The Resources to Adapt:

How the US Networks Responded to Environmental Change

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Abstract

Are smaller firms better at adapting than larger ones? Smaller firms are often viewed as nimble and therefore more likely to adapt as the environment changes. However larger firms have greater resources available and access to those resources could be key to the activities beneficial in the new environment. To provide empirical evidence addressing this question, I use a setting where incumbents heterogenous in size were affected by a common environmental shock: television show production in the United States. Netflix's entry into the industry precipitated a change in the production function of television shows, away from experimentation. My findings show larger firms were better able to manage this transition by marshalling the resources necessary to mitigate the uncertainty involved in creating new television shows without the use of experimentation.

1. Introduction

Understanding the drivers of firm survival over time is central to management research. Scholars have long studied the overall relationship between a firm's size and its survival rate. However, a key aspect of a firm's survival rests on its ability to adapt to changing environmental conditions. In contrast to the overall relationship, empirics on adaptation are lacking and theory points in opposite directions. The skill at exploitive activities which enable a firm to grow large could curtail the exploratory activities necessary to adapt to environmental change (Hannan and Freeman, 1984; March, 1991; Tripsas and Gavetti, 2000). Or the competencies, resources and capabilities that enabled the firm to grow large in the old environment can enable actions in the new environment that smaller firms are unable to replicate (Henderson and Cockburn, 1994; Wernerfelt, 1984; Peteraf, 1993; Teece, Pisano and Shuen, 1997). Hence the need for an empirical examination whether a firm's size is material to how well it responds to environmental change.

I address this question in the context of television in the US, where a set of incumbent television networks manage portfolios of television shows. Historically the development of new television shows involved experimentation: the networks would fund the first episode of a show, termed the pilot, to generate a signal of the show's potential quality. Conditional on a favorable signal, the network would fund the rest of the first season's series of episodes. In 2013, Netflix entered the industry but did not experiment with pilots. This constrained the incumbent network's own ability to experiment as the creators of new television shows demanded similar treatment from the incumbent networks. My results show the larger incumbent networks navigated this environmental change better than the smaller networks.

Although numerous empirical studies of the survival rate of firms exist (Freeman, Carroll and Hannan, 1983; Singh, Tucker, and House, 1986; Audretsch and Mahmood, 1995; Klepper, 2002; Agarwal and Gort, 2002; He and Wong, 2004; Thompson, 2005; Dencker, Gruber and Shah, 2009), previous empirical work on environmental change is limited. This paper is perhaps closest to Seamans and Zhu (2013) and McElheran (2015). Seamans and Zhu (2013) considers how multi-sided markets respond to environmental change, finding a shift towards subscription revenue at

local US newspapers due to Craigslist's entry. McElheran (2015) studies whether larger firms were more likely to adopt new processes available in their environment, using the introduction of information technology (IT) in the US manufacturing sector as a setting. I ask a slightly different question than posed in either of these papers: do larger firms disproportionately benefit from adapting to the new environment?

There are several empirical challenges which have so far prevented this question from being addressed. First, there must be an event that affects all firms in an industry setting up pre and post periods for each firm. When the environment changes more gradually without such an event, attributing a firm's actions or outcomes to the change becomes difficult. Second, an action must be taken by the firm due to the event that can be linked to outcomes. Otherwise there could be no adaptation taken by firms and outcomes would measure only the robustness of existing activities to shocks. Consider one of the effects of the 1973 oil shock in the US: smaller Japanese car manufacturers overtook the larger US ones because of pre-shock fuel efficiency, not because of any adaptation advantage (Klier, 2009). Third, an ideal outcome measure would be independent of an industry's market structure. For example, if large firms competed against each other for large clients while small firms competed for small clients, a market share measure of success would miss heterogeneity in adaptation between large and small firms. Adaptation by large firms could lead to better products relative to small firms but because large firms only compete against each other, no improvement in market share would appear. Fourth, all these measures need to exist at a business unit level. If a firm's outcomes improve due to an unrelated business, at best measurement error would be introduced. At worse, if there is correlation between business unit size and the number of unrelated business units with a firm, empirical estimates would be biased.

My data set on the development of television shows meets these challenges. The environmental event I use is the unexpected success of two of Netflix's shows, *House of Cards* and *Orange is the New Black*, which both were nominated for Emmy and Golden Globe awards for the 2013-2014 television season. For its own idiosyncratic reasons, Netflix never piloted shows. The success of these two shows both changed beliefs about the value of piloting and improved the bargaining position of show creators. This event changed the boundary conditions on piloting

(McGrath, 1997), triggering the incumbent networks to ordering more new shows straight to series as shown in Figure 1. I provide models of the network's decision to pilot that show how both a change in beliefs or a change in bargaining power would lead to this action by the incumbent networks.

[Insert Figure 1 about here]

Since the action taken in response to new environmental conditions was a change in the production of television shows, a natural outcome variable for my setting would be a measure of new television show's success. Multiple measures exist, including viewership numbers from Nielson Media Research and whether a show was renewed for a second season by its network. However, many of these measures are not independent of market structure; the big four networks for example are close competitors and any action that specifically benefited them all relative to the rest of the networks may not significantly change their viewership or renewal rates, at least in the short term. I therefore use Internet Movie Database (IMDb) ratings my outcome measure, which are not as mechanically linked to competitor outcomes and have been shown to provide a consistent measure of television quality (Waldfogel, 2017).

Finally, although many of the incumbent networks share a corporate parent, they operate independently from each other. Even though both are owned by NBCUniversal, the types of shows solicited and broadcast by the NBC network are different from those shown by the SyFy network. Furthermore, each network's brand and ability to attract talent is distinct: Hulu, jointly owned by Fox, ABC-Disney, and NBCUniversal, has for years invested in its creating its own television shows. Yet it's only recently achieved recognition as a producer of prestigious television content (Adalian, 2017).

My main empirical specification measures how the average outcome of the portfolio of network's new shows changed because of the shift towards straight to series production as unexpectedly induced by Netflix. Overall, the increase in share of straight to series shows had no effect on the IMDb ratings. However, when broken out by whether the network was one of the big four US networks, I see a strong positive effect for the big four networks. Further investigation

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suggests this effect was largely driven by the big four's increase in reliance on new shows from creators they had existing relationships with. This is consistent with theories that predict a positive relationship between firm size and successful adaptation; the big four networks had built up the resources necessary to produce quality television shows in an environment where experimenting with a pilot was restricted. In my setting perhaps the resource if existing relational contracts (Gibbons and Henderson, 2012) with the creators enable the larger networks to better navigate this change.

The rest of this paper proceeds as follows. Section 2 describes experimentation in television show production: how it displays characteristics of both real options and commitment as well as how Netflix changed the incumbent's decision to experiment. Section 3 models the network's experimentation decision and the creator's behavior conditional on that decision. Section 4 outlines the data used for this paper. Section 5 lays out my empirical strategy and my empirical results. Section 6 discusses the paper's results and while section 7 concludes.

2.   Data and Measures

To empirically test the above propositions, I pool data from three sources: Film L.A., Gracenote, and the Internet Movie Database (IMDb). Film L.A. is a non-profit dedicated to facilitating film and television production in Los Angeles. They have a proprietary dataset which tracks the production of scripted US television starting at the pilot phase. Importantly, the dataset flags shows that were ordered straight to series phase, a variable crucial to this paper's analysis. Gracenote, a subsidiary of Neilson Holdings, has a dataset provided commercially to the television industry. A record is made whenever a network makes a public announcement of investment in a show idea, by for example paying a writer to produce a script. Metadata is associated with each show such as genre and creators responsible for the show's production. IMDb, a subsidiary of Amazon.com, has a public dataset which includes ratings for shows that made it to a public airing on a network.

Joining these three datasets is non-trivial because of variances in a show's title, year of production and network across the datasets. Since for example Film L.A. creates a show record earlier in the show's production history than IMDb, the title used in Film L.A. may be a working title, different from the official, release title used in IMDb. In both databases, spelling errors can exist in their title fields. Film L.A. tracks shows by their development season while IMDb records the year of a show's first broadcast; a show broadcast early in 2014 according to IMDb might be labeled as part of the 2013 development season according to Film L.A. Film L.A. tracks which network each show was developed for while IMDb's distributors for each show is often incomplete. Similar issues appear when comparing records between Film L.A. and Gracenote or Gracenote and IMDb.

To build my matched dataset, I first treat the smaller, curated Film L.A. dataset my main set of observations. I then build lists of alternative titles for each television show and match these alternative titles across the three datasets using bigram matching to allow for spelling errors. I prioritize records with exact matches across these alternative titles, year and network, but allow for deviations in year and network when exact matches are not available. Table 2 provides summary statistics for the combined dataset.

[Insert Table 2 about here]

The data is restricted to the incumbent networks that circa 2008 were consistently producing scripted television. This includes the prestige networks that would win Emmy or Golden Globe awards (ABC, NBC, FOX, CBS, HBO, FX, USA, Showtime and AMC) as well as other established networks (CW, Freeform, TNT, SyFy, Starz, and A&E). By restricting my dataset to these fifteen networks, my analysis is focused on the incumbents' reaction to Netflix's entry.

Since the Film L.A. dataset is only contains shows between 2008 and 2017, all observations of shows outside those years in the other datasets are not included. Data for 2017 is currently only partially available. The years used are season years; for example, the 2008 season year runs from September 2008 to August 2009.

The funnel from script to pilot to series is represented by the first few rows of Table 2. I restrict my data to show ideas that were developed in some way, either piloted or ordered straight to series. In the period prior to Netflix's entry, only 3% of shows were ordered straight to series, increasing to 15% after Netflix's entry. The genre and show length variables provide some indication of the stability of show types over my period of interest despite this change in production.

Based on Gracenote's data on the past work of a show's creators, I create a binary variable which indicates whether any of the show's creators have previously created a show for the new show's network. Later I show this variable's strong correlation with a network's successful transition to increased straight to series production. Interestingly, the share of shows relying on these types of veteran creators has gone up after Netflix's entry.

I only observe outcomes for shows that were ordered to series, either by first being piloted or directly through a straight to series order. IMDb provides show ratings at both the show level and episode level for all broadcast shows. My primary outcome variable is an average of episode ratings for the show's first season. Table 1 shows correlation between IMDb ratings and two other measures of show performance: the renewal decision made by the networks and breaking into the Nielson Top 30. Renewals have historically been a strong indicator that a show met the network's internal metrics for success. Unlike raw viewership numbers, renewals factor in the value of reaching a specific demographic and the strength of a show's timeslot competition on rival networks. The connection between renewal, Nielson viewership and a show's success is not completely mechanical; sometimes a show will be considered a success if it for example increases cable subscriptions despite having relatively low viewership and lacking plans for renewal (Thaxton, 2017; O'Connell, 2018).

3. Empirical Approach

3.1 Firm Level Outcomes

A first natural question to explore is how the environmental change affected outcomes at firms. To that end I estimate Equation 1:

$$
\begin{aligned}
AverageFirstSeasonRating_{nt} \\
= \beta_S ShareStraightToSeries_{nt} + \beta_{SP} ShareStraightToSeries_{nt} \quad (1) \\
* Post2013_t + \delta_t + \alpha_n + \epsilon_{nt}
\end{aligned}
$$

Equation 1 approaches my dataset as a panel of network observations. For each year t, each network n releases a set of new shows. The average first season rating for those shows is my outcome variable $AverageFirstSeasonRating_{nt}$. Some of those new shows were ordered straight to series, while others were the result of a piloted, staged development process. The share of the network's shows that year that were ordered straight to series is reflected in the dependent variable $ShareStraightToSeries_{nt}$. Netflix's entry into the industry increased the incumbents share of straight to series orders, this time shock is represented by the $Post2013_t$ variable. Fixed effects for networks α_n control for the differences in average show quality across networks; for example, on average HBO shows tend to be rated higher than shows on the big four networks. Fixed effects for year δ_t control for time trends in show quality, if for example the industry is overall getting better at producing higher quality shows at the end of my time period relative to the beginning.

In Equation 1 β_{SP} measures the overall impact of the environmental shock on firm outcomes. A positive coefficient would indicate the environment improved for all firms while a negative coefficient would indicate the environment worsened.

3.2   Big Four Networks

ABC, NBC, CBS and Fox are different from the rest of the U.S. networks. They each fund over a dozen pilots per year, have a long track record of airing original programming, share a history of transitioning from over-the-air broadcasting with affiliate networks to reaching most of their audience through cable, and directly compete for prime-time advertising spend. A natural question is to ask whether the shift towards straight to series orders had different outcomes for the big four networks versus the rest of the incumbents. To do so I extend Equation 1 to a triple diff style estimator.

$$
\begin{aligned}
AverageFirstSeasonRating_{nt} \\
= \beta_S ShareStraightToSeries_{nt} + \beta_{BP} BigFour_n * Post2013_t \\
+ \beta_{SP} ShareStraightToSeries_{nt} * Post2013_t \qquad (2) \\
+ \beta_{BSP} BigFour_n * ShareStraightToSeries_{nt} * Post2013_t \\
+ \delta_t + \alpha_n + \epsilon_{nt}
\end{aligned}
$$

In Equation 2, the depended variable $BigFour_n$ is introduced, set to 1 for the big four networks and 0 otherwise. β_{BSP} captures the change in big four network outcomes relative to the other networks.

Why might the big four networks have faired differently? One reason is that their volume of production means its far more likely to them to work with creators that had a previous show on their network. As depicted in Figure 2, 41% of shows on big four networks have at least one creator with prior experience on that network. Outside the big four, this number is only 22%.

[Insert Figure 2 about here]

To provide some evidence about whether this difference in relationship is related to any difference in performance between the big four networks and the other networks, I reformulate Equation 2.

$$AverageFirstSeasonRating_{nt}$$
$$= \beta_S ShareStraightToSeries_{nt} + \beta_{CP} NetworkVetCount_n$$
$$* Post2013_t + \beta_{SP} ShareStraightToSeries_{nt} * Post2013_t \qquad (3)$$
$$+ \beta_{CSP} NetworkVetCount_n * ShareStraightToSeries_{nt}$$
$$* Post2013_t + \delta_t + \alpha_n + \epsilon_{nt}$$

Equation 3's $NetworkVetCount_n$ is the number of new shows that debuted on network n between 2008 and 2013 that had at least one creator with a prior show on that same network. The coefficient β_{CSP} captures whether more of these types of shows prior to Netflix's entry correlates with a different effect of shifting production towards straight to series orders on outcomes. Although a significant, positive finding of β_{CSP} does not identify exactly what mechanism causes straight to series to improve outcomes, it does illuminate the characteristics of networks that were able to benefit from straight to series orders.

To distinguish the importance of such veterans to a network's straight to series success as opposed to simply having many previous shows, I also estimate Equation 4. In Equation 4, $ShowCount_n$ is the number of new shows that debuted on network n between 2008 and 2013, regardless of whether a show's creator had a prior show on the same network.

$$AverageFirstSeasonRating_{nt}$$
$$= \beta_S ShareStraightToSeries_{nt} + \beta_{CP} ShowCount_n * Post2013_t$$
$$+ \beta_{SP} ShareStraightToSeries_{nt} * Post2013_t \qquad (4)$$
$$+ \beta_{CSP} ShowCount_n * ShareStraightToSeries_{nt} * Post2013_t$$
$$+ \delta_t + \alpha_n + \epsilon_{nt}$$

4.   Empirical Results

Column 1 of Table 3 estimates Equation 1. The coefficient *Share StS * Post 2013* indicates how the environmental change increasing straight to series production affected overall outcomes.

Although the coefficient in Column 1 is negative, it lacks statistical significance, indicating any global effect from ordering a show straight to series is too small to be detectable in my data.

Column 2 of Table 3 estimates Equation 2, effectively breaking out the *Share StS * Post 2013* variable of Column 1 by whether the network was one of the big four networks. Column 2's *Share StS * Big Four * Post 2013* is both positive and significant and indicates the big four networks fared better than the other networks after the environmental change. The magnitude of the effect is very large, suggesting the marginal show that was moved from piloted production to a straight to series order received a much higher IMDb rating because of the switch.

[Insert Table 3 about here]

To explore what might be causing the big four networks to have better results from straight to series production than the other incumbent networks, I estimate Equation 5 in Table 4. *Network Veteran Count* is a count by network of how many shows from 2008 to 2013 had a creator with a previous show on the same network. Column 2 suggests this measure has a strong positive effect on the ability of a network to improve their portfolio after the Netflix shock. To rule out this effect as being driven primarily by the networks simply having more shows, I also estimate Equation 6 in Table 6, which substitutes *Network Veteran Count* with *Show Count*, simply the number of shows each network produced from 2008 to 2013. A higher *Show Count* is uncorrelated with improved outcomes with more straight to series orders after Netflix's entry.

[Insert Table 4 about here]

[Insert Table 5 about here]

5. Conclusion

In this paper I use Netflix's entry into television show creation as an environmental change to test which incumbent firms are better at adapting to such environmental change. I find evidence that the larger incumbent firms did better than the smaller incumbents after the change, suggesting the larger incumbent firms were better able to adapt. This runs counter to theories

positing that more successful, larger firms are worse at exploring environmental changes because of their focus exploiting their current environment. It is however consistent with theories touting the value of resources for a firms success; larger firms just by their size will tend to have more resources than smaller ones, resources that could be valuable in adapting to environmental change. Although I do not uncover exactly why larger incumbents fared better in my setting, improvements in outcomes seemed to accrue to networks with a large stable of repeat creators they draw from for new shows. Perhaps the knowledge these veteran creators have about a network makes the network's feedback on the pilot unnecessary or perhaps they can ramp up production faster, taking full advantage of the longer development time afforded by a straight to series order. Regardless of the mechanism, my summary statistics indicate this relationship has not been lost on the industry, there is a large increase in the use of such veteran creators after Netflix's entry.

My findings speak to both the classic literature on disruption and the more recent discussion about economy wide increases in market concentration. Disruption articulates a healthy fear incumbents should have towards new entrants but lacks clarity about which incumbents are most susceptible to disruptive entry. My research suggests it's the smaller incumbents with the most at risk; they are more likely to lack the resources necessary to adapt to such entry. On market concentration, many mechanisms have been suggested for the dominance of large firms across many industries, from economies of scope to regulatory practices. My research points to an alternate theory; that competition itself increases market concentration as entrants are more likely to cause smaller incumbents to fail.

6.   References

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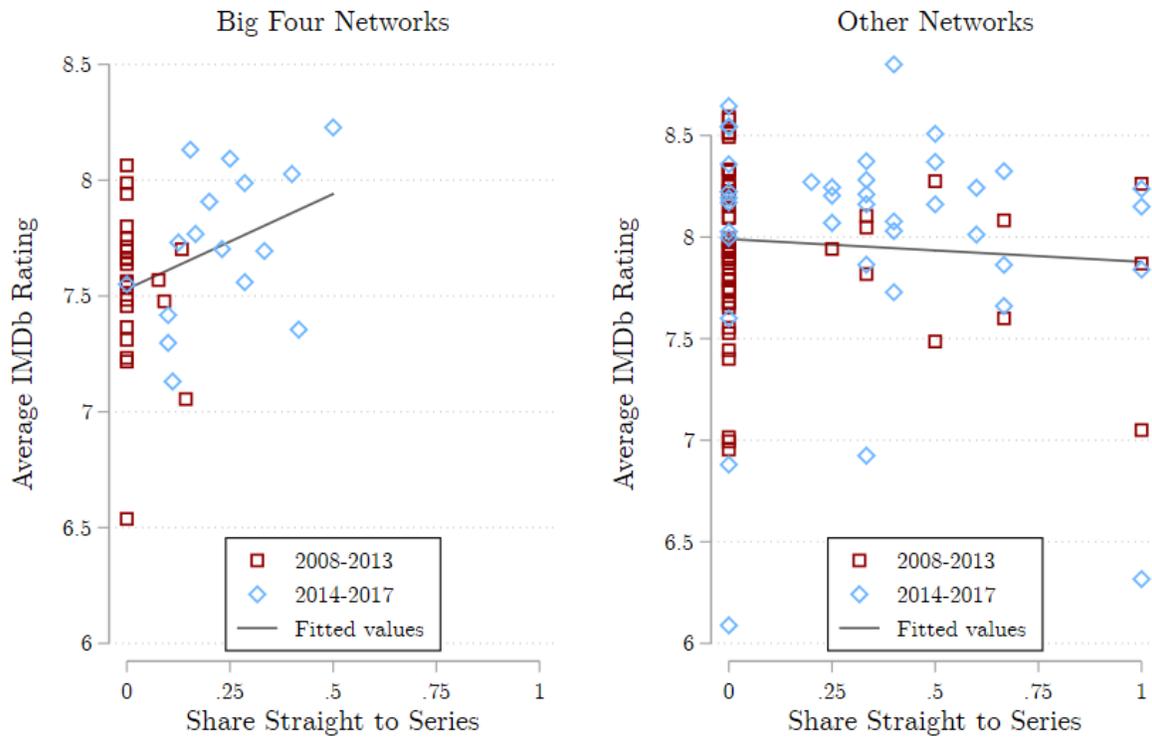
7.   Figures and Tables

6.1   Figures

Figure 1. Share of Shows Ordered that Skipped the Pilot Phase
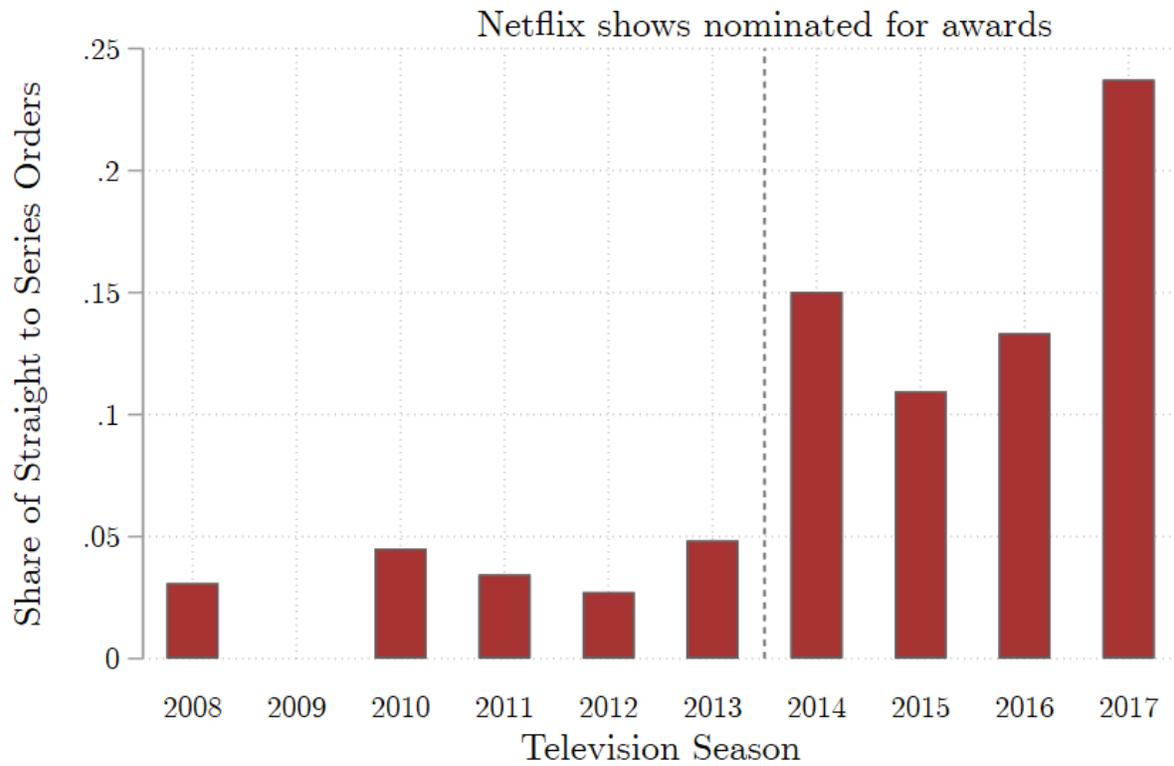

Scripted shows on incumbent networks that were either piloted or ordered directly to series.

Figure 2. Portfolio Relationship Between Straight to Series and IMDb Ratings

Plots of each network's yearly new show average IMDb rating against share ordered straight to series. Big four networks are ABC, NBC, CBS and Fox. Observations restricted to US incumbent networks for 2008 to 2017.

Figure 3. Share of Network Veteran Shows
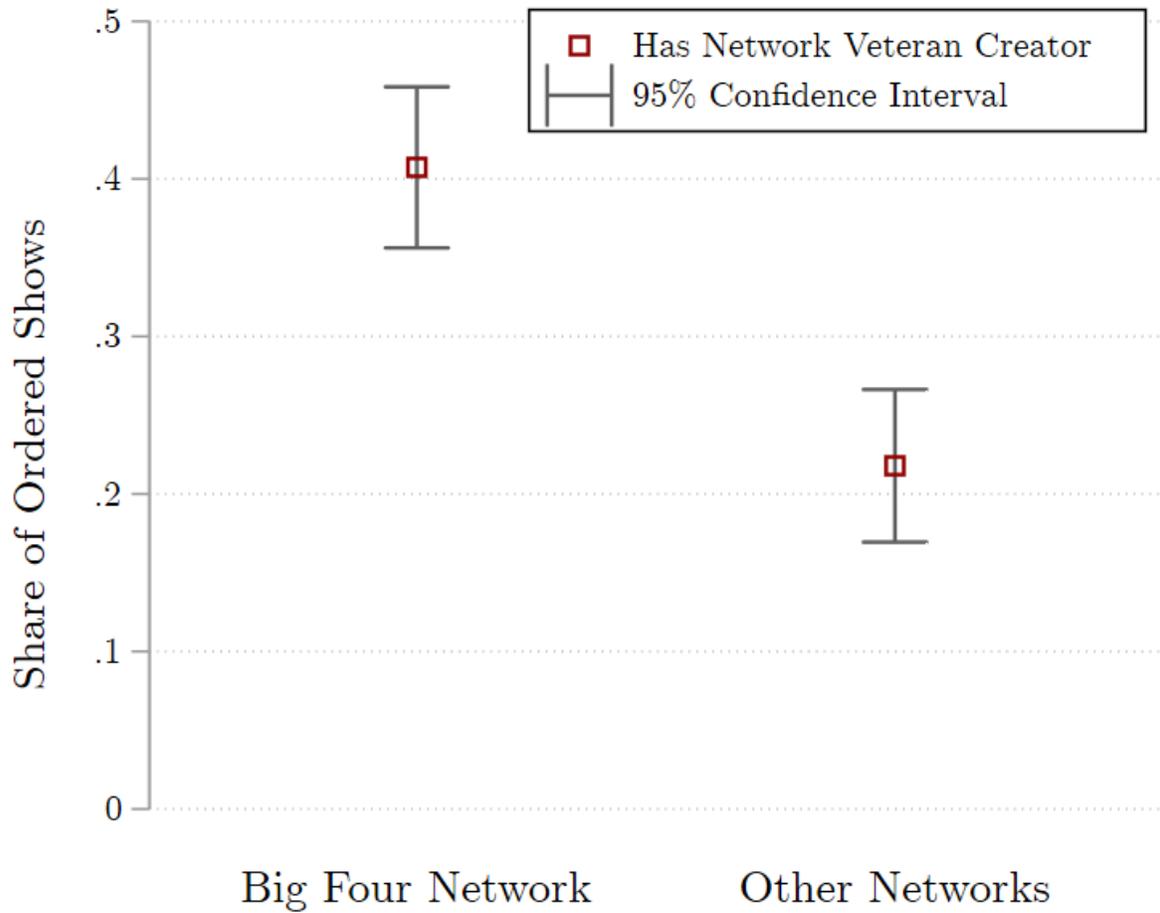
Point estimates and confidence intervals for the share of ordered shows with a creator that had a previous show on the same network. Big four networks are ABC, NBC, CBS and Fox. Observations restricted to US incumbent networks for 2008 to 2017.

6.2   Tables

Table 1. Correlation Between Share of Low Votes and Other Outcome Measures

	1st Season Rating	Renewed or Extended	Nielson Top 30 Show
1st Season Rating	1		
Renewed or Extended	0.291***	1	
Nielson Top 30 Show	0.143**	0.248***	1

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Data is restricted to shows from 2008 to 2016, since renewal and Nielson data missing for 2017. *1st Season Rating* is the average episode IMDb rating for a show's initial series order. *Renewed or Extended* is an indicator for whether a show was either renewed for another season or extended past its original order. *Neilson Top 30 Show* indicates whether the show broke into the Nielson Top 30 highest viewed programs for the season. Renewal correlation is for all incumbent networks while Nielson correlation is just for the big four networks since they are the only networks with enough viewership to potentially enter the top 30.

Table 2. Summary Statistics Before and After Netflix's Entry

	2008-13	2014-17	Overall
Piloted or ordered shows	646	522	1168
Average per year	107.7	130.5	116.8
Piloted shows	625	441	1066
Average per year	104.2	110.3	106.6
Piloted shows ordered to series	328	206	534
Average per year	54.7	51.5	53.4
Straight to series ordered shows	21	81	102
Average per year	3.5	20.3	10.2
Is a comedy	47.1%	44.1%	45.7%
Is a drama	57.9%	55.9%	57.0%
Hour long show	59.3%	59.1%	59.2%
Has creator with prior show on same network	23.8%	46.7%	34.1%
Ordered shows	349	287	636
Average per year	58.2	71.8	63.6
Mean IMDb first season rating	7.7	7.8	7.8
Standard deviation in IMDb first season rating	0.7	0.7	0.7
Renewed past initial order	64.2%	56.1%	60.7%

Table 3. Effect of straight to series on network's portfolio of new shows

	(1) Average IMDB rating	(2) Average IMDB rating
Share StS * Post 2013	0.328	0.225
	[0.507]	[0.558]
Share Straight to Series	-0.181	-0.212
	[0.196]	[0.220]
Share StS * Big Four		-1.166
		[0.797]
Big Four * Post 2013		-0.403
		[0.273]
Share StS * Big Four * Post 2013		3.256**
		[1.104]
Constant	7.547***	7.563***
	[0.0941]	[0.0978]
Network Portfolios (N)	131	131
Deg. of Freedom	14	14
Adj. R-Squared	0.0845	0.110

Robust standard errors in brackets. Star levels: * p < 0.10, ** p < 0.5, *** p < 0.01.
Observations are of each network's yearly porfolio of new shows. Includes year fixed effects. Fixed effect estimator used clustered at network level. Data is restricted to shows from 2008 to 2017 on incumbent networks.

Table 4. Interaction Between Network Veterans and Straight to Series

	(1) Average IMDB rating	(2) Average IMDB rating
Share StS * Post 2013	0.316	0.111
	[0.468]	[0.550]
Share Straight to Series	-0.195	-0.258
	[0.199]	[0.248]
Share StS * Network Veteran Count		-0.0199
		[0.0361]
Network Veteran Count * Post 2013		-0.0277*
		[0.0151]
Share StS * Network Veteran Count * Post 2013		0.189**
		[0.0769]
Constant	7.515***	7.533***
	[0.0898]	[0.104]
Network Portfolios (N)	137	137
Deg. of Freedom	15	15
Adj. R-Squared	0.107	0.139

Robust standard errors in brackets. Star levels: * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$.
Observations are of each network's yearly porfolio of new shows. Includes year fixed effects. Fixed effect estimator used clustered at network level. Data is restricted to shows from 2008 to 2017 on incumbent networks.

Table 5. Interaction Between Show Count and Straight to Series

	(1) Average IMDB rating	(2) Average IMDB rating
Share StS * Post 2013	0.316	0.0338
	[0.468]	[0.559]
Share Straight to Series	-0.195	-0.164
	[0.199]	[0.291]
Share StS * Show Count		-0.00948
		[0.0127]
Show Count * Post 2013		-0.00227
		[0.00468]
Share StS * Show Count * Post 2013		0.0331
		[0.0289]
Constant	7.515***	7.530***
	[0.0898]	[0.0976]
Network Portfolios (N)	137	137
Deg. of Freedom	15	15
Adj. R-Squared	0.107	0.101

Robust standard errors in brackets. Star levels: * $p < 0.10$, ** $p < 0.5$, *** $p < 0.01$.
Observations are of each network's yearly porfolio of new shows. Includes year fixed effects. Fixed effect estimator used clustered at network level. Data is restricted to shows from 2008 to 2017 on incumbent networks.