Can the Media Spur Startup Activity? Evidence from the Television Show "Shark Tank"

David T. Robinson
Duke University and NBER

Angelino Viceisza
Spelman College and NBER

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Abstract

Business leaders and policy makers stress the importance of stimulating entrepreneurship for the continued vitality of the US economy, but many policies to promote startup activity have had mixed success. One reason may be that most policies only affect those who have already decided they are interested in starting a new firm. We combine Nielsen ratings for the ABC show Shark Tank with data from sources such as the Small Business Administration, the US Patent and Trademark Office, and the National Establishment Time Series, to explore whether exposure to a televised business plan competition is associated with startup activity across the US. We instrument TV ratings using basketball games that aired during the same window. Viewership seems to be (1) positively associated with advice-seeking, (2) weakly positively associated with the proportion of new firms, and (3) not associated with patent (application) counts. Our findings suggest that the show encourages people who are unfamiliar with entrepreneurship to explore it, but that it does little to change an individual's fundamental underlying propensity to be an entrepreneur.

JEL Codes: L26, L82, O30
Keywords: Entrepreneurship, media, innovation.

1 Introduction

Entrepreneurship is widely touted as a vehicle for economic growth and job creation. As a result, business leaders, educators, and policy makers often ask how best to create more of it. In this paper we explore a potential mechanism for spurring entrepreneurship that has received relatively little attention: the media, whose impact on a wide range of social outcomes has been relatively well documented (e.g, DellaVigna and La Ferrara, 2015, provide an excellent overview).

We use the ABC reality show *Shark Tank*, which first aired nationwide in August, 2009, as a test-bed for exploring the media's impact on startup activity across different US television markets.[1] The show features would-be entrepreneurs who pitch their business plans to a panel of investor-judges (a.k.a. "sharks"), who pepper the entrepreneur-contestants with questions about their business ideas. Contestants attempt to raise money for their ventures from the investors by specifying investment terms, and each shark ultimately decides whether to invest in a venture. To date, the show has counted an average of 7 million viewers per season, winning the Primetime Emmy Award for Outstanding Structured Reality Program in all four years of that category's existence. Both the popularity of the show and its content make it a good candidate for studying the impact of media on entrepreneurship.

Because Shark Tank was introduced nationwide, not randomly across different television markets, we cannot develop an empirical strategy based on staggered introduction to identify the impact of the show's introduction on entrepreneurship outcomes. Instead, we begin by introducing lags between the measures of entrepreneurship activity and ratings to see how the popularity of current episodes affects future startup activity, controlling for a range of regional covariates. Our main measures of startup activity are (1) advice-seeking created from counseling and training records of the Small Business Administration (SBA), (2) firm creation based on the National Establishment Time-Series (NETS) data, and (3) patent application counts from the US Patent and Trademark Office (USPTO). These measures of entrepreneurial activity vary in terms of their commitment: an individual can seek advice from the SBA as a way of exploring one's suitability to entrepreneurship, without going

[1] For more information see `http://abc.go.com/shows/shark-tank`.

further, but starting a business or undertaking the steps to file a patent require considerably more time and devotion to the task of entrepreneurship.

Our main result is that lagged Nielsen ratings are positively associated with low-stakes actions such as advice-seeking, but largely unrelated to higher-commitment measures of startup activity. For example, increased Shark Tank ratings predict increases in new clients and new clients counseled and new clients who have received training at SBA training facilities. There is no evidence of an impact on outcomes like patent filings or new firm starts.

Previous work has documented several mechanisms through which media exposure can impact behavior. DellaVigna and La Ferrara (2015) discuss a simple framework that highlights two main channels. The first is a direct effect driven by (i) physiological arousal, thoughts, and feelings (e.g., Anderson and Bushman, 2001), (ii) changes in values and attitudes (e.g., Jensen and Oster, 2009; Kearney and Levine, 2015; Lindo et al., 2020), (iii) persuasion or imitation (e.g., DellaVigna and Gentzkow, 2010; Martin and Yurukoglu, 2017; Durante et al., 2019; Armand et al., 2020; Simonov et al., 2020), and/or (iv) aspirations or role models (e.g., Mookherjee et al., 2010; Bernard et al., 2015). The second is an indirect, substitution effect that accounts for media consumption crowding out alternative activities (such as meeting with friends socially) that may have a differential impact on the outcome of interest (e.g., Bjorvatn et al., 2018, discussed further below).

Any of these mechanisms could be at play in our setting, and they could go in either direction. A viewer might watch the show and think "that looks easy–I could do that." Alternatively, the show may discourage viewers, especially when entrepreneurs are unable to raise money successfully or face harsh criticism from judges. This effect could be especially salient for members of groups with traditionally low rates of self-employment, because they may have fewer opportunities to see entrepreneurs in a fundraising setting. To explore this more carefully, we first use an SBA measure of whether an individual is a novice or an experienced entrepreneur. We find that our results are concentrated among novices–those who are first time visitors to SBA training centers and who have no prior entrepreneurial experience. Then, we explore heterogeneous impacts along demographic characteristics, particularly, gender, race, and age given prior literature (e.g., Fairlie and Robb, 2007; Bates and Bradford, 2008; Gompers and Wang, 2017; Howell and Nanda, 2019; Azoulay et al., 2020).

Combined with the weak results on higher-commitment measures of entrepreneurship, these findings suggest that the show encourages people who are unfamiliar with entrepreneurship to explore it, but that it does little to change an individual's fundamental underlying propensity to be an entrepreneur.

Of course, lagging measures of television ratings does not make them immune to endogeneity concerns. Individuals with entrepreneurial intent could be disproportionately likely to view the show in general, generating a spurious positive correlation between ratings and entrepreneurial outcomes. In short, people who would have tried entrepreneurship anyway might have tuned into the show in the weeks before; their latent entrepreneurial interest is an omitted variable. To guard against this possibility, we exploit the fact that professional basketball (NBA) games air at the same time as Shark Tank in many markets to build an instrument for Shark Tank ratings based on the home schedule of that television market's NBA team. The idea is that a popular game should divert attention away from Shark Tank, lowering ratings.

Our work is also related to a large literature that evaluates mechanisms for stimulating entrepreneurship.[2] Perhaps closest to our work is Bjorvatn et al. (2018) who study the impact of an edutainment show on entrepreneurship by conducting a randomized field experiment among a sample of youth in Tanzania. They find some suggestive evidence that the show makes viewers more interested in entrepreneurship and business; however, their main finding is a negative effect – the show discouraged investment in schooling without convincingly replacing it with some other valuable activity. Somewhat consistent with this, prior work suggests that business training programs, which have been a go-to policy response, can have mixed effectiveness. Fairlie et al. (2015) assess the impact of a large randomized evaluation in the US and find a short-run effect on business ownership for those who were unemployed at baseline, but this effect dissipates at longer horizons. Moreover, they find no effects on business sales, earnings, or employees. Similarly, McKenzie and Woodruff (2014) survey the evidence on business training programs in developing countries and find that these impact business creation, but do not improve long-run survival. Finally, Howell (2019) explores

[2]See, for example, Shapero and Sokol (1985); Holtz-Eakin et al. (1994); Carpenter and Petersen (2002); Clementi and Hopenhayn (2006); Kerr et al. (2011); Chatterji and Seamans (2012); Frese and Gielnik (2014); Kerr et al. (2014); McKenzie and Woodruff (2014); Bernstein et al. (2015); Jayachandran (2020).

application and judging data for new ventures in US competitions and finds that receiving negative feedback increases average venture abandonment by 13 percent. The effect appears to reflect feedback regarding the "business" aspects of a startup, rather than the quality of its technology.

The remainder of the paper is structured as follows. We begin in Section 2 with a description of the data. Section 3 discusses the empirical strategy. Section 4 presents our main findings. Finally, Section 5 concludes.

2 Data

2.1 Measures of Entrepreneurial Interest

There are different ways to measure startup activity. One can imagine a spectrum of such activity that requires increasing degrees of effort (Figure 1). The empirical strategy discussed previously will be employed using several outcomes along this spectrum. Specifically, we focus on the following outcomes:

Advice-seeking. One of the lowest-cost ways to respond to show exposure is to seek advice, online and/or in-person, from an agency such as the SBA, which operates the Small Business Development Centers, Women's Business Centers, and SCORE chapters. Through a Freedom of Information Act request, we obtained data for Form 641, which is the client in-take form that is submitted upon physical or virtual arrival at any of the abovementioned centers (see `http://bit.ly/2ZpLV36`). These data enable us to identify (1) the number of people who are seeking advice from SBA centers in a given DMA on a weekly basis, (2) the types of services they require, and (3) the stage of business development they are in, i.e., new or experienced entrepreneurs.

Firm creation. A more radical (higher-cost) response to Shark Tank exposure is to create a business. We acquired the 2014 release of the National Establishment Time-Series (NETS) database, created by Walls and Associates. NETS contains annual time-series information for over 58.8 million U.S. establishments from January 1990 to January 2013. We use such information to create new firm counts by DMA on an annual basis.

Patent applications and grants. An even more demanding (even higher-cost) response to Shark Tank exposure would be to file a patent. This outcome is measured using USPTO's publicly available data from `https://www.patentsview.org/download/`. We use reverse geocoding on inventor location to create patent (application) counts by DMA at a weekly frequency, to be consistent with the variables on advice-seeking.

2.2 Independent Variables

Media exposure. Our main independent variable of interest is Shark Tank viewership, measured by the Nielsen ratings the show receives in a given week. While Shark Tank first aired in Fall 2009, Nielsen does not have ratings available prior to 2010. Thus, we exploit ratings for each telecast (episode) of Shark Tank from 2010 to 2016 for all DMAs. We also use ratings data that are broken out by demographic category, but such data are only available for the most major DMAs, approximately 50 of 210. Viewership appears to vary significantly across the US/DMAs. This can be seen in Figures 2–8, which show maps of annual viewership intensity at the DMA level across the nation.

We use two measures of Nielsen ratings: the rating (RTG), and the share (SHR). RTG represents the average number of individuals (homes or target groups) viewing a TV channel over a given interval, e.g., a program such as Shark Tank. SHR represents the percent of households (or persons) *using their television* who are tuned to a specific program, station or network in a specific area at a specific time. Thus, RTG is relative to the TV-owning population as a whole in a DMA, while SHR is relative to the TV-owning population with their television sets turned on during a specific time period.

To illustrate with a simple example, suppose a particular DMA has 1000 people living in it, of whom 100 tune into Shark Tank in a given week. When Shark Tank is on, 800 people have their television sets tuned onto something. RTG would be 10% (100/1000) for that week, and SHR would be 12.5%. Because the denominator for SHR will always be less than or equal to the one for RTG, SHR will always be greater than or equal to RTG, and the ratio SHR/RTG will provide a measure of the number of households with their television sets turned on at that time.

Demographics and other controls. To control for potentially confounding factors,

we pull demographic data from the US Census. We focus on median household income, unemployment and home ownership as our control variables. Home equity has been shown to be an important source of startup capital in a number of studies. Likewise, household income is correlated with wealth, which may alleviate financial barriers to entry. Finally, unemployment rates could be correlated with entrepreneurship through a variety of channels. On the one hand, individuals may be more likely to try self-employment as a remedy for unemployment; on the other hand, high rates of unemployment likely correlate with low levels of economic opportunity, which may dampen entrepreneurial intentions.

3 Empirical Strategy

For the purposes of establishing a causal link between the show and startup activity, in a perfect world exposure to the show would be randomized. This standard is impossible to meet in our setting. Even a staggered introduction strategy would not be able to address concerns that the show's early markets were chosen because of their strong local interest in entrepreneurship, thus potentially confounding measurement. Indeed, Shark Tank was not broadcast with any of these considerations in mind: it aired nationwide on ABC beginning on August 9, 2009. This creates a number of identification challenges.

Our estimation strategy seeks to identify the impact of Shark Tank on startup activity by exploiting variation in the intensity of viewership over space and time at the designated market area level (DMA). Roughly speaking, a DMA comprises a collection of US counties (there are approximately 210 DMAs in total).[3] In other words, we estimate equations of the following form:

$$Y_{dt} = \beta_0 + \beta_1 * R_{dt-\tau} + \beta_2 * X_{dt} + \theta_t + \delta_d + \epsilon_t, \tag{1}$$

where Y_{dt} is a given outcome measure for DMA d at time period t; $R_{dt-\tau}$ represents Nielsen's ratings data (as a measure of viewership/popularity) for d at $t - \tau$; X_{dt} is a set of time-varying controls (such as demographics); θ_t is a set of time fixed effects; δ_d is a set of DMA fixed effects; and ϵ_t is an error term.

The main concern about this specification is the potential endogeneity of $R_{dt-\tau}$. First,

[3]See `http://www.nielsen.com/intl-campaigns/us/dma-maps.html` for additional information.

at baseline ($t = 0$) differential ratings across DMAs may be driven by differential interest, exposure, and/or other unobserved factors which are the true drivers of entrepreneurship in the future. For example, those who are already engaged in entrepreneurship in some way may be more likely to tune into the show to begin with and thus, be more likely to start a business in the future. Second, over time differential popularity may not only be driven by the above, but also by other unobserved time-varying differences across markets such as changes in policies to promote entrepreneurship. While the DMA fixed effects δ_d take care of time-invariant market-level effects such as the 'aggregate' interests or pre-exposure to entrepreneurship (assuming those are stationary), it is primarily the unobserved, time-variant factors that are of concern.

To deal with this potential endogeneity, our empirical strategy takes the following steps. First, consistent with the field experiment, development, and program evaluation literatures, we assess whether there are observable differences at baseline across DMAs. To the extent that is not the case, it can be argued that post-show differences in outcomes are more likely to be due to Shark Tank's viewership. Table 1 provides this evidence. It suggests that ratings, in particular Nielsen's so-called SHR ratings, seem relatively balanced across the DMAs' baseline characteristics, including outcomes pre-Shark Tank (recall Section 2.2). Consistent with related work on media influence (e.g., Kearney and Levine, 2015), we also map Shark Tank ratings across DMAs to ensure that viewership is not highly geographically or chronologically concentrated (Section 4). Indeed, that does not seem to be the case.

As a second step, we introduce lags so that the current period's measure of entrepreneurial activity is associated with prior periods' variation across television markets (DMAs) in the popularity of the show with startup activity. This guards against a reverse causality concern that changes in interest in entrepreneurship spurs increases in viewership, but it also helps to address a more mechanical, "day of week" problem. Namely, if a show airs on a Friday, it might not be watched until sometime over the weekend, and the entrepreneurial interest it sparks might not be manifest for several additional days.

As a third step, we use the fact that the show airs at the same time as NBA games during parts of the year to develop an instrument for the Shark Tank TV ratings. The idea behind this strategy is that home-market NBA basketball games airing during the same

window as the show will pull viewers away from Shark Tank. Because the NBA schedule is orthogonal to factors related to latent entrepreneurial interest, the portion of ratings explained by the presence of NBA games is purged of the component of the ratings that is driven by entrepreneurial interest itself.

4 Results

4.1 OLS

In Table 5 we report regressions of several measures of advice seeking on lagged Nielsen ratings intensity. The regressions use data that vary at the weekly frequency across the DMAs, for a total of 26,085 panel-data observations, and we use two lags of ratings to make sure that we are capturing any day-of-week effects.

In the first two columns, the dependent variable is *new clients*, which is the number of new clients at local SBA training centers per million households. In each column the point estimate is positive and highly statistically significant. In column (1) we include a year fixed effect, while in column (2) we replace the year fixed effect with DMA-level controls, which include median household income, the local unemployment rate, and the home ownership rate in the region. These measures are intended to capture both financial market effects (household income, home ownership) and labor market effects (unemployment) that could potentially be important for entry into self-employment. Introducing these controls only strengthens the correlation between Nielsen ratings and new client counts.

Columns (3) and (4) replace the dependent variable with *clients counseled*, a measure not just of the new clients walking in the door, but the ones among those who chose to receive counseling. This is presumably a stricter measure of intention to receive information about entrepreneurship, because this counts the number of individuals who actually received information from the SBA. And indeed, this measure shows a higher correlation with lagged Nielsen ratings.

The final four columns go further and examine training measures. Columns (5) and (6) report the number of training events, which shows only a modest increase when we include

the DMA-level controls discussed above. Columns (7) and (8) show much stronger effects when we measure training outcomes by the number of individuals receiving training. This discrepancy is presumably a function of the fact that the number of individuals per training session varies to a much larger extent than does the number of training sessions.

Table 5 thus shows that lagged measures of Shark Tank popularity drive people into SBA training centers to receive training about how to become an entrepreneur. Does this in turn translate into more durable entrepreneurial outcomes?

Tables 2 and 3 suggest not. Table 3 uses NETS data on new firm counts per million households, measured either as the scaled number of new firms, the number of new sole proprietorships, or the share of new firms as a function of total firms. Importantly, these data are at annual frequency, and there are only two years of data (2012-2013) because we add lagged ratings. These ratings are the annual average of weekly viewership numbers over each of two years. We find little evidence of a relation between viewership and entrepreneurship at this level of aggregation. Of course, this may be due to the cross-sectional nature of the regression combined with the degree of aggregation occurring in the ratings measure.

To address this, Table 3 relates weekly variation in patenting activity to lagged Nielsen ratings. Again, there is little evidence that either newly granted patents or new patent applications are positively affected by increases in Shark Tank popularity.

Thus, in sum, the evidence in Tables 1 through 3 illustrates a strong effect on early-stage, low-commitment measures of entrepreneurial interest, but no lasting effects associated with exposure to the show. Of course, perhaps this is unsurprising: this could simply reflect the fact that decisions to enter entrepreneurship play out slowly as people leave jobs or scale back hours in paid employment, arrange financing, negotiate with member of their household about vocational changes, etc. Indeed, we view the lack of evidence on the higher-commitment measures as evidence that the lower-commitment results are unlikely to be driven by spurious correlation owing to geographic-level unobservables.

4.2 IV

TO BE COMPLETED.

4.3 Mechanisms

To explore the mechanism behind the low-commitment results more carefully, in Tables 4 and 5 we use the fact that the SBA subdivides clients into novice and experienced clients. Novice clients have no prior entrepreneurial experience and have never previously appeared at an SBA center, while this is not true of experienced clients.

Tables 4 and 5 largely mirror Table 1, except that the count variables are counts of novice (Table 4) and experienced (Table 5) clients, instead of a total client count. It is reassuring that the all of the positive results found in Table 1 appear to be coming from a surge of novice clients to these training centers. This is consistent with the idea that newcomers to entrepreneurship see a popular episode of Shark Tank, decide that this is something they would like to learn more about, attend a training session, after which there interest fizzles out.

In ongoing work we intend to carry this analysis further by relating content on the episode–whether there were contestants from historically underrepresented populations in entrepreneurship; whether the show featured more or fewer successful funding events–as a way of exploring these mechanisms more deeply.

5 Conclusions and Directions for Future Work

This paper examines the role that media can play in spurring entry into entrepreneurship by relating lagged spatial variation in viewership of a popular reality TV show, Shark Tank, to measures of entrepreneurship and innovation. We focus on a range of measures of entrepreneurship that vary in terms of their commitment to a new endeavor. At the low-commitment end of the spectrum, we measure visits to SBA training centers; at the high-commitment end, we measure patent filings and new firm starts.

A priori, the effects of exposure to a television program that features would-be entrepreneurs pitching their business plans to seasoned investors in order to raise capital are unclear. On the one hand, a viewer could be spurred into entrepreneurship by seeing someone pitch and thinking that they could do that too. On the other hand, a viewer who might have otherwise been tempted to try entrepreneurship could be deterred from entry by seeing

the difficulties that contestants faced while they attempted to raise money.

We find that increases in viewership predict increases in startup activity, but only for low-stakes measures. More specifically, we find evidence of increased numbers of visits to SBA training centers, but we find no reliable increases in higher-stakes measures of startup activity. Moreover, we find that the results are concentrated in the subset of visitors who are unfamiliar with entrepreneurship.

Understanding the possible reasons for these mixed results are important for pointing to directions for future work. Under one interpretation of these findings, the results speak to a ongoing policy discussion concerning whether we have *enough* entrepreneurs. The fact that the show spurs people to learn more, but upon learning more, few people act upon the new information suggests that relatively few individuals who harbor latent entrepreneurial talent go unrecognized. This interpretation implicitly assumes, however, that the training individuals receive at SBA training centers is relevant to their specific entrepreneurial interests. Of course, the mixed results could also be considered as evidence that the training centers themselves are ineffective at breaking down the barriers to entrepreneurship. Distinguishing between these potential explanations is important for future work.

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Figure 1: Spectrum of startup activity

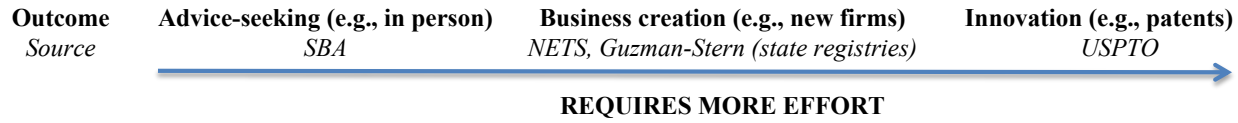


Figure 2: Shark Tank viewership based on Nielsen ratings by DMA, 2010

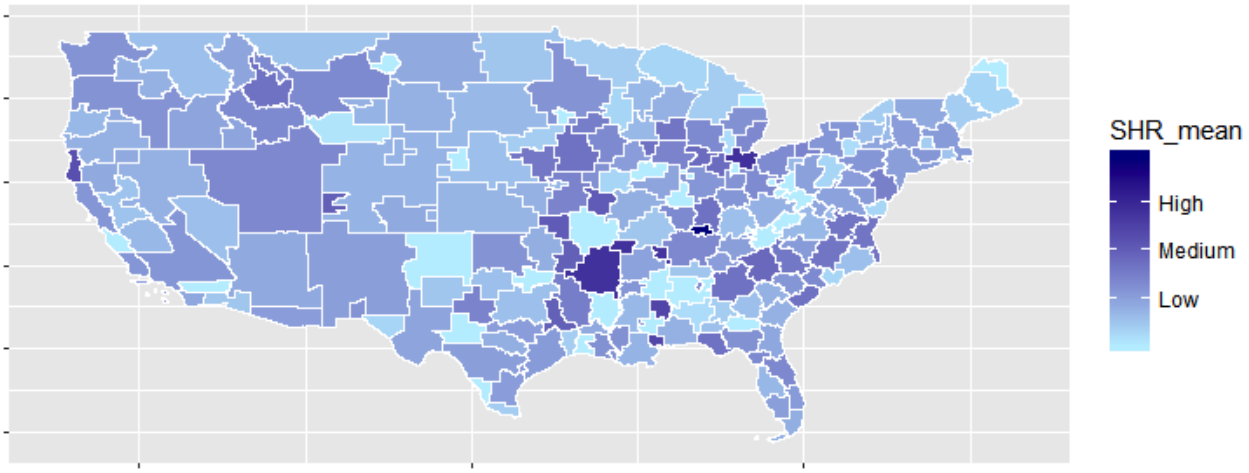


Figure 3: Shark Tank viewership based on Nielsen ratings by DMA, 2011

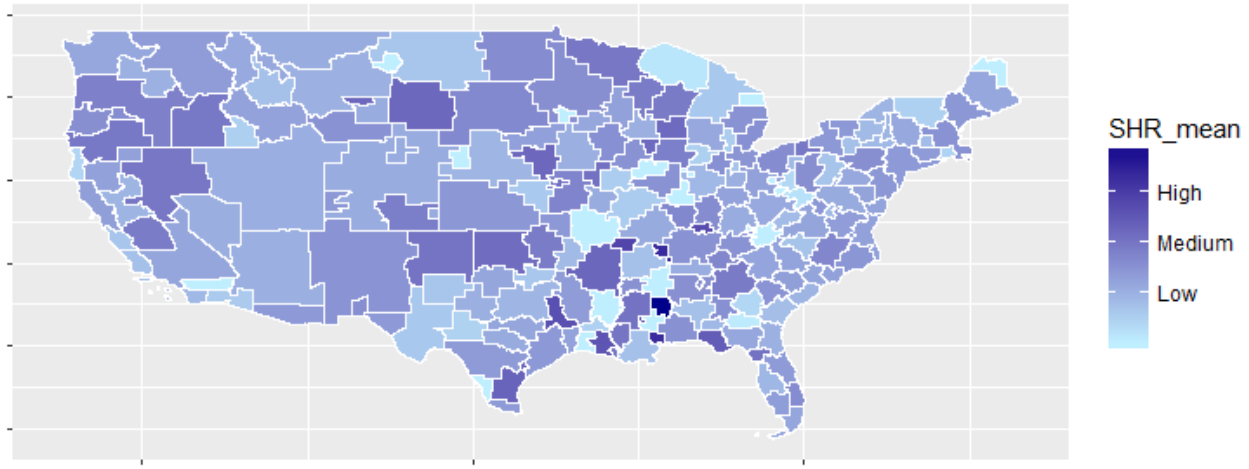


Figure 4: Shark Tank viewership based on Nielsen ratings by DMA, 2012

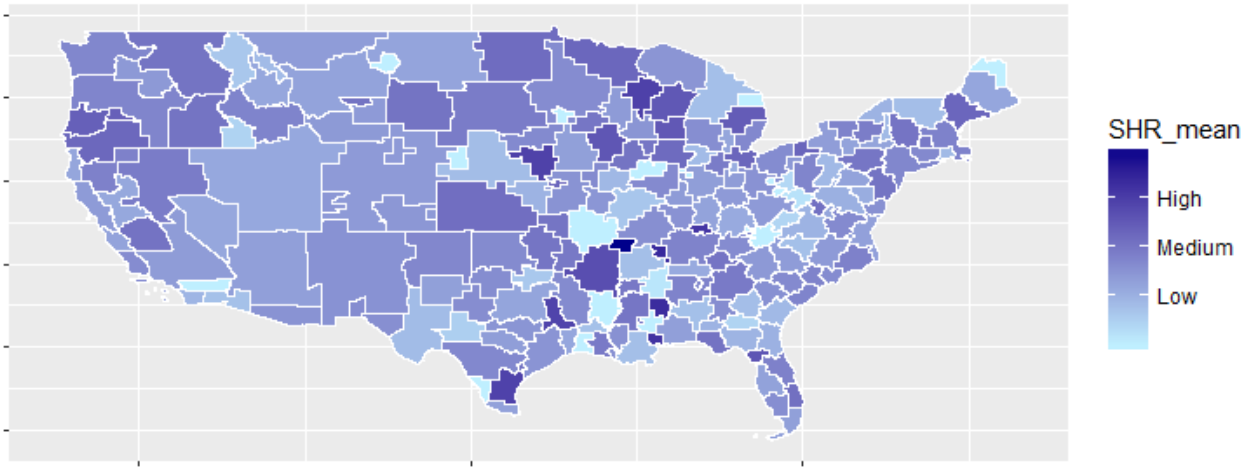


Figure 5: Shark Tank viewership based on Nielsen ratings by DMA, 2013

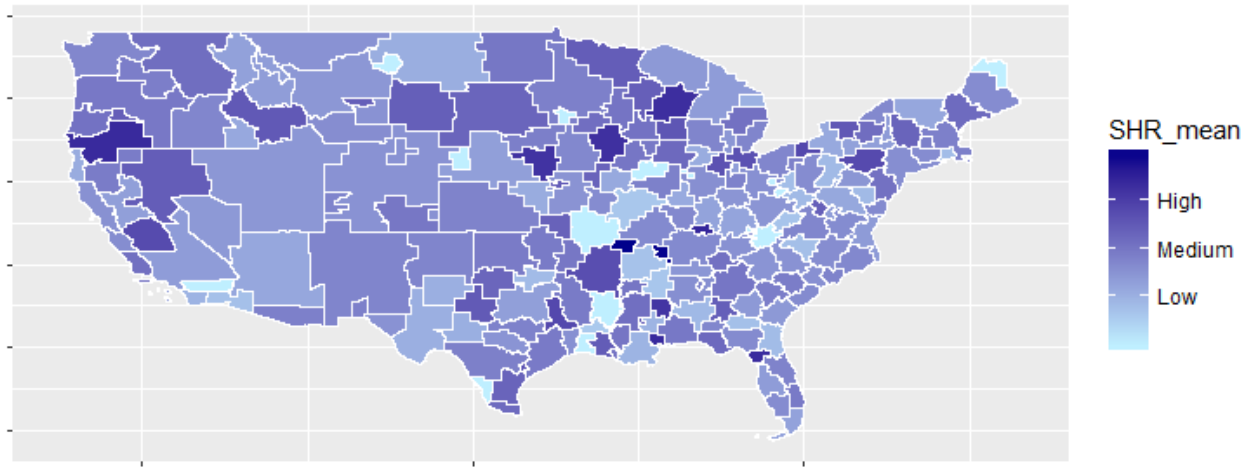


Figure 6: Shark Tank viewership based on Nielsen ratings by DMA, 2014

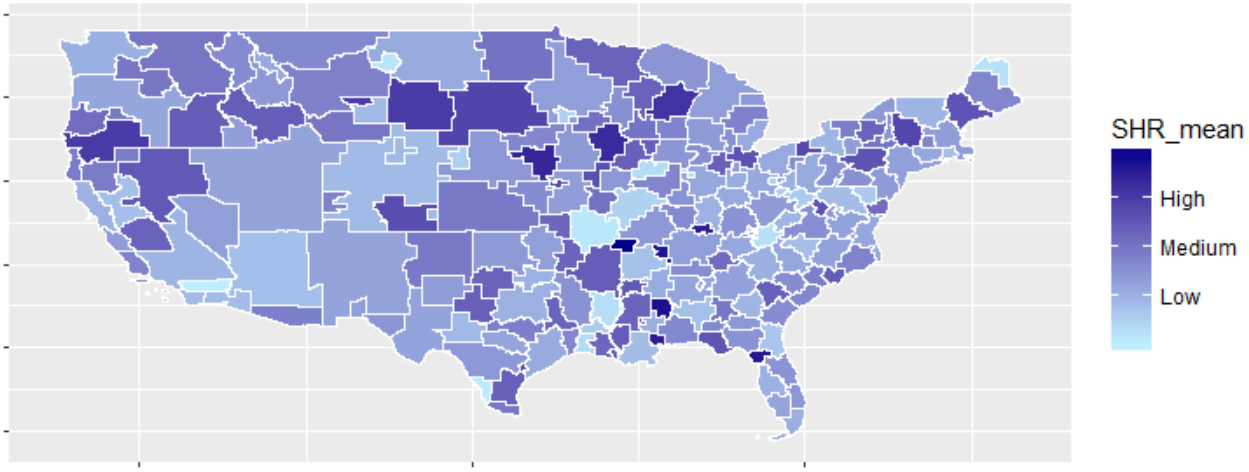


Figure 7: Shark Tank viewership based on Nielsen ratings by DMA, 2015

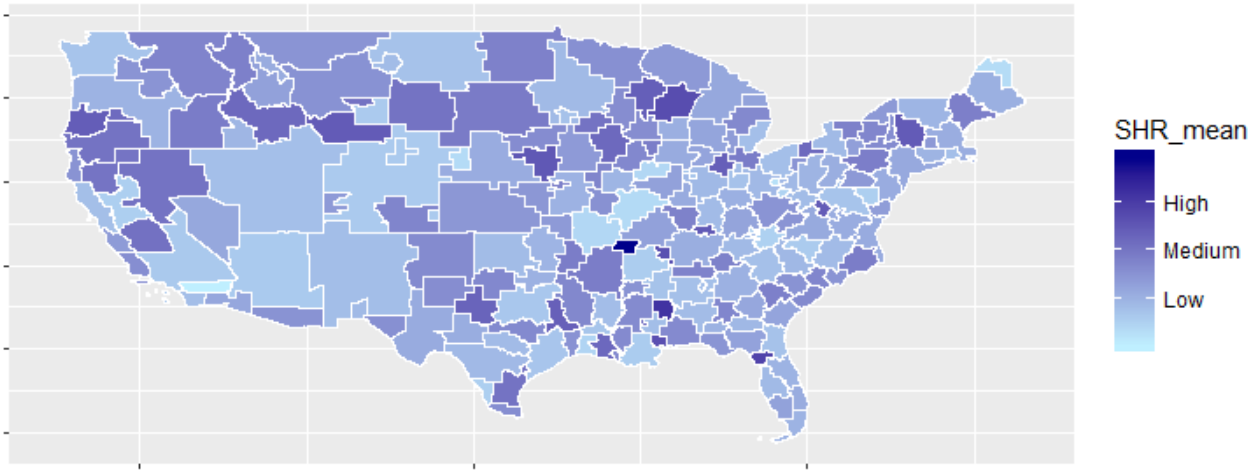


Figure 8: Shark Tank viewership based on Nielsen ratings by DMA, 2016

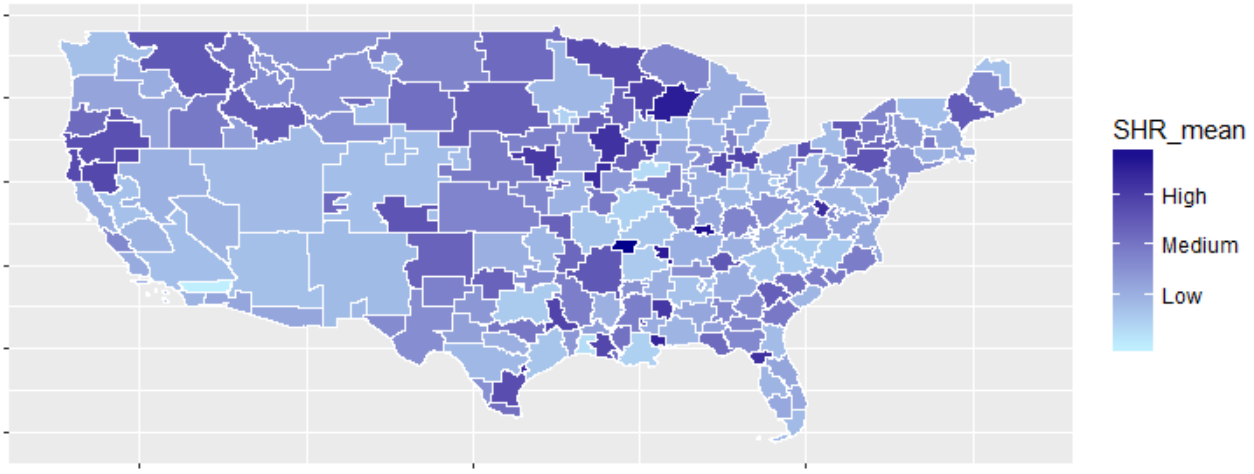


Table 1: The Effect of Lagged Nielsen Ratings on SBA Outcomes

Data are at weekly frequency. New clients=Number of new clients registered per million HHs. All dependent variables are scaled by number of HHs in DMA. Standard errors in parentheses. Training events=Number of new training events per million HHs. Clients counseled=Number of new counseling cases per million HHs. Clients trained=Number of clients trained per million HHs. Ratings=% HHs who are using a TV and tuned into Shark Tank. Controls: (1) HH income; (2) Unemployment; (3) Home ownership. All median, annual, at DMA level. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	New clients$_{dt}$		Clients counseled$_{dt}$		Training events$_{dt}$		Clients trained$_{dt}$	
Ratings$_{dt-1}$	0.23***	0.42***	0.74***	0.71***	0.03	0.05**	1.86***	2.39***
	(0.056)	(0.053)	(0.220)	(0.206)	(0.023)	(0.022)	(0.600)	(0.562)
Ratings$_{dt-2}$	-0.04	0.07	-0.14	-0.11	0.10***	0.11***	0.94	1.30**
	(0.054)	(0.054)	(0.213)	(0.209)	(0.022)	(0.022)	(0.581)	(0.570)
N	26,085	26,085	26,085	26,085	26,085	26,085	26,085	26,085
R^2	0.474	0.453	0.639	0.636	0.296	0.292	0.125	0.123
DMA Fixed eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed eff.	Yes	No	Yes	No	Yes	No	Yes	No
Controls	No	Yes	No	Yes	No	Yes	No	Yes
F(lags equal)	0.00176	9.99e-05	0.0128	0.0195	0.0698	0.104	0.335	0.255

Table 2: Effect of lagged Nielsen ratings on NETS outcomes

Data are at annual frequency. All dependent variables are scaled by number of HHs in DMA. New firms=Number of new firms per million HHs. New proprietorships=Number of new sole proprietorships per million HHs. Share of firms=Number of new firms divided by total number of firms in the DMA last year. Ratings=% HHs who are using a TV and tuned into Shark Tank. Controls: (1) HH income; (2) Unemployment; (3) Home ownership. All median, annual, at DMA level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)
VARIABLES	New firms$_{dt}$	New proprietorships$_{dt}$	Share of new firms$_{dt}$
Ratings$_{dt}$	-4.82	-0.58	0.06
	(6.234)	(0.655)	(0.037)
Ratings$_{dt-1}$	-11.88**	-1.10**	0.05*
	(4.650)	(0.489)	(0.027)
Ratings$_{dt-2}$	-8.98***	0.05	0.04*
	(3.145)	(0.331)	(0.019)
N	378	378	374
R^2	0.823	0.611	0.336
DMA Fixed eff.	Yes	Yes	Yes
Year Fixed eff.	No	No	No
Controls	Yes	Yes	Yes
F(lags equal)	0.642	0.230	0.891

Table 3: Effect of lagged Nielsen ratings on USPTO outcomes

Data are at weekly frequency. All dependent variables are scaled by number of HHs in DMA. Newly granted patents=Number of newly granted patents per thousand HHs. New patent applications=Number of new patent applications per thousand HHs. Ratings=% HHs who are using a TV and tuned into Shark Tank. Controls: (1) HH income; (2) Unemployment; (3) Home ownership. All median, annual, at DMA level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
VARIABLES	Newly granted patents$_{dt}$		New patent applications$_{dt}$	
Ratings$_{dt-1}$	-0.00	-0.01	-0.01	-0.00
	(0.010)	(0.009)	(0.008)	(0.007)
Ratings$_{dt-2}$	-0.05***	-0.05***	-0.01	-0.01
	(0.010)	(0.009)	(0.007)	(0.007)
N	26,085	26,085	26,085	26,085
R^2	0.078	0.075	0.080	0.080
DMA Fixed eff.	Yes	Yes	Yes	Yes
Year Fixed eff.	Yes	No	Yes	No
Controls	No	Yes	No	Yes
F(lags equal)	0.0109	0.0227	0.946	0.701

Table 4: Effect of lagged Nielsen ratings on SBA outcomes for novice entrepreneurs

Data are at weekly frequency. All dependent variables are scaled by number of HHs in DMA. New clients=Number of new clients registered per million HHs. Clients counseled=Number of new counseling cases per million HHs. Training events=Number of new training events per million HHs. Clients trained=Number of clients trained per million HHs. Ratings=% HHs who are using a TV and tuned into Shark Tank. Controls: (1) HH income; (2) Unemployment; (3) Home ownership. All median, annual, at DMA level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	New clients$_{dt}$		Ratio of new clients$_{dt}$		Clients counseled$_{dt}$		Ratio of clients counseled$_{dt}$	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ratings$_{dt-1}$	0.226***	0.417***	0.000	0.002***	0.467***	0.529***	0.001***	0.001***
	(0.044)	(0.042)	(0.000)	(0.000)	(0.130)	(0.123)	(0.000)	(0.000)
Ratings$_{dt-2}$	0.058	0.182***	0.001***	0.002***	0.091	0.188	0.001**	0.001***
	(0.042)	(0.042)	(0.000)	(0.000)	(0.126)	(0.124)	(0.000)	(0.000)
N	26,085	26,085	25,746	25,746	26,085	26,085	26,006	26,006
R^2	0.413	0.395	0.158	0.145	0.610	0.603	0.333	0.326
DMA Fixed eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed eff.	Yes	No	Yes	No	Yes	No	Yes	No
Controls	No	Yes	No	Yes	No	Yes	No	Yes
F(lags equal)	0.0161	0.000862	0.211	0.541	0.0705	0.102	0.704	0.762

Table 5: Effect of lagged Nielsen ratings on SBA outcomes for experienced entrepreneurs

Data are at weekly frequency. All dependent variables are scaled by number of HHs in DMA. New clients=Number of new clients registered per million HHs. Clients counseled=Number of new counseling cases per million HHs. Training events=Number of new training events per million HHs. Clients trained=Number of clients trained per million HHs. Ratings=% HHs who are using a TV and tuned into Shark Tank. Controls: (1) HH income; (2) Unemployment; (3) Home ownership. All median, annual, at DMA level.Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	New clients$_{dt}$		Ratio of new clients$_{dt}$		Clients counseled$_{dt}$		Ratio of clients counseled$_{dt}$	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ratings$_{dt-1}$	0.008	0.003	-0.000	-0.002***	0.271**	0.182	-0.001***	-0.001***
	(0.026)	(0.025)	(0.000)	(0.000)	(0.134)	(0.126)	(0.000)	(0.000)
Ratings$_{dt-2}$	-0.101***	-0.111***	-0.001***	-0.002***	-0.230*	-0.300**	-0.001**	-0.001***
	(0.026)	(0.025)	(0.000)	(0.000)	(0.130)	(0.128)	(0.000)	(0.000)
N	26,085	26,085	25,746	25,746	26,085	26,085	26,006	26,006
R^2	0.356	0.340	0.158	0.145	0.546	0.544	0.333	0.326
DMA Fixed eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed eff.	Yes	No	Yes	No	Yes	No	Yes	No
Controls	No	Yes	No	Yes	No	Yes	No	Yes
F(lags equal)	0.00959	0.00690	0.211	0.541	0.0197	0.0244	0.704	0.762