Can the media spur startup activity? Evidence from the ABC show Shark Tank

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Abstract

Business leaders and policy makers stress the importance of stimulating startup activity for the continued vitality of the US economy, but many policies to promote entrepreneurship have had mixed effectiveness. One reason is the lack of exposure to the processes of innovation and starting a new firm. We combine Nielsen ratings for the ABC show Shark Tank with data from 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 find that 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 to date 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 acknowledged as a vehicle for economic growth. This has spurred academics and policy makers alike to ask how best to stimulate entrepreneurial activity. 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 (see for example DellaVigna and La Ferrara, 2015, for an overview). Specifically, we use the ABC reality show *Shark Tank* as a case study to explore the media's impact on startup activity in the United States (US).[1] On the show, would-be entrepreneurs pitch their business plans to a panel of investor-judges (aka "sharks") who pepper entrepreneur-contestants with questions. 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. In short, the show seems like a suitable candidate for studying the research question of interest.

Our identification strategy relates variation across television markets in the popularity of the show, as measured by Nielsen ratings, to localized measures of startup activity. Because Shark Tank was not introduced randomly across markets, we introduce lags between the measures of entrepreneurship activity and the ratings to see how the popularity of current episodes affects future activity, controlling for a range of covariates at the regional level. 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) and `http://startupcartography.com` (further discussed by e.g. Guzman and Stern, 2016), and (3) patent application counts from the United States Patent and Trademark Office (USPTO). These measures of entrepreneurial activity vary in terms of their commitment: an individual can go into an SBA training center as a way of exploring one's suitability to entrepreneurship, without going further, but starting a business or undertaking the steps to file a patent require considerably more time

[1] Shark Tank aired nationwide on August 9, 2009, see `http://abc.go.com/shows/shark-tank`.

and devotion to the task of entrepreneurship.

We find that lagged variation in Nielsen ratings are positively associated with advice-seeking, but largely unrelated to higher-commitment measures of startup activity, such as patent filings or new firm starts. Previous literature has documented several mechanisms through which media-like sources can impact behavior; for example, physiological arousal, thoughts, and feelings (e.g., Anderson and Bushman, 2001), aspirations and role models (e.g., Mookherjee et al., 2010; Bernard et al., 2015), and imitation and/or changes in attitudes (e.g., DellaVigna and La Ferrara, 2015). In our context, any of these mechanisms could be at play and could go in either direction. For example, by giving the viewer a glimpse into a pitch/negotiation process, the show has the potential to stimulate interest, boost confidence, and generally encourage a viewer to take the 'entrepreneurial plunge'. This effect could be especially salient for members of historically underrepresented groups, who may have relatively few opportunities to see people 'like them' engaging in entrepreneurship. On the flip side, the intensity of such process may *discourage* the viewer.

Indeed, using 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. Combined with the weak results on higher-commitment measures of entrepreneurship, this suggests 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.

Our work is broadly related to a large literature that evaluates mechanisms for stimulating entrepreneurship. (see for example Shapero and Sokol, 1985; Holtz-Eakin et al., 1994; Carpenter and Petersen, 2002; Fairlie and Robb, 2007; Bates and Bradford, 2008; 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, and the references within). The closest is perhaps Bjorvatn et al. (2018), which is one of the few to look at this question directly, but for a sample of youth in Tanzania. They find some suggestive evidence that the edutainment 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. Indeed, recent research 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 United States (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 application and judging data for 4,328 new ventures in 87 competitions and finds that receiving negative feedback increases average venture abandonment by 13 percent.

The remainder of the paper is structured as follows. Section 2 discusses the empirical strategy. Section 3 presents our main findings. Finally, Section 4 concludes.

2 Empirical strategy and data

For purposes of establishing a causal link between the show and startup activity, in a perfect world exposure to the show would be randomized. This is an almost impossibly high standard given the nature of the exposure we are exploring. 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. Thus, in the parlance of the program evaluation literature, the US population went from being "untreated" one day to "treated" the next. This creates a number of identification challenges.

Our estimation strategy instead 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).[2] In other words, we estimate

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

equations of the following form:

$$Y_{dt} = \beta_0 + \beta_1 * R_{dt-\tau} + \beta_2 * X_{dt} + \theta_t + \delta_d + \epsilon_{t+\tau}, \quad (1)$$

where Y_{dt} is a given outcome measure for DMA d at time period $t - \tau$; $R_{dt-\tau}$ represents Nielsen's ratings data (as a measure of viewership/popularity) for d at time t, $\tau > 0$; 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 $\epsilon_{t+\tau}$ is an error term.

A primary concern with this specification is that $R_{dt-\tau}$ is unlikely to be exogenous. First, 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 ($t + \tau$). 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. If so, $\hat{\beta}_1 > 0$ may be the result of pure unobserved selection rather than media impacts. 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.[3]

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 SHR, seem relatively balanced across the DMAs' baseline characteristics, including outcomes pre-Shark Tank. As such, we mainly run regressions using Nielsen's so-called SHR ratings, although in unreported analysis we have assessed robustness with respect to the other two ratings measures (RTG and IMP respectively). Consistent with related work on

[3]This issue is also discussed by Kearney and Levine (2015) who study the impact of the MTV show 16 and Pregnant on teen birth rates.

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 3).

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 final step, we ask whether some subgroups – in particular, more or less experienced entrepreneurs – are more sensitive to viewership than others. Future versions of the paper will include other types of mechanism regressions.

2.1 Data

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 US Small Business Administration's (SBA) Office of Entrepreneurial Development (OED), which operates the Small Business Development Centers, Women's Business Centers, and SCORE chapters. We submitted a Freedom of Information Act (FOIA) request to the SBA and obtained data for Form 641 (see `http://bit.ly/2ZpLV36`), which is the client in-take form that is submitted upon arrival at any of the above-mentioned centers. These data enable us to identify the types of services people are seeking advice for and the stage of business development they are in, i.e., new or experienced entrepreneurs.

Firm creation (NETS and `http://startupcartography.com`). A more radical (higher-cost) reaction to Shark Tank exposure is to create a business. For now, we only report findings

based on using the National Establishment Time Series (NETS) data.

Patent (application) counts (USPTO). An even more demanding (even higher-cost) response to Shark Tank exposure would be to file a patent. This outcome is measured by creating patent counts at the DMA level using USPTO's publicly available data.

The main "treatment" variable is Shark Tank viewership, measured by show ratings. Nielsen media ratings have been the go-to for viewing popularity for decades. At its highest frequency, the data can tell you minute-by-minute what viewership looks like. This study exploits ratings for each telecast (episode) of Shark Tank from 2010 to 2016 for all DMAs. When disaggregating ratings by demographics, 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.

Finally, 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 Results

The main results are presented in Tables 2, 3 and 4. A deeper analysis of potential mechanisms is presented in Tables 5 and 6.

In Table 2 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 still and examines training. 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 there are more individuals per training session to a much larger extent than there are increases in the number of training sessions.

Table 2 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 3 and 4 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 4 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 2 through 4 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.

To explore the mechanism behind the low-commitment results more carefully, in Tables 5 and 6 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 5 and 6 exactly mirror Table 2, except that the count variables are counts of novice (Table 5) and experienced (Table 6) clients, instead of a total client count. It is reassuring that the all of the positive results found in Table 2 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.

4 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 entrepreneurship activity



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

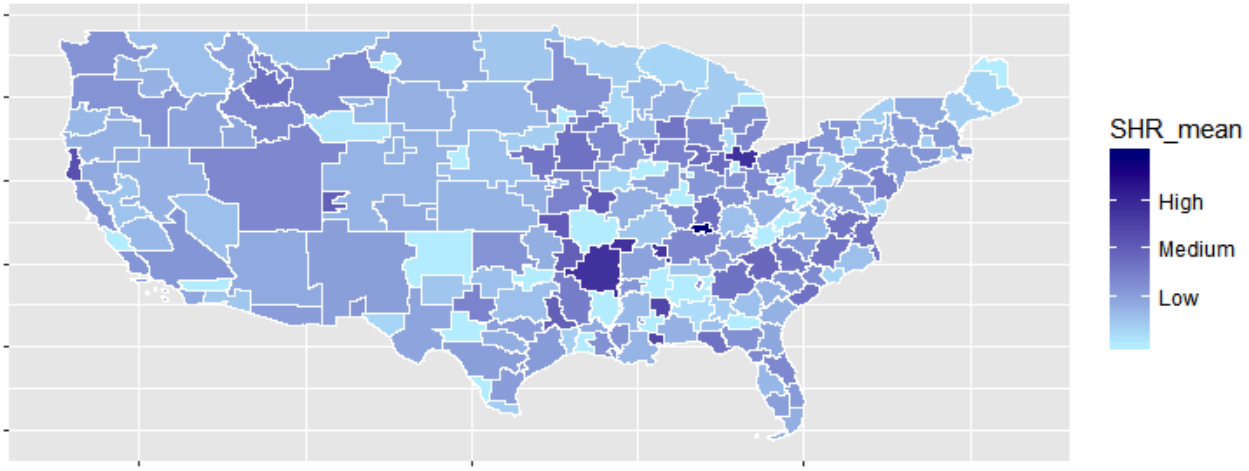


Figure 3: Shark Tank viewership based on Nielsen ratings by DMA, 2011

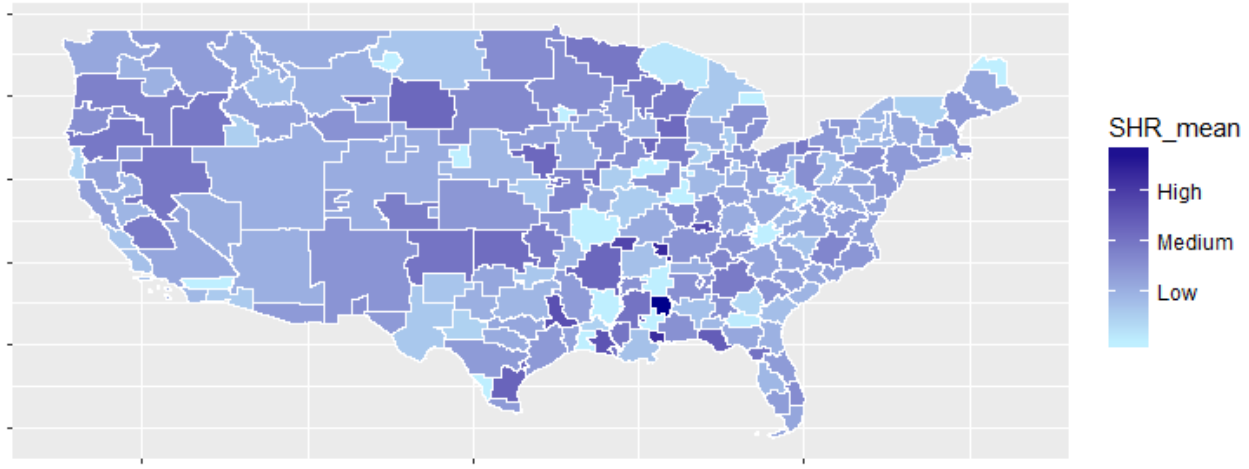


Figure 4: Shark Tank viewership based on Nielsen ratings by DMA, 2012

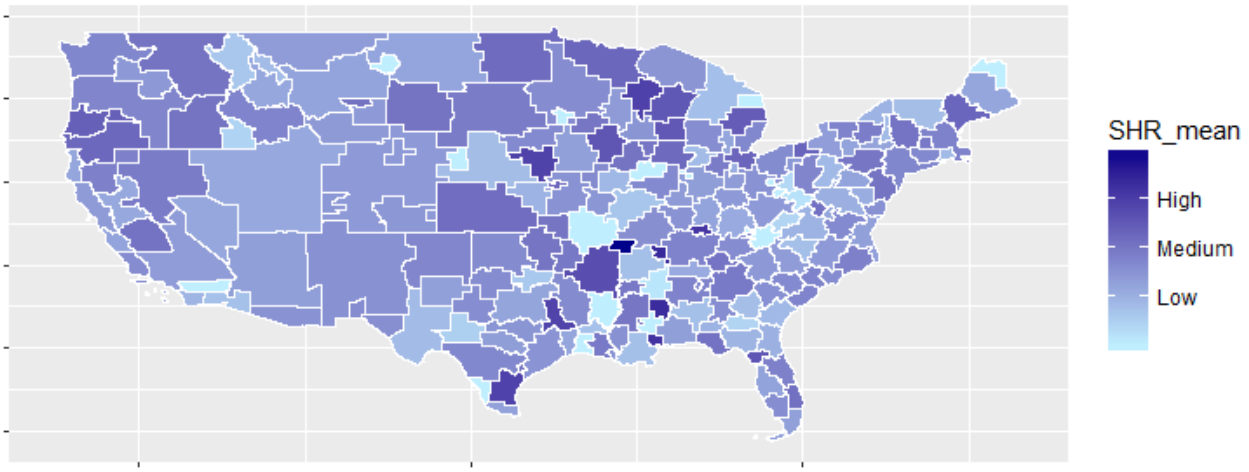


Figure 5: Shark Tank viewership based on Nielsen ratings by DMA, 2013

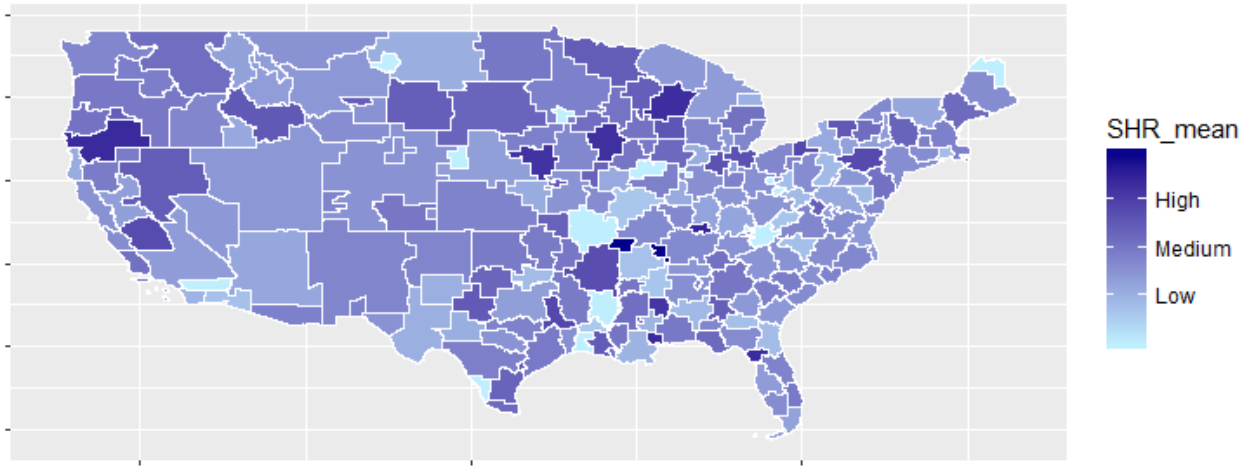


Figure 6: Shark Tank viewership based on Nielsen ratings by DMA, 2014

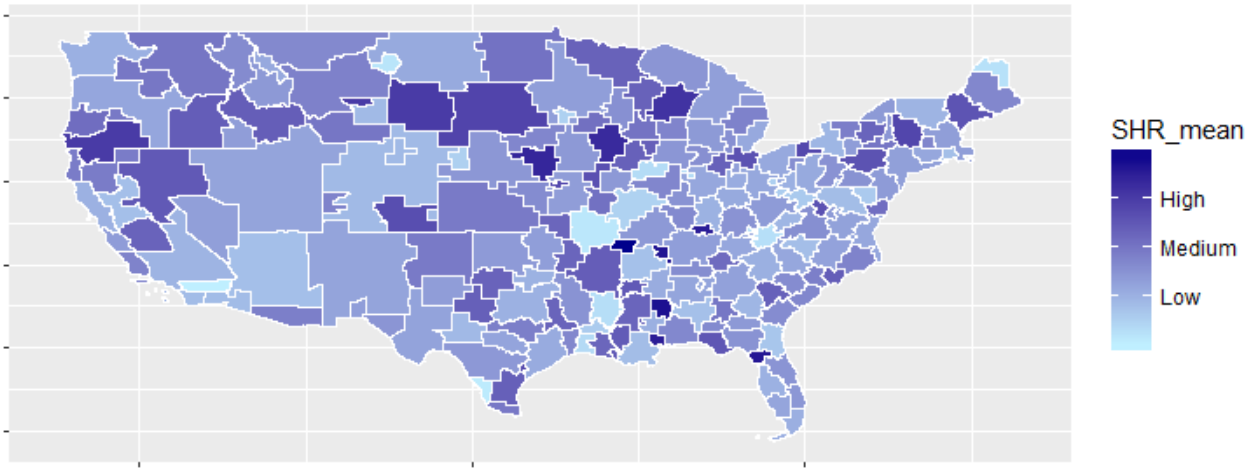


Figure 7: Shark Tank viewership based on Nielsen ratings by DMA, 2015

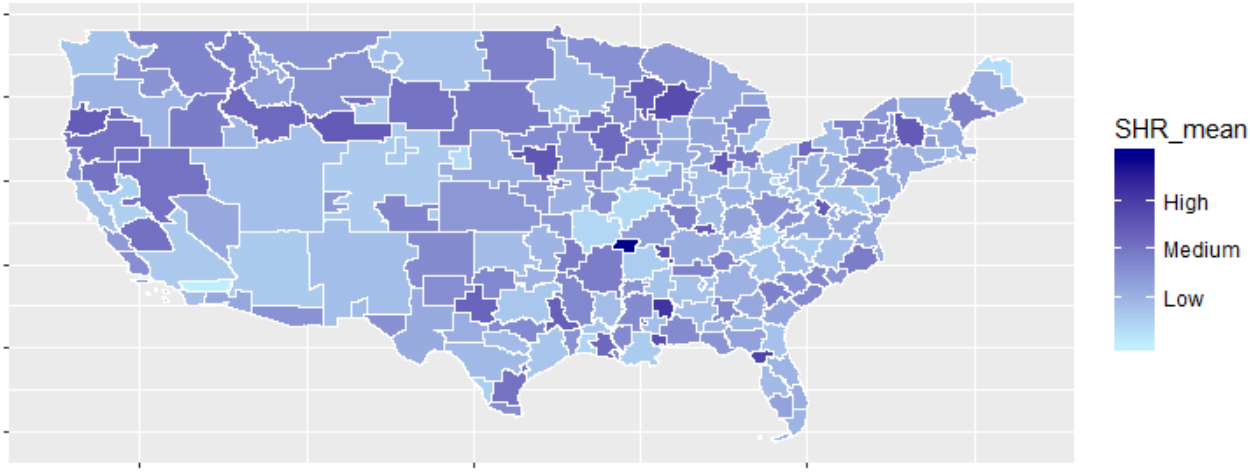


Figure 8: Shark Tank viewership based on Nielsen ratings by DMA, 2016

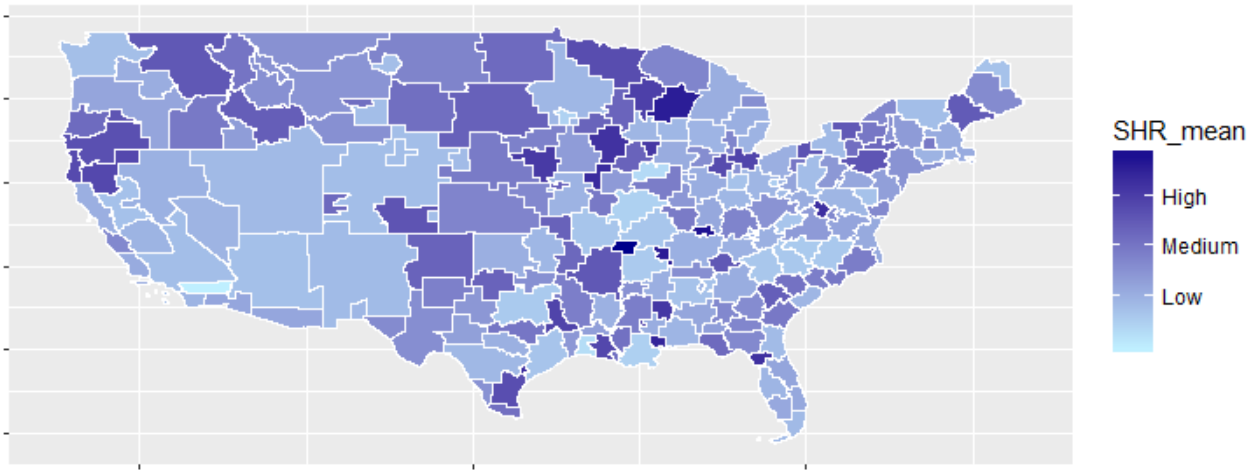


Table 1: Do baseline characteristics predict average Nielsen ratings?

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. New firms=Number of new firms per million HHs. HH income; Unemployment; Home ownership are all annual, at the DMA level. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) RTG Ratings	(2) SHR Ratings	(3) IMP Ratings
New clients	-8.22	-9.89	-83.05
	(6.263)	(12.757)	(106.498)
Clients counseled	12.30	42.23***	27.74
	(7.804)	(15.897)	(132.712)
Training events	70.00**	105.41	965.17
	(35.211)	(71.724)	(598.765)
Clients trained	-1.16*	-1.91	-16.87
	(0.657)	(1.339)	(11.181)
New firms	0.49	0.78	-13.18
	(0.626)	(1.275)	(10.647)
Median HH income	0.02**	0.02	1.38***
	(0.009)	(0.018)	(0.148)
Median unemployment	0.07*	0.12	1.16
	(0.045)	(0.091)	(0.760)
Median home ownership	0.01	-0.01	0.41*
	(0.014)	(0.029)	(0.241)
Constant	-0.64	1.63	-102.92***
	(1.071)	(2.181)	(18.206)
N	178	178	178
R^2	0.088	0.070	0.390

Table 2: 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 3: 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 4: 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 5: 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 6: 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