	1,068	359,204	11.77	40.34	730.99	0.97	–33.22
Female Sharks	107	260,671	14.26	6.82	–65.94	0.99	445	298,424	12.06	9.57	486.34	0.97	–2.75
Sharks Statistics by Group of Six Main Sharks													
Main Sharks	258	261,780	12.44	10.76	–50.34	0.99	233	309,980	12.68	10.64	1,984.53	5.83	0.12

NOTES: This exhibit shows relevant descriptive variables and measures of success for companies with which each Shark did or did not make deals, based on whether they were on the show. Given that the website traffic data was used, we restricted the sample to companies that aired on Shark Tank between August 2015 and February 2019. The amount indicated is the average amount requested by the companies to which the sharks made or did not make an offer, and equity is the average equity offered in return. GCWTG is the geometric mean of the monthly web traffic growth, and CCWTG is the cumulative monthly web traffic growth of all the companies in the shark portfolio within the category and time period described. Shark Statistics by Gender groups the sharks by their gender and summarizes the results. The Main Sharks grouping includes Kevin O'Leary, Mark Cuban, Robert Herjavec, Lori Greiner, Daymond John, and Barbara Cocoran.

EXHIBIT 16
Shark Website Traffic Offer and Deal Portfolios

Name		Offer	No Offers	O – NO	Deals	No Deals	D-ND
Kevin O'Leary	Average WTG	1321.04	2413.36	–1092.32	5825.21	145.27	5677.68
		(1.10)	(2.74)	(–0.72)	(1.01)	(1.47)	(0.99)
Mark Cuban	Average WTG	240.71	2418.97	–2237.46	255.51	30.68	224.84
		(1.54)	(2.78)	(–2.47)	(1.55)	(2.23)	(1.34)
Robert Herjavec	Average WTG	55.56	2250.21	–2194.64	59.71	52.64	7.71
		(4.76)	(2.75)	(–2.69)	(3.05)	(4.95)	(0.37)
Lori Greiner	Average WTG	1997.53	2093.36	–95.84	199.84	8201.48	–7998.66
		(1.09)	(2.64)	(–0.05)	(1.49)	(1.00)	(–0.98)
Daymond John	Average WTG	230.08	1870.27	–1640.19	48.58	375.96	–327.38
		(1.31)	(1.79)	(–1.55)	(3.00)	(1.20)	(–1.04)
Barbara Cocoran	Average WTG	4256.79	2281.79	1975.00	870.01	7567.28	–6697.27
		(1.13)	(1.64)	(0.49)	(2.20)	(1.01)	(–0.89)

NOTES: This exhibit shows the average monthly web traffic growth (in percentage) of the cumulative monthly portfolios of companies that Sharks encountered on the show depending on whether they made an offer and/or agreed on a deal or not. Cumulative monthly portfolios were calculated by separating the data into monthly periods, iterating through them, and adding the companies into whose respective categories the sharks made an offer/deal (or did not), and calculating the average web traffic growth per period. For deals vs. no deals, no deals were computed conditional on making an offer on the company. Given that the website traffic data were used, we restricted the sample to companies that aired on Shark Tank between August 2015 and February 2019. The Cumulative WTG is the cumulative monthly web traffic growth across the entire time period analyzed. The *t*-stats of coefficients are listed directly under the parameter estimates in parentheses.

shows the difference in average portfolio returns between the deal and no-deal portfolios. We will focus our discussion on column 8, which avoids issues with aggressiveness and phony offers to companies. Although Cuban and O'Leary have deal portfolios that do better than non-deal portfolios, none of the Sharks have a statistically significant difference between deal companies and non-deal companies.

In summary, we do not find any ability of the Sharks to pick winning companies as judged by future website traffic and the portfolio of companies with which they make deals.[34]

COMPARISON OF SHARK TANK WITH OTHER ANGEL STUDIES

As discussed, we found only statistically weak and inconsistent evidence that the characteristics of Shark Tank investors affect the firms receiving investment. Again, as Shark investors are atypical, and research on these investor characteristics for typical angel investors is limited, we can only wonder if the same may be true for typical angels and to what degree. Wood et al. (2020) affirm that angel investing has largely been transformed from individual deal-making to more venue-driven forums, where multiple angels view investor pitches (not unlike popular TV shows). Therefore, the impact of the Shark Tank show/venue, while atypical, may be worth exploring as an abstraction of standard angel venues. Of course, whether art is imitating life or vice versa remains a question.

There are limited scholarly research findings on the financial performance of angel investors. Previous research found that firms that receive angel investments perform better than those that do not (Kerr et al. 2011). We found some evidence for this.

[34] We also tested whether the returns of the deal portfolios of the main Sharks were persistent, following the method of Carhart (1997), i.e., whether past Shark deal success predicted future Shark deal success. We found no evidence of persistence.

Smith et al. (2010) studied whether angel investors learn from experience, and they found their learning was primarily in their approach to investing and how they conduct due diligence. Harrison, Mason, and Smith (2015) found that business angels learn from their individual and collective experience; furthermore, skill has been associated with superior angel investing (Kaplan and Schoar 2005; Korteweg and Sorensen 2017). Croce et al. (2021) found mixed results when comparing angel entrepreneurial experience with their investments among varying types of ventures.

Among our Shark investors, we found some evidence that experience played a role in performance of the firms in which they invested, but it was not statistically strong or consistent. We did find that more experienced Sharks seem to make more attractive offers and have a higher likelihood of converting deals, perhaps suggesting they prioritize deal flow over picking winners.

Regarding syndication of investments among our Sharks, Brander et al. (2002), sampling Canadian venture capital firms, found that joint (syndicated) investments between VC firms tended to have larger returns. Tian (2011) found that firms that are funded by venture capital firm syndicates tended to have more successful exits and earn higher valuations at exits. We found some evidence that joint investing by our Shark Tank investors enhanced the firms in which they invested, but this again was inconclusive. Mason et al. (2016) found that angel investors tended to form organizations for their investment efforts. We found that more popular and less diversified Sharks are significantly more likely to invest as part of a syndicate. Wood et al. (2020) also suggested that angel investing has moved from individual deal-making to collaborative efforts in open venues. Thus, the relevance of insights gleaned from Shark Tank investment decisions, albeit from an atypical sample of angel investors, may provide some insight into this group dynamic.

CONCLUSIONS, LIMITATIONS, AND SUGGESTIONS FOR FUTURE RESEARCH

We studied angel investor actions and venture performance by examining the characteristics of perhaps the most well-known of angel investors—those appearing on the widely viewed TV show Shark Tank. Of course, these celebrity angel investors are not representative of typical angel investors. However, we believe some value may come from a better understanding of how some relevant angel investor characteristics may hold at this extreme end of the angel investing universe. Of course, any insights gained need to be taken with caution and calibrated to typical angel investors before any generalizations can be made (Harrison et al. 2016; Mitteness et al. 2012).

We find that while appearing on Shark Tank does boost venture prominence as measured by website traffic increase, receiving an angel investment on Shark Tank and the relative experience or reputation of the individual Shark making the investment do not consistently and significantly enhance the success of the venture. Thus, while reputational effect (e.g., Resource-Based Theory) does not appear to hold at the individual Shark level as a key resource to the venture, it does appear to hold at the institutional level (Shark Tank Show) in supporting the success of the venture appearing on the show. Given this disparity in the impact of individual reputation vs. the reputation of the venue, entrepreneurs may wish to consider the venue of presentation, particularly when the venue provides a greater promotion or has larger audiences.

We do not find evidence that ventures receiving investment from a Shark angel investor with broad industry associations benefit from that cross-industry exposure (Hypothesis 1c). Thus, the "Strength of Weak Ties" does not seem to hold for this sample of celebrity investors. In other words, no "connecting the dots" effect or capability comes from an investor who has exposure across multiple industries. It would be interesting to learn if this effect holds with more typical angel investors.

We find some evidence that syndicate investing among Sharks has an impact on venture success (Hypothesis 1d), but it is not consistent across specifications. While the syndication literature in venture capital suggests positive results from syndication for investment returns, our results for this sample of famous angel investors are not persuasive. This finding is more akin to recent research that found a non-linear relationship when angel investors diversified their investments (Antretter et al. 2020).

We do find some evidence that companies that receive an angel investment perform better in the short as well as the long run (Hypothesis 2), but it is not conclusive across specifications. Our results are mixed and somewhat different than the impact of angel investment in other studies (Smith and Viceisza 2018).

Another aspect of our study of Shark Tank involves the area of market efficiency. We do not find evidence that the main Sharks are able to create portfolios of companies that do much better than companies with which they do not make deals (Hypothesis 3). This finding is somewhat in line with recent work by Blohm et al. (2020) that found that only business angels who had extensive investment experience and avoided their own biases outperformed an algorithm of investment selections.

In this respect, our results lend credence to the throwing darts approach to angel investing, as early-stage investments simply have too many unknowns. We therefore reason that more but smaller investments across seed-stage new ventures may be the best approach. We do find evidence that investor characteristics matter for predicting whether an investor is more likely to make offers and deals and for the characteristics of those deals.

Taken together, our results suggest that in the realm of angel investing, the attractiveness of a potential angel investor as a partner, and the angel's ability to make deals both alone and with others, are more important than his or her ability to pick winners. We also found the reputational impact of Shark Tank as a venue is significant. Thus, for a well-respected angel investor venue, throwing darts may improve the odds of successful angel investing. Interestingly to this point, we find that the most popular and experienced Sharks make more deals per appearance on the show, perhaps indicating that deal flow is a priority among angels.

Again, these findings from this unique sample of angel investors need to be taken with caution before extrapolating to the broader angel investor community. Still, we propose to liken this study of unique, high visibility investors to the study of high performance race cars that are not typical of the standard cars the rest of us drive. Understanding the limitations of characteristics at an extreme end of the spectrum may provide some longer term learning or hint at what we may expect in time for more practical vehicles or angel investments. Additionally, as the deal structure and terms on Shark Tank are publicly available, the transparency and reliability of the data and outcomes can be verified.

APPENDIX A: CONVERTING ROYALTIES TO EQUITY

APPENDIX A.1 THEORY

We start with the simplest assumptions, the value of a firm to equity holders is the residual income after all obligations have been paid. Another way of saying this is that the value of equity is the present discounted value of net income. Thus,

$$E = NI_1\delta + NI_2\delta^2 + \ldots + NI_n\delta^n \tag{A1}$$

where E = the equity value of the company, $\delta = \frac{(1+g)}{(1+r)}$ equals some positive discount rate, which includes the growth rate of the company's net income and the required return on equity of the company (see Appendix B of Chincarini and Kim (2022) for more details). If we assume that the net income value is constant over time, other than the growth in net income, then the expression is given by

$$E = NI\delta\left(\frac{1-\delta^{n}}{1-\delta}\right) \tag{A2}$$

As long as $\delta < 1$, as the time horizon increases to infinity, the formula simplifies to

$$E = NI\left(\frac{\delta}{1-\delta}\right) \tag{A3}$$

However, in practice, our growth rates and our discount rates may be such that $\delta > 1$.[35] Thus, we can use a two-stage model of equities, such that the value of the company in the absence of royalties is

$$E = NI\delta_h\left[\left(\frac{1-\delta_h^{n_h}}{1-\delta_h}\right) + \delta_h^{(n_h-1)}\left(\frac{\delta_l}{1-\delta_l}\right)\right] \tag{A4}$$

where $\delta_h = \frac{(1+g_h)}{(1+r)}$, and $\delta_l = \frac{(1+g_l)}{(1+r)}$, g_h and g_l represents the high and low rates of growth in the first and second stages, respectively, n_h represents the periods of high growth.

Thus, we can think of a royalty as a claim on future revenues, which is implicitly a claim on future net income. One way to think of the value of equity that a royalty represents is the present discounted value of the royalty as a fraction of the present discounted value of the net income. If we think of the royalty as a percentage of revenues or sales, ηS, then the value of royalties will be equal to

$$R = \begin{cases} \eta S\delta_h\left(\frac{1-\delta_h^{n_r}}{1-\delta_h}\right), & \text{if } n_r \le n_h. \\ \eta S\delta_h\left[\left(\frac{1-\delta_h^{n_h}}{1-\delta_h}\right) + \delta_h^{(n_h-1)}\delta_l\left(\frac{1-\delta_l^{(n_r-n_h)}}{1-\delta_l}\right)\right], & \text{if } n_r > n_h \end{cases} \tag{A5}$$

Thus, the percentage of equity that the royalty represents is given by the ratio

$$RPerc = \begin{cases} \frac{\eta}{NPM}\frac{\left(\frac{1-\delta_h^{n_r}}{1-\delta_h}\right)}{\left(\frac{1-\delta_h^{n_h}}{1-\delta_h}\right) + \delta_h^{(n_h-1)}\left(\frac{\delta_l}{1-\delta_l}\right)}, & \text{if } n_r \le n_h. \\ \frac{\eta}{NPM}\frac{\left(\frac{1-\delta_h^{n_h}}{1-\delta_h}\right) + \delta_h^{(n_h-1)}\delta_l\left(\frac{1-\delta_l^{(n_r-n_h)}}{1-\delta_l}\right)}{\left(\frac{1-\delta_h^{n_h}}{1-\delta_h}\right) + \delta_h^{(n_h-1)}\left(\frac{\delta_l}{1-\delta_l}\right)}, & \text{if } n_r > n_h \end{cases} \tag{A6}$$

[35] At a deeper level, this could be some problem with our way of thinking about valuing equities, behavioral bias on the part of analysts, or the need for a two-stage model.

where *NPM* is net profit margin. One should note that whenever the royalty is paid forever, the equation simplifies to $RPerc = \frac{\eta}{NPM}$.

Let's take some simple examples. Suppose that the royalty is \$2 on a \$100 product and net profit margin per product is 20%.[36] If the royalty is paid forever, then the amount of equity the royalty represents is easy to calculate. The royalty represents 2% of revenues and 10% of net profit margin. Thus, this \$2 royalty converts to 10% of equity. More examples are shown in Exhibit A2.

When the royalty has only a limited period, the calculation becomes trickier and depends on our assumptions. For example, suppose the royalty is only paid for three years. The first part of the calculation is still straightforward, the royalty represents 10% of the net profit margin. However, we must calculate the second term, which can be calculated with $n = 3$, but depends critically on g and r. For example, if the discount rate is assumed to be 30% and the growth rate of earnings is assumed to be 29%, the factor is 0.412, if growth is lower at 9%, the factor is 0.503. This would cause the percentage of equity to equal a range of 4.1% to 5.03% instead of 10%.

APPENDIX A.2 DATA

The royalty conversion method proposed will require data on each company's percentage of royalty for every \$1 of revenue, profit margin, average annualized return of the company's industry over time, and earnings per share (EPS) growth rate for the high growth stage, and long-run growth rate for the low growth stage.[37]

However, due to the lack of publicly available information for the startup companies, we were not able to obtain the profit margin or EPS growth rate for each specific company. Thus, we used industry variables for publicly available companies instead. We collected information from Bloomberg on each industry of which a particular company might be part of, including average profit margin, average industry growth, and average ROE from 10 standard GICS industries. These numbers were used to help with some of our equity conversions.

Appendix A.2.1 Industry Groups

In order to compensate for the lack of available information on the individual companies, we utilized industry standards as a proxy for each company's profit margin, as well as EPS growth rate for the royalty conversion method. We categorized each company using S&P 600 Industry Groups (smaller companies) based on the products and/or services that each company was offering during their appearance on the Shark Tank show.

Appendix A.2.2 Profit Margin

If we did not have profit margins available for the individual products or even for the companies, we used the profit margin of the corresponding industry, determined by establishing a comparable GICS sector for each startup and using the profit margin of the corresponding S&P 600 Industry. We calculated profit margin as net income divided by revenue multiplied by 100. We downloaded monthly profit margin data from January 1, 2009, to December 7, 2018, from Bloomberg for each industry group listed in Exhibit A1

[36] This is different than the actual net profit margin of the company, but it will be easier to calculate for our purposes.

[37] There are 55 special deals in the Shark Tank data. Ten are marked as loan deals. Of the remaining 45, 15 are special deals that are not royalty deals. From the 30 deals that are marked as royalty deals, 1 deal is excluded from the exhibit because the company appeared on the show in 2019 and all the data we downloaded for the royalty conversion were up to the end of 2018.

EXHIBIT A1

List of Industry Groups

Sector in Raw Spreadsheet	Code	Description
Automobiles & Components	S6AUCO	S&P 600 Auto & Comp IDX
Commercial Services & Supplies	S6COMS	S&P 600 Commercial & Professional Services IDX
Consumer Durables & Apparel	S6CODU	S&P 600 Consumer Durable & Apparel IDX
Consumer Services	S6HOTR	S&P 600 Consumer Services IDX
Diversified Financials	S6DIVF	S&P 600 Diversified Financial IDX
Food & Staples Retailing	S6FDSR	S&P 600 Food & Staples Retailing IDX
Food, Beverage & Tobacco	S6FDBT	S&P 600 Food, Beverage, and Tobacco IDX
Health Care Equipment & Services	S6HCES	S&P 600 Healthcare Equipment & Services Industry Group
Household & Personal Products	S6HOUS	S&P 600 Household and Personal Products
Media	S6MEDA	S&P 600 Media & Entertainment
Retailing	S6RETL	S&P 600 Retailing Industry Group
Software & Services	S6SFTW	S&P 600 Software and Services Industry Group
Technology Hardware & Equipment	S6TECH	S&P 600 Technology Hardware & Equipment Industry Group

NOTES: This exhibit shows the industry groups used as a proxy for each company's profit margin, ROE, and EPS growth rate for the royalty conversion. We had to use these to work around the lack of available information on the individual companies. We categorized each company using S&P 600 Industry Groups based on the products and/or services that each company was offering during the appearance on Shark Tank. We utilized Bloomberg to gather the data for this analysis.

and then created a yearly average profit margin for the years 2009 to 2018. We then utilized the profit margin data for each company based on its specific industry group and the year it aired on Shark Tank.

Appendix A.2.3 Return on Equity (ROE)

Since ROE for each individual company was not readily available, we used the ROE of the corresponding sector. We calculated ROE as the 12-month net income available for common shareholders divided by the average total common equity multiplied by 100. We downloaded monthly ROE from January 1, 2009, to December 7, 2018, from Bloomberg for each industry group listed in Exhibit A1 and then created a yearly average ROE for the years 2009 to 2018. We then utilized the ROE data for each company based on its specific industry group and the year it aired on Shark Tank.

Appendix A.2.4 EPS Growth Rate

Since the growth rate in EPS for each individual company was not available, we used Bloomberg's estimates of the growth rate of earnings per share of the corresponding sector. The BEst (Bloomberg Estimates) LTG EPS is the estimated compounded annual growth rate (CAGR) of the operating EPS over the company's next full business cycle (typically around three to five years). We downloaded yearly BEst LTG EPS from January 1, 2009, to December 7, 2018, from Bloomberg for each industry group listed in Exhibit A1. We then utilized the BEst LTG EPS data for each company based on its specific industry group and the year the company aired on Shark Tank.

Appendix A.2.5 Long Term Growth Rate

We downloaded quarterly US GDP data and calculated a historical growth rate.

APPENDIX A.3 IMPLEMENTATION

For deals that involved perpetual royalty contracts involving a percentage of revenue, we used the following formula to convert royalty to equity:

$$E = \frac{\eta}{NPM} \tag{A7}$$

For deals where the royalty was not expressed as a percentage of the revenues, the computation was more difficult. When the royalty was expressed as a dollar amount per unit sold of the product, we went to the company's website to obtain the price of the product. In the case of multiple products, we took an average of the whole range of products sold by the company. We used price data as of January 2019. The royalty percentage was calculated as:

$$E = \frac{\eta}{NPM} = \frac{\frac{\text{Royalty}}{\text{Product Price}}}{NPM} \tag{A8}$$

For deals that involved non-perpetual royalties, the calculation was even more complicated. A typical arrangement was that the royalty would be paid until a total amount of dollars were collected (e.g., $1 royalty until $350,000 is recouped).[38] When the royalty specified a total amount to be collected, we computed the approximate number of years until collection as follows.

Let's call the required total amount *RT* for the royalty total. The royalty stops once the entire amount is collected, which will depend on the number of units sold each year. Thus, if we set the amount to be collected equal to the number of units produced each year multiplied by the royalty per unit, we can rearrange the equation to know the number of years before the entire royalty is paid.

Our method to calculate n proceeded in two steps. First, we calculated n assuming that the royalties would be paid off in the high growth stage. If this $n > n_h$, then we calculated all royalties paid up to the end of the high growth stage and subtracted them from the total royalties to be collected, and then calculated n^* based upon the remaining royalties to be collected, which is the number of additional periods required to capture all royalties.

$$n = \frac{\ln(\psi)}{\ln(1+g_h)} = \frac{\ln\left(1 + \frac{g_h RT}{\eta S(1+g_h)}\right)}{\ln(1+g_h)} \tag{A9}$$

where RT is the total royalty to be collected, g is the industry's growth rate according to analysts, r is the royalty per unit sold, S is sales or revenue, and η is the royalty percentage of revenues.[39] If $n > n_h$, then after subtracting the remaining royalties, the new calculation is:

$$n^* = \frac{\ln\left(1 + \frac{g_l RT^*}{\eta S(1+g_h^{n_h})(1+g_l)}\right)}{\ln(1+g_l)} \tag{A10}$$

where RT^* is royalty left to be collected after the initial high growth phase and the final n^f years will be given by $n^f = n + n^*$.

[38] There is also the situation where royalty payment is demanded for a certain number of years.

[39] The following might also be helpful to calculate revenues, $\eta S = ru_t$ where u_t is the number of units sold in the current year.

APPENDIX A.4 PERPETUAL ROYALTIES WITH A NON-PERPETUAL ROYALTY COMPONENT

There were a few cases where the royalty deal involved an expiring royalty component, which tends to be at a higher rate and decreases to a perpetual royalty after the investor recoups a certain threshold amount. We treated these as a combination of the perpetual and the non-perpetual royalty deals. We calculated the two parts independently and took the sum of the two values. The ideas and mathematics are very similar to the other cases but slightly different. In the first step, we calculated the present discounted value of the expiring royalty (Equation A5). To this we added the present discounted value of the perpetual royalty once it started accruing. Thus,

$$RPerp = \begin{cases} \dfrac{\eta' S(1+g_h)^{n_f}\,\delta_h\left(\dfrac{1-\delta_h^{n_h-n_f}}{1-\delta_h}\right)}{(1+r^{n_f})} + \dfrac{\eta' S(1+g_h)^{n_f}(1+g_h)^{n_h-n_f}\left(\dfrac{\delta_l}{1-\delta_l}\right)}{(1+r^{n_h})}, & \text{if } n_f \le n_h, \\ \dfrac{\eta' S(1+g_h)^{n_h}(1+g_l)^{n_f-n_h}\left(\dfrac{\delta_l}{1-\delta_l}\right)}{(1+r^{n_f})}, & \text{if } n_f > n_h \end{cases} \quad \text{(A11)}$$

This value should be added to the numerator of Equation A6 and the combination percentage will be known. For a full list of the summary statistics of royalty deals in our sample, see Exhibit A3.

EXHIBIT A2

Hypothetical Perpetual Royalty Conversion in Terms of Original Equity

	Perpetual Royalty (%)					
NPM (%)	**3**	**5**	**7**	**9**	**12**	**14**
0.2	1500	2500	3500	4500	6000	7000
1.5	200	333	467	600	800	933
2.5	120	200	280	360	480	560
3.5	86	143	200	257	343	400
4.5	67	111	156	200	267	311
5.5	55	91	127	164	218	255
6.5	46	77	108	138	185	215
7.5	40	67	93	120	160	187
8.5	35	59	82	106	141	165
9.5	32	53	74	95	126	147
10.5	29	48	67	86	114	133
11.5	26	43	61	78	104	122
15	20	33	47	60	80	93
20	15	25	35	45	60	70
25	12	20	28	36	48	56
30	10	17	23	30	40	47
35	9	14	20	26	34	40

NOTES: This exhibit shows the hypothetical ownership of equity as a percentage of original equity from a perpetual royalty on a company's product with the assumption that cost improvements are not part of the future company's growth in earnings. All numbers are in percent. Thus, a perpetual royalty of 5% for a company that typically makes a 6.5% net profit margin would be equivalent to owning 77% of the company's equity.

APPENDIX A.5 EXAMPLES

Let's go over two examples of the royalty conversion. Bottle Keeper came to Shark Tank requesting $1 million for 5% equity, implying a valuation of $20 million. They ended up getting $1 million for 5% of the company plus a royalty deal where they had to pay $1.50 for every unit sold until a total of $2 million was collected. We used this and divided by the product price to get the percentage of revenue for the royalty, which was 3.75%. We then used our formula to understand how many years it would take to pay off this royalty. For this calculation, we needed forecasted industry growth in revenues by analysts (9.68%) as our high growth stage, the average US GDP growth rate since 1990 as our long-term growth rate (4.48%), $n_h = 5$, revenue of the company in the most recent year ($9 million).

$$n = \frac{\ln\left(1 + \dfrac{0.0968 \cdot 2{,}000{,}000}{0.0375 \cdot 9{,}000{,}000 \cdot (1+0.0968)}\right)}{\ln(1+0.0968)} = 4.55 \quad \text{(A12)}$$

Thus, it would take 4.55 years to pay off the royalty using our basic assumptions, which was less than the five years of our high growth period. We then computed the amount of equity this royalty represented using the formula above, to find 10.85%. Thus, the royalty was similar to a 10.85% stake in the company.

EXHIBIT A3

Royalty Conversion Summary Statistics

Variable	Description	Nobs	Mean	Median	S.D.	Min	Max
Shark Deal	Dummy indicates whether a firm obtained funding from Sharks	40	1.00	1.00	0.00	1.00	1.00
Firms Received Offers	Dummy indicates whether a firm received offers from Sharks	40	1.00	1.00	0.00	1.00	1.00
Perpetual Royalty	Dummy indicates whether the royalty expires after a certain amount is recovered	40	0.30	0.00	0.46	0.00	1.00
Conditional Perpetual Royalty	Dummy indicates whether the royalty amount reduces after a certain amount is recovered	40	0.10	0.00	0.30	0.00	1.00
Total Royalty Amount Sharks Request	The total royalty amount the Sharks request in return	28	348,750	150,000	421,392	50,000	2,000,000
Equity Conversion	The equity conversion value	36	0.17	0.29	2.07	–5.48	5.19
Broken Deals	Dummy indicates whether firms actually got Shark funding after the show	40	0.70	1.00	0.46	0.00	1.00
Investment Size	The amount of capital Sharks actually invested at the end of show	40	0.30	0.15	0.33	0.04	1.40
Presenter Gender	Indicates gender of Entrepreneurs on the show (male, female, or both)	40	0.93	1.00	0.53	0.00	2.00
Firm Equity Offer	The equity stake companies initially offered	40	0.14	0.10	0.10	0.05	0.40
Amount Requested	The amount of capital companies initially requested	40	0.26	0.15	0.29	0.04	1.40
Original Valuation	Firm values imputed from Amount Requested and Firm Equity Offer	40	3.35	1.50	5.47	0.10	28.00
Company Existence	Dummy indicates whether a company still exists during the analysis period	40	0.95	1.00	0.22	0.00	1.00
Success Qualitative Indicator	Dummy indicates company success with subjective judgments of authors	40	0.88	1.00	0.33	0.00	1.00

NOTES: This exhibit shows a summary of some of the key variables for all companies in the entire dataset that agreed to a royalty-based deal. It includes the number of observations, the mean, the median, the standard deviation, and the minimum and maximum values of these relevant variables. The Min. and Max. illustrate the minimum and maximum value of each corresponding item over the examined period.

Another company that went on Shark Tank was HoneyFund. They requested $400,000 for 10% of the company, reflecting a $4 million valuation. The final deal was for $400,000 with "no equity lost." Instead, they requested a royalty deal whereby the company would pay back $1.2 million in royalties distributed 33% in each year. The company's revenue at the time was $987,000. Based on our model, the royalty was expected to be paid back in 2.89 years and represented 172.26% of equity. Thus, implicitly, these entrepreneurs gave up 172.26% of the company, representing a much worse deal for them than their initial request to give equity of 10%. The calculations for all companies are contained in Exhibit A4. Some of these calculations of royalty equity are very large or very negative. This is partly due to some of the assumptions we were forced to use. If an investor has better information about a specific company, he or she should use that information instead of industry averages.

APPENDIX A.6 IMPLICATIONS OF ROYALTIES AND BEHAVIORAL BIAS

Our original motivation for converting the companies with royalties to an equivalent equity amount was to analyze the equity stakes and resulting performance metrics of the companies. We also wanted to understand whether entrepreneurs understood the value of royalties. In general, we found that due to simple perceptions, entrepreneurs do

EXHIBIT A4
Royalty Conversion Parameters

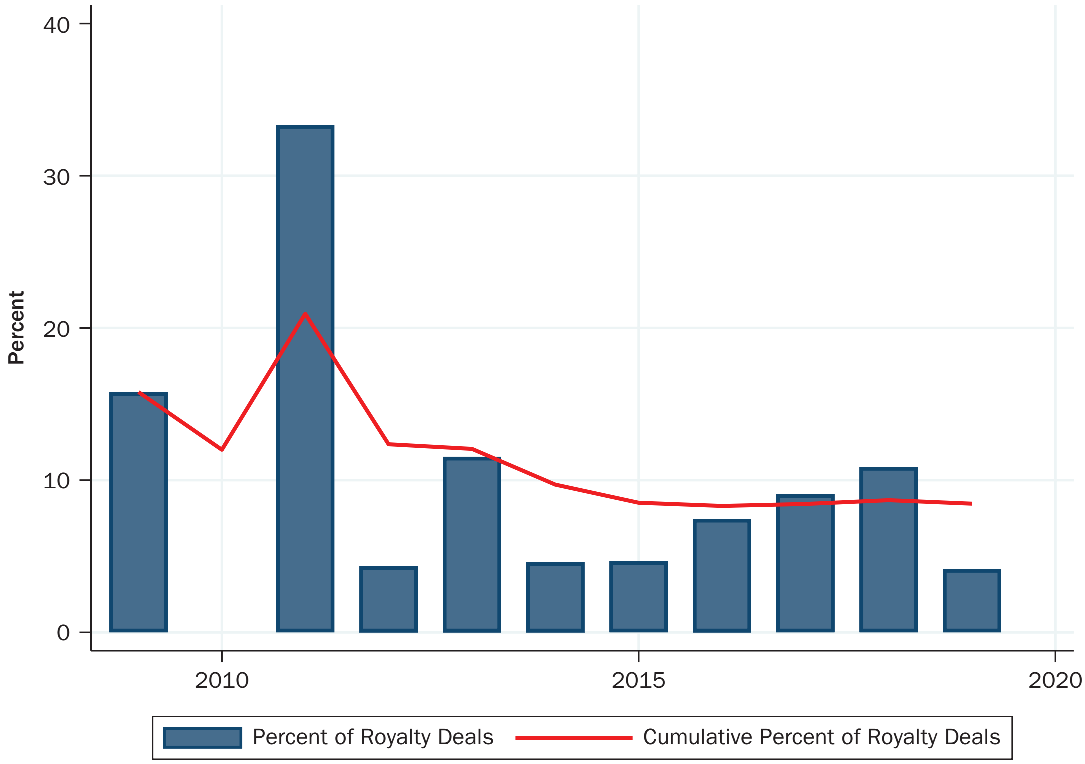
Name	Amt Req	Equity O.	I.V.	Amt Rec	Equity R.	Post Value	Royalty AR	Revenue	% Rev	g_l	$P.M._l$	P.R.	r	δ_h	δ_l	n_r	RoyEq
Bottlekeeper	1,000,000	5.00	20,000,000	1,000,000	5.00	20,000,000	2,000,000	9,000,000	3.75	9.68	3.42	0	7.17	1.02	0.97	4.55	10.85
BrilliantPad	500,000	5.00	10,000,000	500,000	5.00	10,000,000	500,000	1,200,000	1.92	13.43	2.16	0	7.17	1.06	0.97	11.43	21.19
Classroom Jams	250,000	10.00	2,500,000	250,000	100.00	250,000	NA	0	–5.00	12.15	0.91	1	9.65	1.02	0.95	NA	–547.95
Coffee Joulies	150,000	5.00	3,000,000	150,000	0.00	NA	150,000	575,000	1.82	9.26	3.42	0	13.93	0.96	0.92	9.42	59.82
Cool Wraps	100,000	40.00	250,000	250,000	100.00	250,000	NA	NA	–3.00	17.68	4.97	1	7.17	1.10	0.97	NA	–60.41
Daisy Cake	50,000	25.00	200,000	50,000	25.00	200,000	50,000	108,000	1.46	12.08	2.96	0	13.93	0.98	0.92	15.70	35.87
DigiWrap	150,000	10.00	1,500,000	150,000	20.00	750,000	450,000	500,000	0.57	13.00	3.52	0	7.17	1.05	0.97	39.47	10.06
Eggmazing Egg Decorator	350,000	7.00	5,000,000	350,000	10.00	3,500,000	350,000	1,200,000	10.67	9.68	3.42	0	7.17	1.02	0.97	2.34	15.46
Element Bars	150,000	15.00	1,000,000	150,000	30.00	500,000	NA	50,000	–4.00	11.61	3.37	1	13.93	0.98	0.92	NA	–118.72
First Defense Nasal Screen	500,000	10.00	5,000,000	750,000	30.00	2,500,000	NA	1,300,000	10.00	14.60	3.59	1	13.26	1.01	0.92	NA	278.75
Gameface	450,000	25.00	1,800,000	450,000	35.00	1,285,714	450,000	102,000	10.00	17.68	4.97	0	7.17	1.10	0.97	16.83	66.69
Guard Llama	100,000	5.00	2,000,000	100,000	18.00	555,556	100,000	NA	20.00	11.24	3.04	0	12.80	0.99	0.93	NA	NA
Hill Billy Brand	50,000	25.00	200,000	75,000	100.00	75,000	NA	50,000	–7.00	10.49	4.91	1	12.48	0.98	0.93	NA	–142.59
Hire Santa	200,000	10.00	2,000,000	200,000	10.00	2,000,000	200,000	1,200,000	NA	14.15	3.59	0	12.80	1.01	0.93	NA	NA
HoneyFund	400,000	10.00	4,000,000	400,000	0.00	NA	1,200,000	987,000	33.00	12.96	2.03	0	9.65	1.03	0.95	2.89	172.26
How do you Roll	1,000,000	12.00	8,333,333	1,000,000	20.00	5,000,000	NA	1,250,000	NA	9.26	3.42	1	13.93	0.96	0.92	NA	NA
Hy-Conn	500,000	40.00	1,250,000	1,250,000	100.00	1,250,000	NA	0	–7.50	13.14	1.71	1	7.17	1.06	0.97	NA	–439.67
Innovation Pet, Inc	250,000	5.00	5,000,000	250,000	12.50	2,000,000	NA	2,500,000	25.00	13.05	4.82	1	12.48	1.01	0.93	NA	519.21
Invisiplug	125,000	10.00	1,250,000	125,000	10.00	1,250,000	125,000	60,000	2.18	14.85	3.00	0	5.28	1.09	0.99	29.21	37.08
Light Film	100,000	5.00	2,000,000	100,000	70.00	142,857	750,000	0	–75.00	13.14	1.71	0	7.17	1.06	0.97	NA	NA
Loctote Industrial Bag Company	150,000	5.00	3,000,000	150,000	10.00	1,500,000	150,000	1,400,000	8.21	13.05	5.77	0	12.48	1.01	0.93	1.14	8.87
Modern Christmas Tree	90,000	25.00	360,000	90,000	33.00	272,727	90,000	34,000	7.50	13.14	1.71	0	7.17	1.06	0.97	16.38	307.82
ModMom	100,000	10.00	1,000,000	100,000	18.00	555,556	100,000	200,000	1.07	13.43	2.16	0	7.17	1.06	0.97	19.64	18.86
No Mo Stache	100,000	25.00	400,000	100,000	25.00	400,000	200,000	300,000	7.14	13.43	2.16	0	7.17	1.06	0.97	5.98	41.37

Pop It Pal	250,000	10.00	2,500,000	250,000	5.00	5,000,000	750,000	940,000	11.55	9.68	3.42	0	7.17	1.02	0.97	5.16	38.09
Posture Now	100,000	15.00	666,667	100,000	30.00	333,333	100,000	100,000	12.52	17.28	0.77	0	13.26	1.04	0.92	4.88	444.41
Potato Parcel	50,000	10.00	500,000	50,000	10.00	500,000	150,000	200,000	4.88	13.00	3.52	0	7.17	1.05	0.97	8.92	26.12
Rokblok	300,000	15.00	2,000,000	500,000	100.00	500,000	NA	350,000	–5.62	14.86	3.15	1	5.28	1.09	0.99	NA	–178.63
Rounderbum	150,000	10.00	1,500,000	150,000	5.00	3,000,000	300,000	700,000	6.78	9.93	3.95	0	12.48	0.98	0.93	4.77	46.99
Shark Wheel	100,000	5.00	2,000,000	225,000	7.50	3,000,000	500,000	549,000	10.00	11.94	4.65	0	7.17	1.04	0.97	6.09	27.95
SiliDog	100,000	15.00	666,667	100,000	30.00	333,333	100,000	200,000	1.25	13.05	4.82	0	12.48	1.01	0.93	17.87	18.69
Smart Baker	75,000	25.00	300,000	75,000	40.00	187,500	75,000	140,000	5.00	11.47	2.82	0	7.17	1.04	0.97	7.02	26.76
Teddy Needs a Bath!	50,000	10.00	500,000	100,000	30.00	333,333	100,000	24,000	10.00	17.68	4.97	0	7.17	1.10	0.97	16.19	64.48
Third Wave Water	100,000	10.00	1,000,000	100,000	25.00	400,000	100,000	120,000	6.90	5.10	4.18	0	13.93	0.92	0.92	9.34	91.16
Trunkster	1,400,000	5.00	28,000,000	1,400,000	10.00	14,000,000	NA	0	0.25	11.94	4.65	1	7.17	1.04	0.97	NA	5.45
Turbo Baster	35,000	35.00	100,000	35,000	100.00	35,000	NA	0	2.00	13.41	–12.34	1	7.17	1.06	0.97	NA	–16.20
Two Guys Bowtie Company	150,000	10.00	1,500,000	150,000	17.50	857,143	150,000	407,000	10.00	13.51	4.01	0	12.48	1.01	0.93	2.87	38.75
Wall Rx	150,000	10.00	1,500,000	150,000	0.00	NA	NA	600,000	–25.03	11.69	5.27	1	7.17	1.04	0.97	NA	–475.35
Wicked Good Cupcakes	75,000	20.00	375,000	75,000	0.00	NA	75,000	360,000	4.30	9.26	3.42	0	13.93	0.96	0.92	3.89	71.73
Wondercide	500,000	5.00	10,000,000	500,000	3.00	16,666,667	500,000	400,000	3.85	13.05	4.82	0	12.48	1.01	0.93	15.49	53.23

NOTES: This exhibit shows the key variables and parameters used for the royalty conversion as well as the royalty conversion itself based on the methodology in the appendix. For companies where the equity conversion is missing, we were unable to complete the calculation due to lack of information about the company. Amt Req represents the amount of funds requested by the company, Equity O. represents the amount of equity the company was willing to give up for the funding, I.V. represents the implied value of the company based on the proposed offer of the firm, Amt Rec represents the amount of funds actually received by the company, Equity R. represents the amount of equity the company forgave in the final deal without considering the royalties, Post Value represents the implied valuation of the company based only on the funding and equity percentage given up, Royalty AR represents the dollar amount of royalty requested by the Sharks in the deal, Revenue is the most recent annual value of revenues that the firm provided, % Rev represents the percentage of revenue the royalty represents on an annual basis, g_l is the assumed growth rate for the company during the high-growth stage lasting five years and based upon average analyst forecasts of industry growth rates, $P.M._l$ is the profit margin of the firm's industry in the year they appeared on Shark Tank, P.R. is a dummy variable indicating whether or not the royalty requested is a perpetual royalty (1) or not (0). r is the required return on equity of the company, which we obtained by using historical S&P 600 industry average returns. δ_h represents the discount factor used in the appendix for the high-growth stage, δ_l represents the discount factor used in the appendix for the low growth stage, n_r represents the number of years to which the royalty applies, and RoyEq represents the percentage of equity the royalty represents to a company without any royalties.

EXHIBIT A5

Percentage of Deals Containing Royalties



NOTE: This exhibit shows the percentage of deals in a given year of the show that contain royalty terms.

not understand how substantial the royalties are. In many cases, even a small perpetual royalty can result in a Shark owning more than 100% of the equity of the company.

For example, Two Guys Bowtie Company arrived on Shark Tank asking for $150,000 for 15% of the company, with an implied valuation of $1.5 million. Negotiations lasted several rounds, with an offer of $150,000 for 20%, another offer of $150,000 for 30%, and a counter-offer of the entrepreneurs of $150,000 for 20% and a 5% royalty until the $150,000 was paid off. Then the Sharks savored the introduction of a royalty by the entrepreneur and offered $150,000 for 20% and a 10% royalty. Another Shark offered $150,000 for 10% equity and a 7.5% royalty. The entrepreneurs eventually settled on $150,000 for 17.5% equity and a 10% royalty. The estimated time to pay off the royalty was 2.87 years. However, in terms of equivalent equity, it cost the company 38%! Thus, the entrepreneurs unintentionally gave up the equivalent of 55.5% of their company. There are other similar examples of what appears to be a lack of understanding of the value of royalty payments vs. equity.

It is worth noting that the percentage of deals involving royalties has declined since the show first aired, perhaps indicating that there has been some learning about the impact of royalties (see Exhibit A5).

ACKNOWLEDGMENTS

We would like to thank Ethan Elliott, Andrew Shamiya, William Soepriatna, Markus Krieger, and especially Shaul Nirpaz Arevalo and Tuan Anh Le for research assistance. We would also like to thank Ricardo Villareal, Barry Doyle, Thomas Maier and the FDC committee of the University of San Francisco for funding. We would like to thank Pierangelo DePace, Asmath Damodaran, David J. Pedersen, Russ Wermers, and Jinming Zue for comments. Also, a thank you to Torben Voetmann.

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