Series superstars: How streaming-video-on-demand (SVOD) content popularity informs SVOD platform demand

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Abstract

High competition among the major SVOD platforms (Amazon Prime Video, Hulu, HBO Max, Apple TV+, Netflix, and Disney+) has led to an increased focus on acquiring and creating high performing popular content (termed *superstar series)* to attract subscribers from competing SVOD platforms. In this paper, we use a novel audience demand dataset that considers factors like downloads, views, online searches, and social media posts to construct a new measure of popularity at the series level. We then use this measure in a Berry, Levinsohn, and Pakes (1995) structural demand estimation to understand how much consumers value series popularity and series superstars when subscribing to SVOD platforms. Findings indicate that consumers prefer a more uniformly popular catalog over one with a few superstars. Additionally, results show that consumer demand is relatively inelastic with respect to changes in a SVOD platform's average catalog popularity, and even more so to changes in the percentage of superstar series. Furthermore, results suggest that increasing the average popularity of a SVOD platform's content can lead to price increases and a higher share of new subscribers, with larger effects than just adding more superstar series. We explore the implications of these findings for SVOD content strategies.

Keywords: *Streaming, Superstar Effect, Television, SVOD, Demand Estimation*

Introduction

Competition among the limited set of SVOD platforms, including Amazon Prime Video, Hulu, HBO Max (Max), Apple TV+, Netflix, and Disney+, has intensified in recent years as the SVOD market has become saturated and barriers to entry have increased. As a result, there has been a larger emphasis on acquiring and creating highly popular content in order to attract subscribers from other SVOD platforms. In the context of the superstar effect (Rosen, 1981), it is possible to consider high-performing original content series as *superstars*, which are exceptionally popular series that not only draw in new subscribers, but result in other positive externalities, such as allowing SVOD platforms to raise their prices or enhancing the visibility and popularity of other series in a SVOD platform's catalog. This raises questions for SVOD management surrounding how much content should be created, whether efforts should be focused on superstars versus the SVOD's entire catalog, and how persnickety executives should be in content adoption and development.

In this paper, we pursue three research questions regarding series popularity and consumer demand in the context of the current SVOD market. First, how much do consumers care about superstar (i.e., highly popular) series, the average popularity of a SVOD platform's catalog, and the variance of this popularity (RQ1)? Second, how much does consumer demand for a SVOD provider change if they do improve the overall popularity of their catalog or increase the amount of superstar series (RQ2)? Answering RQ1 and RQ2 can help inform tailored approaches for SVOD platforms surrounding what the best strategy is to attract and retain new subscribers: either by focusing on improving the overall popularity of their respective content library, or focusing on developing a few big superstar series, or perhaps some combination of both. However, these decisions are not made in a vacuum. The decisions of one SVOD platform affects the outcomes of subscribers and other SVOD platforms, particularly in such a saturated and intensely competitive market with few outside options. This leads us to our third research question - How does the landscape of the streaming market change if a SVOD platform increases their catalog's average popularity or the percentage of superstar series within their catalog (RQ3)?

To answer these questions, we use a novel and manually collected Parrot Analytics dataset to measure daily SVOD series audience demand that can help shed light on the SVOD industry more so than traditional measures. The Parrot Analytics data aggregates audience demand by considering factors such as downloads, views, online searches, and social media posts, factors not often considered by more traditional audience demand measures. For instance, Nielsen, the producer of the widely used Nielsen TV ratings that rely on more traditional audience demand measures such as views, has recently buckled from perpetual inertia in their own respective research and development departments. Though the firm has reclaimed its accreditation from the Media Rights Council, it has not been able to reclaim its industry-leading reputation in the eyes of many of its advertising and content clients (Cahillane, 2022; Moffett, 2022). New audience measurement firms seek to capture data beyond mere views (Aquilina, 2022c) empowering executives to understand not just the entire consumer journey, but also available entry points to engage further with consumers.

In this paper, we collect daily demand data for a sample of 110 series from prominent SVOD subscription platforms using stratified and systematic sampling techniques to ensure a diverse representation of series with varying popularity levels for each platform. This study focuses on the six largest SVOD platforms: Amazon Prime Video, Hulu, HBO Max, Apple TV+, Netflix, and Disney+. Daily demand data was collected from the third quarter of 2021 through the second quarter of 2022 for a total of 35,112 data points at the series-day level. From this demand data, we construct a measure of relative *popularity* by standardizing the Parrot audience demand measure within each day. We also construct a measure of *superstars*, defined as series that are in the top 1% according to this popularity measure, on average within a quarter. Additionally, we collect information regarding SVOD platform plans, prices, as well as shares of new and total subscribers.

Due to the novelty of this dataset, we begin our analysis by discussing three key observations from the data that help improve our understanding of the streaming market. First, popularity across SVOD platforms follows seasonal trends, regardless of the individual popularity of the platform. Second, possessing the highest subscriber share is not necessarily correlated with the highest percentage of superstar programs. Third, SVOD platforms with lower (higher) prices are inclined (disinclined) to gain new subscribers but retain less (more) overall subscriber shares. Across immutable seasonal exogenies, demonstrated disconnection between highest subscriber share and concentration of superstar series, and ability to effectively retain consumers, these insights illustrate the limitations of superstar series. They also demonstrate that nuanced content strategies are available to different streaming platforms, based in part on how much their own consumers demand these select series. These observations elicit our subsequent inquiry into the relationship between superstar series and consumer demand.

To understand how series popularity affects consumer demand, and thus what content strategies might be best to pursue for SVOD providers, we conduct a demand estimation using a standard Berry, Levinsohn, and Pakes (1995) structural model in the spirit of Nevo (2000). This model allows us to obtain estimates of the *average* utility that consumers derive from the overall popularity of a platform’s series as well as the percentage of series in a SVOD platform’s catalog that are superstars, in addition to the distribution of these preferences across consumers. Our demand estimation results allow us to answer our first research question (RQ1): the higher the average popularity of a platform's catalog, the higher is consumer mean utility. However, consumers derive lower utility on average when there is a large popularity range among series on a platform. In other words, consumers notably value a SVOD platform when it has content that is (1) more popular on average and (2) when there are fewer unpopular series.

The estimates also demonstrate that the average utility that consumers derive from superstar series is positive, but not different from zero at the 10% confidence level. However, the results show that the standard deviation of individual preferences regarding superstar series is quite large, indicating that some individuals highly value superstar series, whereas other individuals derive little utility. Therefore, *in general*, audiences do not meaningfully value superstar series. However, there are likely some segments of audiences that do highly value superstar series and other segments that do not. This provides further illumination surrounding the balance that SVOD platforms need to consider between focusing on overall content library popularity, and investing in superstar series, as there is a considerable amount of heterogeneity among consumers.

To answer our second research question (RQ2), we use our demand estimates to calculate the responsiveness of consumer demand for different SVOD platforms to changes in (1) the average popularity of a SVOD platform's catalog and (2) the percentage of superstar series within a SVOD platform's catalog compared to the overall streaming market landscape. We find that consumer demand increases for SVOD platforms that experience a rise in the average popularity of their content and the percentage of superstar series, whereas demand for other SVOD platforms falls. However, we find that consumer demand is, on average, relatively inelastic with respect to average series popularity and is even more inelastic to the percentage of superstar series that a platform has. In layman's terms, consumer demand does not change *that* much relative to the change in average popularity of a SVOD platform's catalog and consumer demand changes even *less* in response to a change in the percentage of superstar series.

To answer our third research question (RQ3), we use our demand estimates to conduct two counterfactual simulations. Given a change in either the average popularity or the amount of superstar series a platform has, we investigate variation across (1) consumer surplus, (2) platform prices, and (3) the share of new subscribers. Our simulations show that when there is a 10%

increase in the average popularity of a SVOD platform's content, this platform can raise their prices (at minimum by 0.12% for Hulu, and at most by 1.09% by Amazon) and will increase their share of new subscribers relative to other SVOD platforms (at minimum by 3.22% for Amazon Prime and at most by 5.45% for Hulu). This comes at a cost to the other SVOD providers in the market who do not experience a rise in popularity, as they not only have to lower their prices, but they still experience a loss in their new subscriber share. In response to a 10% increase in a SVOD platform's percentage of superstar series, changes in prices and subscriber shares are smaller in magnitude; price increases range from 0.01% (Hulu) to 0.51% (Disney+) and subscriber share increases range from 0.30% (Amazon Prime) to 1.98% (Disney+). In the highly competitive SVOD marketplace, it takes a larger change in average content popularity to elicit an increase in consumer demand, and an even larger change in the percentage of superstar series. Therefore, it is important for SVOD management to carefully weigh the costs of meaningfully improving either of these metrics against these marginal increases in prices and new subscribers.

The contributions of this paper are threefold. First, this paper presents a new daily measure of audience demand, which is capable of evaluating a series' popularity. This is a breakthrough measurement against traditional time-appointment TV ratings (such as Nielsen), as it acknowledges that streaming series, much like other products and platforms, vary in their daily consumption and desirability from consumers. Second, this paper evaluates how series popularity and superstar series can affect consumer demand. A formerly intangible (that is, unmeasurable) feature, we show that consumers do indeed value popularity. However, consumers value accessing content libraries that have a wide selection of reasonably popular series more so than libraries with only a few wildly popular superstar series. Third, our framework ignites a warranted discussion surrounding content strategy, illustrating that a balance must be struck between overall content library popularity and superstar series. In spite of potential short-term gains from chasing superstar series, this may not be the proper focus for most SVOD platforms, which, based on the results of this paper, should focus on reducing the amount of highly unpopular series.

The remainder of this paper is organized as follows. The SVOD industry and the superstar effect will be discussed along with related media and economics literature, identifying notable research gaps this paper aims to inform. Subsequently, this paper will present the data used and key observations about the SVOD industry revealed by this novel dataset. This will be followed by our empirical methodology, and results. Thereafter, this paper will discuss the implications of our results for the SVOD industry and offer a conclusion for this study.

Literature review

The SVOD industry & series superstars

In this section, we discuss the competitive landscape of the streaming industry and describe the emergence of the development of original *superstar series* used by SVOD platforms to differentiate themselves. We further discuss how this emphasizes the need to overcome the limitations of previous measures of audience engagement and to rely on more recent measurement techniques that are capable of capturing the popularity of streaming content.

The SVOD industry has recently completed its first phase in the marketplace, determining its key members and creating high barriers to entry. Amazon Prime Video, Hulu, HBO Max (Max), Apple TV+, Netflix, and Disney+ are all primary members in the industry itself, boasting enviable subscription numbers and content at the forefront of the cultural zeitgeist. In the last few years, however, a saturated United States SVOD marketplace has led to these platforms facing heightened competition for existing and new subscribers, who are increasingly becoming sensitive to SVOD platform prices (Palomba, 2021; Krouse & Toonkel, 2022; Maas, 2022b). In 2022, Deloitte predicted at least 150 million subscriptions would be canceled around the world, though it was still expected that the market would realize net gains in overall subscriptions (Arkenberg, 2022).

In response to this increasingly competitive landscape, SVOD firms have turned to acquiring as well as producing popular content to retain and compete for new subscribers. Initially, Netflix and Hulu were the only two major SVOD platforms with original content series, and so churn was a lesser factor compared to content production. As competitors came into the marketplace, each SVOD platform competed to communicate a superior value proposition by swelling content libraries to attract consumers to subscribe to their respective platforms. As illustrated by Diesel Labs in a Variety VIP+ article, original content releases by SVOD platforms have increased by a staggering compounded annual growth rate of 52% (Aquilina, 2022b). In fact, scripted and unscripted originals across cable, broadcast, and streaming in the United States increased by an annual 14.18% compounded annual growth rate (CAGR), from 125 in 2002 to

2,024 in 2022 (Bridge, 2022). In 2021, for the first time, SVOD original series (896) eclipsed cable (785) and broadcast (206).

To stand out from the crowd, many SVOD platforms have focused on the development and/or purchase of *superstar series* – original content series crafted to cut through the vast sea of streaming content available to serve as lucid marketing beacons for parent SVOD platforms. Rosen (1981) first used the superstar effect to describe the phenomenon of particularly talented people who earn remarkable salaries and create positive spillover effects on productivity, profits, or customer engagement. While originally conceptualized with respect to individuals, we apply the idea of Rosen's (1981) *superstar effect* to high-performing streaming series, hereafter referred to as *superstar series*. The concept of superstars in media related industries will be elaborated on in the related literature section.

By focusing on the development of original *superstar series*, SVOD providers hope to draw in new subscribers, retain current subscribers, and benefit from the possible positive externalities. As consumers countenance seemingly infinite content, due to time and practical constraints, they may elect to view what is popular - that is, *superstar series* - as determined by what has been written about in media, what is highlighted on a SVOD kiosk menu, or through word of mouth from confidants (Cadario, 2015; Romaniuk, 2007; Yeh, 2015). In addition to attracting and retaining subscribers, as in Rosen's (1981) original conceptualization of the idea, there are several positive externalities that can increase profits when developing original *superstar series*. A consumer once subscribed is likely to view other content provided by the SVOD platform, increasing the likelihood of other content provided by this SVOD's platform becoming popular, thus attracting additional new subscribers. Furthermore, if demand for superstar series is relatively inelastic, SVOD providers can raise their prices and earn additional profits. In light of volatile SVOD churn rates and refractured conversation surrounding how much content is needed in the SVOD marketplace, this necessitates a further inquiry into how much audiences actually value superstar series. Should SVOD providers work on improving the overall popularity of their content, or focus on developing superstar series?

Theoretical framework

This section establishes the current body of research most relevant to our investigation. Our work sits at the intersection of three key areas of SVOD related research. First, our work directly examines popular content relevance and how strong the superstar effect is in the SVOD industry. Second, this paper illuminates advancements in audience demand measurement, and how this may be used to distill consumer demand for content. Third, this study relates to research surrounding content value and optimizing content libraries under SVOD platforms. A table has been included that encompasses some of the literature that will be discussed further.

Related Literature					
Related Literature	**Journal**	**Title**	**Author(s)**	**Method**	**Findings**
Superstar effect	The American Economic Review	The economics of superstars.	Rosen, S. (1981)	A demand and supply structure model is created to illustrate and trace how a relatively small amount of outstanding people can earn enormous financial compensation and significant influence in a marketplace.	The superstar effect empowers a smaller proportion of people to dominate the lion's share of a marketplace, creating a "winner-take-all" effect.
Superstar effect	Journal of Marketing	How critical are critical reviews? The box office effects of film critics, star power, and budgets.	Basuroy, S., Chatterjee, S., & Ravid, S. (2003)	Time series and cross section regressions are used on movie data.	The sentiment behind critic reviews is connected to box office receipts, particularly in the early week of release, though they are moderated by star power and budgets to some extent.
Superstar effect	Information Systems Research	Long tails vs. superstars: The effect of information technology on product variety and sales concentration patterns.	Brynjolfsson, E., Hu, Y., & Smith, M. (2010)	A taxonomy is built to illustrate what drives longtails and superstars.	Based on technology evolutions, superstars may be positioned to take over across numerous product categories.

Superstar effect	Journal of Sports Economics	Superstars, uncertainty of outcome, and PGA tour television ratings.	Gooding, C., & Stephenson, E. (2017)	An ordinary least squares model was built to predict Nielsen Ratings for golfing series from 2010-2013.	Nielsen ratings were largely driven by the superstar effect, impacting PGA Tour television contract negotiations.
Superstar effect	Journal of the Academy of Marketing Science	The impact of superstar and non-superstar software on hardware sales: The moderating role of hardware lifecycle.	Gretz, R., Malshe, A., Bauer, C., & Basuroy, S. (2019)	A structural discrete choice model was built to look at how consumers maximize utility by using NPD market research point of sale video game console data from 1995-2007.	Superstar and non-superstar software influence hardware demand, the superstar software is most impactful in the beginning of a video game console life cycle.
Superstar effect	Applied Economics	The superstar effect in gymnastics.	Meissner, L., Rai, A., & Rotthoff, K. (2021)	An econometrics model was built using data from the USA Gymnastics website for women's gymnastics competitions from 2011 to 2016.	Gymnasts are inclined to take greater risks in events that Simone Biles, a gymnastics superstar, is weak in, as a way to compete against her.
Audience measurement	Journal of Broadcasting & Electronic Media	Does streaming TV change our concept of television?	Leiner, D. & Neuendorf, N. (2022)	A web-based survey is deployed and t-tests are executed to understand consumer expectations of streaming platforms.	Consumers who stream television expect greater flexibility and are more inclined to seek out entertainment content.

Audience measurement	Journal of Media Economics	The show must go on(line): the impact of content and system quality on the usage of television streaming content libraries.	Zabel,C., Kunz, R., Telkmann, V. & O'Brien, D. (2024)	A web-based survey was deployed and a structural equation model was built to explore how content quality, system quality and habit may influence use of streaming platforms.	It is important for consumers to cultivate habit formation, emphasizing the need for consistent content delivery and personalization. In particular, content quality impacts actual usage, word of mouth, and brand perception of SVOD platforms.
Audience measurement	Journal of Digital Convergence	A study on the factors influencing continuous intention to use of OTT service users: Focused on the extension of technology acceptance model.	Lee, M., Kim, W., & Song, M. (2019)	A web-based survey was deployed and a structural equation model was built to understand variables that may impact intent to use OTT platforms.	Perceived usefulness, perceived playfulness, and perceived innovativeness impacts continued intent to use OTT (SVOD) platform.
Audience measurement	Computers in Human Behavior	Consumer adoption of mobile TV: Examining psychological flow and media content.	Jung, Y., Perez-Mira, B., & Wiley-Patton, S. (2009)	A web-based survey was deployed and a structural equation model was built to understand how content, perceived usefulness, perceived ease of use, and cognitive concentration could impact intention to use mobile TV.	Cognitive concentration and content are indirectly related to perceived usefulness and intention to use mobile TV, while perceived usefulness and perceived easy of use are directly related to it.

Audience measurement	First Monday	Relative advantages of online video platforms and television according to content, technology, and cost-related attributes.	Cha, J. & Chan-Olmsted, S. (2012)	A web-based survey was deployed and multiple linear regressions were run to understand how content, cost, and technology influence perceived relative advantages of online video platforms.	Content variety and quality impact perceived advantages of online video platforms.
Audience measurement	Management Science	Bundling information goods: Pricing, profits, and efficiency.	Bakos, Y. & Brynjolfsson, E. (1999)	An econometric model is built to examine the profitability and value behind bundling information goods.	Bundling information goods allows for realized efficiencies, profits, and sales.
Content strategies	Journal of Cultural Economics	Content valuation strategies for digital subscription platforms.	Kubler, R., Seifert, R., & Kandziora, M. (2021)	A conceptual framework is developed that series how digital video platform providers (DSPs) may evaluate content.	Bundled content types impact the type of customer along with total content value for digital video subscription platforms.
Content strategies	Management Science	Bundling information goods of decreasing value.	Geng, X., Stinchcombe, M., & Whinston, A. (2005)	Microeconomic theory is used to devise propositions to test the efficacy in bundling information goods.	There is clear predictive equity in bundling information goods, which may lead to optimized efficiencies and higher profits.

Content strategies	Management Science	An empirical analysis of digital music bundling strategies.	Danaher, B., Huang, Y., Smith, M., & Telang, R. (2014)	Data collected over time from a record label is utilized to conduct quasi-experimental analyses and develop an econometrics model. Both approaches aid in depicting the price elasticities for albums and songs.	Maintaining lowered album prices along with tiered pricing strategies can lead to robust revenue growth.
Content strategies	Information Economics and Policy	Business models for streaming platforms: Content acquisition, advertising, and users.	Carroni, E., & Paolini, D. (2020)	Microeconomic theory is used to illustrate interactions across content, advertisers, and users on a monopolistic platform.	A larger audience can influence a platform to expand its advertising and content quality offerings. It is expected that this will lead audiences toward a premium price tier on the platform.
Content strategies	Journal of Marketing Research	Competition of content acquisition and distribution under consumer multi purchase.	Jiang, B., Tian, L., & Zhou, B. (2019)	A spatial model is built to examine and illuminate taste and content among consumer multi product and single product purchases.	In multiproduct purchase settings, content creators are inclined to sell content to only one content distributor. Differently, in a single purchase setting, a content creator may be more inclined to sell to multiple content distributors.

Content strategies	Marketing Science	Estimating demand for subscription products: Identification of willingness to pay without price variation.	Chou, C. & Kumar, V. (2024)	An econometrics model is built to create price estimation results for distribution of willingness to pay.	High-use engagement and subscriptions can illustrate consumer willingness to pay for subscription platforms.
Content strategies	Production and Operations Management	Competition through exclusivity in digital content distribution.	Chiang, I., & Jhang-Li, J. (2020)	Microeconomic theory is used to create utility functions and models to examine new content impact on windowing as well as subsequent window negotiations.	Windowing, the practice of cycling content through successive distribution channels, can impact how streamers' subscription and advertising revenue streams may vary, and how content owners may diversify benefits from streamers and cable networks.

The superstar effect

First, our work furthers the application of superstar series to content, elevating our understanding on how consumers demand content, and how this may create stark differences surrounding what types of content are impactful on consumer propensities to subscribe. The prevalence of top-tier content on SVOD platforms indicates evidence of the superstar effect, including the resulting inequalities accelerated by technology. The *superstar effect* was first coined by Rosen (1981), who illustrated that in many occupations, there are particular people who earn remarkable salaries based on extraordinary output. In these industries, there is skewed demand in the marketplace for the most talented people. This can lead to great disparities in income, in spite of these differences. Regardless of consumer demand, creatives must put out the same amount of energy and effort, and overall costs do not always rise based on the targeted total addressable market. Technology can further enhance and expand how scale can be achieved, resulting in higher incomes across CEOs, attorneys, and other high-achieving professionals, and leading to inequalities among these groups (Gabaix & Landier, 2008; Garicano & Hubbard, 2009; Kaplan & Rauh, 2010). A study by Elson and Ferrere (2013) demonstrated that this trend was found among executives, as powerful board dynamics and market inefficiencies allowed executives to reap the rewards of significant compensation and perks.

Across the vast constellation of media and entertainment industries, the superstar effect can be applied to actors, creatives, and content, but there is a notable gap in understanding how the superstar effect specifically plays a role in the SVOD industry. Koenig (2023) demonstrated that the introduction of a television station could increase audiences for top entertainers and artists, but also lead to further revenue loss for lower-tiered counterparts. Meissner, Rai, and Rotthoff (2021) found that this effect exists in gymnastics, in which competitors attempt riskier performances in the presence of a superstar, seeking to eclipse them. The presence of high-profile NBA stars patently impacts arena attendance (Hausman & Leonard, 1997; Humphreys & Johnson, 2020). Star presence is a positive externality spillover benefit for all other teams, raising attendance levels. This has also been shown to exist on an individual level in golf, as past matches that featured Tiger Woods helped increase the purse for the ultimate tour champions (Gooding & Stephenson, 2017). Differently, in the video game industry, superstar video game software can help accelerate hardware console sales in the beginning of the product life cycle, though this effect diminishes later in the cycle (Gretz et al., 2019). In the movie industry, superstar actors can insulate movies that receive negative criticism from critics (Basuroy et al., 2003), generating up to just over ten million dollars at the box office (Hofmann et al., 2017). Clearly, not all products will garner similar levels of demand, which may skew attention toward actual sales figures (Schmittlein et al., 1993).

While some content series may appear as imperfect substitutions to other available series, risk averse consumers may be less interested in taking a chance on other, niche series. There is evidence that such a strategy may prove fruitful for SVOD platforms. According to Tan et al. (2017), demand for the top 0.1% of movies increased nearly four times as fast as for the top 10% of movies. However, the authors noted that Netflix's recommendation system migrated consumers to the same products. Online consumers tend to be more interested in providing feedback on popular items, too (Dellarocas & Narayan, 2007). Overall, hits continue to propel markets, as they are inclined to draw people together, create engagements, and serve as a cultural mirror of society (Mittell, 2009).

However, as illustrated, while the superstar effect has been applied to myriad subject areas, it has not been applied to streaming video series. Against the backdrop of the superstar effect (Rosen, 1981), it is possible to consider original content series as similar to creatives, high-performing original content series as superstars, and each episode as an output of talent. First, content series function as imperfect substitutions, since there are particular creative expertise, artistic viewpoints, and other inimitable resources that are not incorporated across all content series (Chan-Olmsted, 2006). Second, there is a clear reliance on technology from SVOD platforms, which are equipped to stream content to consumers, and through recommendation systems and user experiences, push particular content to consumers. This fresh application to content, rather than creatives, can help illuminate audience demand variance across content series.

In sum, there is a clear gap in understanding whether or not popular series exhibit a superstar effect in the SVOD industry, and, if this effect exists, how pronounced it may be. This paper contributes to the literature studying the superstar effect in media by applying the concept to popular SVOD series and evaluating how relevant this effect is in the SVOD industry. We find that consumers of SVOD platforms do not, *on average*, value significant numbers of superstar series provided by SVOD platforms. However, we do find that consumers are quite heterogeneous in how much they care about superstars; therefore, there may be a mild superstar effect since there are some consumers that have a high valuation of superstar series.

Audience measurement

Understanding the superstar effect across SVOD platforms necessitates a re-evaluation of how audience viewership of TV series is conceived and measured in the audience measurement marketplace. In the past, audience measurement revolved around capturing mass audience viewing habits, and using these data points to forecast future viewership (Phalen, 2006; Napoli, 2011). To do this, television audience panels were largely relied upon to evaluate macro audience demand, though these metrics invited a notable level of forecast error.

Moreover, gaining viewership cooperation with viewers for active measurement has proven difficult to do (Hessler, 2021), requiring nuanced and external approaches to collect viewing data as well as looking at external sources. As previously stated, Nielsen has struggled to regain its footing in the broader television industry, leaving room for other firms to enter the space to create robust and accurate metrics (Moffett, 2022; Neff, 2024).

Recent audience measurement literature considers how consumers engage streaming platforms, and in particular how consumers find value. According to Webster (2014), audience measurement should be geared toward measuring available attention supply, and different forms of engagement, across SVOD platforms. Particularly structured-based approaches to audience measurement consider platform availability and content schedules. However, the use of external data-driven structures, such as social media posts or shopping data (Liu-Thompkins & Malthouse, 2017; Kim & Kim, 2018; Webster, 2018) demonstrate avenues to further enhance and refine audience measurement by exploiting other structures that audiences engage in. This is symptomatic of a shift toward network audiences, in which audiences can connect with and interact with each other (Webster, 2018). Under the auspices of market information regime (Anand & Peterson, 2000), a new marketplace manifests when a set of actors seek to make sense of an environment through a new manner of information production and distribution. A greater emphasis is placed on harvesting granular metrics that consider daily demand for content, even when audiences may not be directly exposed to particular content each day. This acknowledges that daily audience demand may fluctuate, as some audience members may view content on one day, not engage in it at all for several days, and may conduct searches or social media engagement on other days. Working together in concert, disparate metrics can come together to create an audience attention mosaic based on data-driven media structures (Webster, 2018). It is imperative for consumers to harness strong habit formation and user experiences on streaming platforms (Jung et al., 2009; Lee et al., 2019; Leiner & Neuendorf, 2022; and Zabel et al., 2024). More importantly, it is imperative that consumers perceive strong content variety (Cha & Chan-Olmsted, 2012) which is found particularly among bundled platforms (Bakos & Brynjolfsson, 1999), leading to further consistent experiences. As consumers countenance seemingly infinite content, due to time and practical constraints, they may elect to view what is popular - that is, these *superstar series* - as determined by what has been written about in media, what is highlighted on a SVOD kiosk menu, or through word of mouth from confidants (Romaniuk, 2007; Cadario, 2015; Yeh, 2015).

This has forced scholars as well as practitioners to reconcile how audiences should be measured in this age. In the ever-evolving audience marketplace, there is a new generation of firms working to innovate unique ways to assess, judge, and measure audiences. These firms include Samba TV, VideoAmp, Diesel Labs, and Parrot Analytics among others (Diesel Labs, 2022; Parrot Analytics, 2022b; Samba TV, 2022; VideoAmp, 2022). At this juncture, the audience measurement industry is at an intertidal point, in which there is momentum among audience measurement firms to redefine their marketplace, and institutionalize these manners of measurement (Meyer & Rowan, 1977). In particular, Parrot Analytics has been able to separate itself from other new audience measurement tools based on its ability to track viewer passion for content, rather than simply size of viewing audience (Lee, 2020).

This work contributes to the literature on audience demand measurement by formulating a new way to consider audience engagement. Previous measures have proved inadequate for addressing important questions regarding the SVOD industry. This paper creates a new measure of content popularity based on a dataset from a new audience measurement firm, Parrot Analytics, which uses multiple measurements to approximate consumer demand for content. Using this dataset, this study endeavors to introduce a new way to understand how consumers evaluate content, and how this may impact propensities to subscribe to streaming platforms.

Content strategies

Finally, this work relates to studies that explore what content strategies SVOD platforms should pursue and addresses a relatively understudied aspect of content management: how integral are superstar series in ascertaining subscribers and consumer demand? Moreover, how much do consumers demand superstar series, and how might this inform content strategy? Currently, in the marketplace, all streaming platforms have price tiered options, with premium options bereft of advertisements, while lower priced platforms offer some level of advertisements. From a platform standpoint, understanding how to migrate consumers toward premium and ad-tiered platforms in part aids in understanding particular content strategies. Netflix was the first entrant to harness data science and big data to inform all areas of content strategy, including which types of series to create. It has attempted to scale content series at great lengths, and with mixed results. HBO has retained its prestige television brand image, producing far less content than Netflix, but most of which has been celebrated by critics in the industry, and Apple TV+ has adopted a similar strategy. Hulu, until recently, has served as a streaming platform providing free cash flow for its parent Disney company. Disney+ has worked assiduously to appeal to children and families as an early entry point into its brand for young consumers.

There is a notable gap surrounding how superstar strategy and overall content library popularity interact with each other. Content bundling can impact content value for SVOD platforms (Geng et al., 2005; Kubler et al., 2021). There is a significant impact on the number of content choices surrounding willingness to pay for content (Gupta et al., 2023). Moreover, the manner in which windowing strategies are executed, in which content may be available among several competitors or exclusively to one, can create a massive competitive advantage (Chiang & Jhang-Li, 2020). Naturally, consumer demand for content will determine willingness to pay, which is why it is adamant that streaming platforms consider manners in which to increase and elongate engagement periods (Chou & Kumar, 2024), as well as increase its user base to attract advertisers and content producers interested in being showcased on their platform (Carroni & Paolini, 2020). Naturally, tiered pricing has been demonstrated to be an angle from which to foster an audience base (Danaher et al., 2014). Of course, these prices are determined in part by how content creators elect to sell content, as exclusive deals or multi-party deals are lucrative in different settings (Jiang et al., 2019). Therefore, while these disparate elements of strategy are understood, it is still unknown how superstar series may interact with other content in a content library, and in particular, what the appeal of superstar series are compared to the rest of the library.

Collectively, this work contributes to these literature streams by exploring how content popularity and superstar series drive demand for SVOD platforms. Our findings suggest that consumers value a SVOD streaming catalog that has more uniformly popular series. While superstars are somewhat valued, consumers on average value a catalog more when more series are on the whole more popular. This result directly informs SVOD platform content strategies by demonstrating that pursuing potentially costly superstar series (at the expense of high series content variability and low-quality content populating a content library) may not be the most effective strategy.

Data & observations

This study leverages a novel measure of audience demand capable of capturing the popularity of SVOD content over time. The authors manually collected data from Parrot Analytics to incorporate aggregate daily demand for streaming series. Parrot Analytics specializes in measuring aggregate audience streaming and video content consumption through accounting for 1) downloads and views, 2) online searches, and 3) social media posts (Parrot Analytics, 2022a). These metrics feed into aggregate TV demand ratings each day that function like stock tickers to calibrate demand for content. Due to how this dataset is calculated, we consider the Parrot Analytics measure of audience demand as a reasonable measure of *popularity*. This measure of popularity offers a holistic and granular assessment of individual series popularity across consumer journey functions.

In this study, we selected one hundred and ten (N=110) series across prominent SVOD subscription platforms first through stratified sampling (e.g., superstar, mild popularity, and low popularity - valued content) and subsequently systematic sampling based on aggregate demand on the first day of sampling. This was done to ensure that there was a broad distribution of series tracked that 1) illustrated variance in quantity demanded and 2) demonstrated the range of popularity in content on each platform. In this paper, we focus on the following SVOD platforms: Amazon Prime Video, Hulu, HBO Max, Apple TV+, Netflix, and Disney+. These 6 platforms comprised 81.3% of the demand share in 2021 (Parrot Analytics, 2022a). The list of series for each SVOD series that data was collected for is listed in the appendix in Table A.1. Across one hundred and ten series, daily aggregate demand was collected for 327 (T=327) days, from August 23, 2021 (Q3 2021) through July 16, 2022 (Q2 2022). However, there were several days in which the site was down due to maintenance, which precluded data collection. In total, there are thirty-five thousand one hundred and twelve (NT=35,112) data points in the data set.

Since the demand measure is relative only on a daily basis, and not over time, we create a measure of *popularity*. We first normalize the daily raw demand measure to between 0 and 1 where 1 is the highest in demand, or the most *popular*. This allows us to compare relative popularity over time. A series with a popularity measure of 1 on a given day indicates that it was highest in demand relative to the other series in the sample. This series then may have a different relative popularity the next day, and so on.

Table 1 displays the summary statistics of this popularity measure by platform for the entire sample period, and Table 2 for each quarter. The median series popularity by platform is quite high, varying from 0.86 to 0.95. Over our entire sample period, we see that for each platform, there is some right-skewness to the data; most of the series-day observations in our sample tend to be relatively more popular, with fewer less popular series-day observations. The average popularity and standard deviation in popularity for each SVOD platform reflect their catalog strategy. Apple TV+, and HBO Max have positioned themselves as providers of smaller but higher quality catalogs, and so exhibit higher popularity scores on average with lower standard deviations - that is, a lower variation in popularity. Disney+ enjoys similar results with a larger content library, which is targeted toward children and families. On the other hand, Netflix and Hulu focus on providing a large variety of content, and so exhibit lower average popularity scores and a wider variation in popularity. Since SVOD platform data (e.g., number of subscribers) is only available at the quarterly level, we additionally average these measures by platform. Figures 1 and 2 display both the average mean and average standard deviation of series demand, or popularity.

[Table 1 about here]

[Table 2 about here]

We also define a measure that we call *superstars*. Superstar series are series that have, on average, a relative demand measure in the top 1% of series for that quarter - that is, they have a popularity measure of, on average within a quarter, 0.99. To capture how many superstar series a platform has relative to other platforms, we look at the percentage of series that a platform has that are superstars. Figure 3 displays the percentage of superstar series for each quarter and SVOD platform considered in this paper, from Q3 2021 to Q4 2022. As is shown, Disney+ is the leader in superstar series (about 20%-32%), with Netflix the closest follower (10-15%). The remaining percentage of superstar series at other SVOD providers most often lies in the 5-10% range.

[Figure 1 about here]

[Figure 2 about here]

[Figure 3 about here]

We also collected information regarding SVOD platform plans and prices in the U.S. and internationally. Plans and prices are measured on a monthly basis. In the U.S. market, SVOD providers often have multiple monthly price tiers available with different features, such as the number of screens able to be used at one time or HD viewing options. Additionally, some providers offer cheaper ad-support tiers while others offer only ad-free options. For example, Netflix has 3 ad-free plans: Basic, Standard, and Premium. Higher cost plans provide HD options and multiple screens. Both Hulu and HBO Max have a lower-tier ad supported plan, and a higher tier no-ads plan. Both Disney+ and Apple TV+ have only one subscription option, and it is ad-free. Amazon Prime Video is a special exception. Customers can access Amazon Prime Video through their general Amazon Prime subscription, or through a separate subscription for Amazon Prime Video only. Content can be ad-free or ad-supported, and there are additional add-on options for specific channels.

Given the variety of options available, we construct two measures of prices for each quarter. First, we construct an average SVOD provider price. For each month, we take the average over the prices of a provider's available plans, both ad-free and ad-supported. For Amazon Prime Video, we use the average of the video-only price and the full Prime Membership price. We believe using this is reasonable since the cost of a full Prime Membership is comparable to the prices of the other SVOD providers we are interested in, but we caution the reader to consider estimates as rough approximations as there are other factors than just Amazon's SVOD platforms that drive a consumer's choice of an Amazon Prime membership.

Second, we consider the median ad-free price. For each month, we use the price of the middle-of-the-road ad-free option, if applicable. In the case of Netflix, we use the price of the 'standard' plan. In the cases of Hulu, HBO Max, Disney+, and Apple TV+, there is only one ad-free plan, and so we use this price. For Amazon Prime Video, here we use the video-only price. Finally, we use the monthly price measures to create a quarterly price measure. In the case where SVOD prices changed during the quarter, for both price measures, we use the price that was effective during the majority of the quarter. If the price changes occurred in the middle of the quarter, we use the average price. Figures 4 and 5 display the average price and the median ad-free price measures by platform.

[Figure 4 about here]

[Figure 5 about here]

Lastly, we collected information regarding subscriber shares in the U.S. market for our SVOD providers of interest. First, we collected information on new subscriber shares, that is, the percentage of *new* subscriptions that a given SVOD subscriber obtains each quarter. We also collected information on total subscriber shares, or the percentage of *existing* subscriptions a SVOD subscriber holds each quarter. Figures 6 and 7 present the quarterly new and total subscriber shares for each platform. Unfortunately, total subscriber data is not available for Amazon Prime Video. Moreover, data collection ended during Q2 2022, before the Q2 2022 total share announcements from SVOD platforms.

[Figure 6 about here]

[Figure 7 about here]

These measures of new and total subscriber shares capture different types of consumer decisions, and as such, different types of market leaders. The first measures current consumer choices: in each quarter, a consumer chooses whether to subscribe to a given provider. This decision is instant, and more akin to the traditional notion of selling a good to a consumer. The second reflects both the new consumer's decision to sign up with a provider, but also the existing consumer's decision to *stay* subscribed to a particular SVOD subscriber, that is, a decision *not to cancel*. This type of decision by the existing consumer is likely to be characterized by some persistence over time for several reasons. First, a consumer already subscribed to a given SVOD provider will face some switching costs if they decide to move to another provider either monetarily, such as an increase in the monthly subscription fee, or indirectly. A consumer might take some time to get used to a new user interface, or feel they are giving up on future content they might enjoy. Second, this decision is much more passive. An existing subscriber does not have to do anything to continue to be a subscriber, whereas to cancel they must act. As the monthly price of streaming platforms is not like that of a larger purchase such as a television set or a gaming console, there may be consumers who simply forget to cancel even if they do not highly value the platform. Particularly in this second example, an existing subscriber of a SVOD platform may not respond linearly to an increase in price - it may take a large price hike for the existing subscriber to make the active decision to cancel their subscription.

Observations from the data

As previously discussed, the Parrot Analytics demand data used in this paper is differentiated from other standard audience measurements used to track SVOD content, as it incorporates not only audience views, but engagement with online content and social media. As this is a novel dataset, before conducting our formal empirical investigation, we first discuss several important observations this data reveals about the SVOD industry during our sample period.

Observation #1: Popularity across SVOD platforms follows seasonal trends, regardless of the individual popularity of the platform. Television and video industries have evolved toward a more fragmented universe, in which new content is made available all the time. However, it is not without its seasonal constraints. The holiday season is largely a popular time for holiday specials and premieres, and the spring is also positioned for new original content series just before good weather and vacations lure consumers away from screens and portable devices.

Figure 1 displays the average mean series demand over time for each SVOD platform, reflecting the popularity of programs in each quarter, from Q3 2021 to Q2 2022. Figure 2 depicts the new subscriber share by SVOD platform over time. As is shown in these figures, for the HBO Max platform, Q1 2022 included combined growth of 3 million subscribers, and it also saw a rise in average mean series demand by 2%: Q1 2022 saw the return of original content series *Euphoria*, *The Righteous Gemstones* (Strout, 2021) as well as the return of *Last Week Tonight* (White, 2022). Another platform that saw a rise in average mean series demand in Q1 2022 and Q2 2022 and rise in new subscriber share in Q2 2022 was Amazon Prime Video. Amazon finally closed on the long-discussed acquisition of the MGM library in Q2 2022 (Maas, 2022a). In comparison, Netflix struggled during this period, hemorrhaging roughly 200,000 subscribers in Q1 2022 and nearly one million subscribers in Q2 2022 (McCluskey, 2022). Finally, Figure 2 presents the average standard deviation of series demand by platform over time. A higher standard deviation indicates a larger range in the aggregate popularity measure over the series for the considered platform. Movements in the standard deviation of popularity are remarkably correlated across SVOD platforms, suggesting that aggregate demand for SVOD content follows industry seasonal and market forces.

Observation #2: Possessing the highest subscriber share is not necessarily correlated with the highest percentage of superstar programs. It is difficult for consumers to fully realize the benefits of a SVOD platform. As SVOD platforms create content at an exponential rate, it becomes exceedingly difficult for consumers to be aware of all available content. SVOD platforms that charge high premiums are most inclined to be able to offer the most superstar series. However, these SVOD platforms also cost more for subscribers (Aquilina, 2022b). The churn rate among SVOD subscribers has become an outstanding issue for SVOD platforms. Therefore, it is possible that there will not be a correlation between the number of subscribers and the amount of superstar series.

Figure 3 illustrates the percentage of superstar series among the sample of series studied in this paper for each platform. Recall that superstar series are those that are on average in the top 1% of series each quarter. It is clear that Disney+ and Netflix possess a great amount of superstar series - however, Disney+ and Netflix do not have higher new subscriber shares than other SVOD platforms. In fact, Amazon Prime Video has the largest new subscriber share despite having a low percentage of superstar series. Apple TV+ and HBO offerings on Max differ from their peers in that their content is highly curated and limited (Pegoraro, 2021). Therefore, when an original content series debuts on either SVOD platform, it may receive more interest (and subscriptions for SVOD platforms) because it is one of a few original content series that debut annually on either platform.

Observation #3: SVOD platforms with lower (higher) prices are inclined (disinclined) to gain new subscribers but retain less (more) overall subscriber shares. Over the past five years, SVOD market entrants have attempted to accrue new subscribers, and, until recently, most were disinterested in airing advertisements. The subscription model places tremendous pressure on SVOD platforms with small budgets to not only accrue, but maintain subscriber share against larger competitors. Moreover, consumers are inclined to chase content rather than SVOD platforms, and since switching costs among SVOD platforms are notably low, high consumer buying power allows them to switch from platform to platform, making it increasingly difficult for SVOD platforms to maintain subscriber gains. However, it is likely that those that can afford to invest in higher-end SVOD platforms may be less inclined to leave them.

As Figures 6 and 7 show, a higher new subscriber share does not necessarily reflect a higher total subscriber share. We can see smaller SVOD platforms, such as Apple TV+ and Max, realize notable new subscribers in Q2 and Q1 of 2022 respectively, though these gains appear to be immaterial to total subscriber share. This trajectory came in the wake of the end of the first lifecycle phase of the SVOD marketplace, as consumers were able to subscribe to several SVOD platforms, and were beginning to learn how to quit and sign up for different SVOD platforms on a month-to-month basis. It should be noted that this is an extraordinary new media behavior, as nearly all of these consumers were (or continue to be) cable and satellite TV subscribers. These SVOD platforms employ high switching costs, making it difficult for consumers to switch from one plan to another. Moreover, each of these SVOD platforms largely offer access to similar content, and so price served as a primary value proposition. On a different plane, this signified the reduced impact of Netflix in the marketplace. A first mover in this space, Netflix established new patterns of video consumption, including binge-watching, using search queues, and categorizing content based on starkly different labels than traditional genres. Still, while price hikes have persisted, so have the churn rates of SVOD subscribers. The SVOD market average churn rate during this time frame varied from 4% in September 2021 to 5.5% in July 2022 (Aquilina, 2022a).

As Figures 4 and 5 show, Apple TV+ was the lowest cost option in both the average and median price measures followed by Disney+, while Netflix and Max were on the higher end of both price measures. Amazon Prime Video and Hulu occupied the middle positions, but flipped between measures. Recall that the median ad-free price for Amazon Prime Video is Amazon’s video-only price, whereas the average measure includes the full Prime membership which can be viewed as more ‘premium.’ Hulu’s premium platform is also its ad-free tier, resulting in a higher median-ad free price and a lower average price than Amazon Prime Video. Netflix had the highest average price measure by quite a large margin, but was quite close to the median ad-free price of Max.

This price and subscriber data mirror trends in the SVOD marketplace, in which there is positive price persistence. In other words, the price moves alongside aggregate demand, though this does not discount the possibility of shifts in price pullbacks over time. However, in the

SVOD marketplace, there have not been price decreases from SVOD platforms, though there have been instances of price discrimination campaigns, including discounts for college students for SVOD platforms like Hulu, Apple TV+, and Amazon Prime Video (Schindler, 2012; Anderson, 2022). Instead, tiered offerings have been offered based on consumers' willingness to pay alongside each SVOD's platform level interest with each consumer segment (e.g., some tiered SVOD platforms may offer limited content). Up until the last few years, SVOD platforms have largely experienced annual subscription increases in respective consumer bases. However, stiff competition among a crowded SVOD marketplace also means higher costs for licenses and continued iteration over consumer experiences (Richter, 2022).

Empirical methodology

In this section, we outline our empirical strategy. We first review the structural model used to estimate consumer demand for SVOD platforms. We follow the economics literature in industrial organization and use a standard Berry, Levinsohn, and Pakes (1995) structural demand estimation model (hereafter referred to as BLP) in the spirit of Nevo (2000). Second, we discuss the model's assumptions and validity in the context of the SVOD market.

Demand estimation method

We estimate demand for a given SVOD platform by using a random coefficient discrete choice model as in BLP (1995) and Nevo (2000). There are $J = 6$ SVOD platforms, Netflix, Hulu, Amazon Prime Video, Apple TV+, Disney+, HBO Max, and 4 quarters, $t = \{\text{Q3 2021}, \text{Q4 2021}, \text{Q1 2022}, \text{Q2 2022}\}$. We assume indirect consumer utility takes the following form for individual consumer i, SVOD platform j, and quarter t:

$$u_{ijt} = X'_{jt}\beta_i + \alpha_i(m_i - p_{jt}) + \zeta_{jt} + \epsilon_{ijt}$$

Where m_i is the individual's income, p_{jt} is the platform's monthly subscription price during the quarter, and ϵ_{ijt} is the individual error term that is independently and identically distributed with mean 0. Consumers can also choose the outside product $j = 0$, for which utility is normalized. The term ζ_{jt} captures the unobserved SVOD platform characteristics at time t: any characteristics we do not explicitly control for, such as user interface design, customer service, catalog variety, or even simply name-recognition of the brand. X_{jt} is a $K \times 1$ vector containing K SVOD platform characteristics that we specifically control for. In this paper, we are interested in how series popularity and superstars play a role in consumer's utility, and so we use quarterly level summary measures of series popularity for each platform and the percentage of superstar series as described in the previous section. We define the individual slope coefficients (α_i, β_i) as:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma v_i$$

Where $v_i \sim N(0, I_{K+1})$ and Σ is a scaling matrix. This is slightly different from the canonical BLP model since we lack demographic information on SVOD customers. We can then decompose consumer utility u_{ij} into mean and heterogeneous utilities using the definition of the random coefficients:

$$u_{ijt} = \delta_{jt} + v_{ijt}$$

Where $\delta_{jt} = X'_{jt}\beta + \alpha(m_i - p_{jt}) + \zeta_{jt}$ and $v_{ijt} = X'_{jt}(\beta_i - \beta) + (\alpha_i - \alpha)(m_i - p_{jt}) + \epsilon_{ijt}$. Utility is the sum of the mean utility earned from platform j at time t, δ_{jt}, and the individual deviations from the mean for platform j at time t, v_{ijt}. Heterogeneity enters through this second term. We assume the probability that individual i chooses platform j at time t is logit:

$$P(j = J|i,t) = \frac{\exp\left(\delta_{jt} + X'_{jt}(\beta_i - \beta) - (\alpha_i - \alpha)p_{jt} + \epsilon_{ijt}\right)}{1 + \sum_{i=1, i \neq j}^{J} \exp\left(\delta_{jt} + X'_{jt}(\beta_i - \beta) - (\alpha_i - \alpha)p_{jt} + \epsilon_{ijt}\right)}$$

Since $\alpha_i m_i$ does not differ between platform choice j, it is not relevant for the consumer's choice between platforms j. It is important to note that the canonical BLP model assumes that consumers may only choose one SVOD platform - survey data strongly suggests that individuals have multiple streaming platforms at once. Therefore, we consider this model as simply a rough approximation.

Let $G(v_i)$ denote the normal distribution of v_i previously mentioned. Let $s_{jt}(\delta_{jt})$ represent the market share of platform j at time t. We can write the market share as the weighted sum of probabilities over all individuals:

$$s_{jt}(\delta_{jt}) = \int_i P(j = J|i,t) dG(v_i)$$

That is, the market share at time t is a function of not only the mean utilities δ_{jt}, but also of the distribution of individual parameters of the multivariable normal distribution (α, β, Σ). The parameters of interest for estimation are $\theta = (\alpha, \beta, \Sigma)$. The method and algorithm used for estimation is described in the appendix.

Identification and instruments

Identification in our model relies on the assumptions that (1) demand shocks in the U.S. SVOD market are independent across SVOD markets geographically, (2) that cost shocks to a SVOD platform are correlated geographically, and finally (3) that our observed SVOD product characteristics are independent of unobserved SVOD platform characteristics.

First, we assume that a sudden change in valuation of the unobserved features of a SVOD platform, ζ_{jt}, in the U.S. does not affect the valuation in other countries, $\tilde{\zeta}_{jt}$. For example, say Netflix acquires the rights to stream a particular series but due to legal issues, they can only stream it in the U.S. and not the United Kingdom. Here, there is change in the valuation of unobserved features in the U.S. as a result of the addition of this series to Netflix's catalog. However, there is no change in the valuation of unobserved features in the United Kingdom since there is no change to Netflix's U.K. catalog. This assumption then implies that prices in the SVOD markets of another region or nation, $\tilde{p}_{jt}$ are uncorrelated with U.S. demand shocks ζ_{jt}: $Corr(\tilde{p}_{jt}, \zeta_{jt}) = 0$. There are some cases in which this assumption does not hold, however. For example, if Netflix rolls out a global change in the design of its user interface, then the unobserved valuation in both the U.S. and other countries may be correlated.

Second, we rely on the assumption that a cost shock to a SVOD platform affects pricing decisions worldwide. For example, a sudden increase in production costs for Netflix will affect their pricing decisions in all markets. This implies that SVOD prices in the U.S. market and in other markets for a given SVOD platform outside of the U.S. are likely to be correlated $Corr(p_{jt}, \tilde{p}_{jt}) \neq 0$. This assumption is more reasonable than the former. For example, say the sudden rise in production costs is only in the U.S. due to some legal change requiring Netflix to provide more compensation to actors. Instead of increasing prices only in the U.S. by a significant amount which can result in some customers switching to other platforms, Netflix may decide to increase prices in all markets by a very small amount to recuperate the increased costs.

Lastly, we assume that the vector of SVOD product characteristics X_{jt} are independent from unobserved SVOD platform characteristics ζ_{jt}. Our measure of SVOD platform characteristics X_{jt} rely on the popularity of a subsample of series in each platform's catalog, whether it is the average popularity or the percentage of higher popular series. As previously mentioned, unobserved platform characteristics can include things such as user interface design, customer platform, or catalog variety. There may be some cases in which the assumption that $Corr(X_{jt}, \zeta_{jt}) = 0$ may be violated: for example, a SVOD platform may follow a 'quality over quantity' strategy where they focus on purchasing or producing high popular series, which may have a higher probability of becoming popular.

Since prices in markets outside of the U.S. are correlated with U.S. prices but assumed to be uncorrelated with U.S. demand shocks, and since SVOD platform characteristics X_{jt} are exogenous from unobserved platform characteristics ζ_{jt}, we use international prices $\tilde{p}_{jt}$ and the platform characteristics X_{jt} as our instruments.

Empirical results

In this section, we present the results of the empirical strategy described in the previous section. First, we present our demand estimation results using the BLP model and discuss how much consumers value the average popularity, the range of this popularity, and the percentage of superstar series in streaming platform’s catalogs (RQ1). We also discuss the robustness of these results to different measures of subscriber shares and prices.

Second, a unique feature of a BLP estimation is that, once estimated, one can easily examine the responsiveness of consumer demand to changes in a SVOD’s catalog (elasticities), as well as how prices and subscriber shares adjust (counterfactual simulations). We discuss both the responsiveness of consumer demand to changes in both the average popularity of a SVOD provider’s catalog, as well as the percentage of superstar series within a SVOD’s catalog (RQ2). Additionally, we conduct two counterfactual simulations using our BLP demand estimates. We examine how the landscape of the SVOD market changes in response to a 10% increase in the average popularity of a given SVOD platform’s catalog as well as a 10% increase in the percentage of superstar series (RQ3).

Demand estimation results

For our baseline model, we define the product characteristics as the mean and standard deviation of the popularity of a SVOD platforms’ catalog: $X_{jt} = \{\text{mean}_{jt}, \text{standard deviation}_{jt}\}$. That is, we consider in the customer's utility (1) the average popularity of the SVOD platform’s series considered and (2) the *range* of average series popularity for the platform. For our baseline, we define market shares through new subscriber shares and we use the average price measure. Let

Q_t be the number of new SVOD subscribers in the U.S., and let q_{jt} be the number of new subscriptions for each platform in the U.S. at time t. The new subscriber share for platform j at time t is $s_{jt} = \frac{q_{jt}}{Q_t}$.

Table 3 (in the appendix) regression (1) displays the results from our baseline specification: robust standard errors are included in parentheses, and bootstrapped 90% confidence intervals are included in brackets. We construct these bootstrapped 90% confidence intervals using 2000 draws from the data. Regression (1) presents the demand estimation using new subscriber shares. Recall that the estimated coefficient α refers to the average consumer utility that is derived from the SVOD platform's price. This coefficient on prices is negative, as is expected: when a SVOD platform increases their prices increase, average consumer utility falls.

The estimates of β refer to the average utility derived from the corresponding SVOD platform features: the mean series popularity of the platform (*Mean*) and the standard deviation of the series popularity (*SD*). The estimated coefficient for Mean is positive and for SD, negative. This indicates that (1) the higher the average popularity of a platform's catalog, the higher consumer mean utility is but that (2) consumers derive lower utility when there is a large range in the popularity of a platform's series. A higher standard deviation could mean that a platform has many very popular or unpopular series, or some extreme combination of both. A negative coefficient indicates that an increase in standard deviation is more likely due to the existence of more low popularity series than high popularity series in this sample and that, on average, consumers prefer a lower volatility in popularity. The estimated coefficients on prices, Mean, and SD all differ from zero at the 10% level as shown by the bootstrapped 90% confidence intervals.

Further, recall that the estimates of Σ govern the distribution of *individual preferences*. That is, these estimates capture how much individual utility varies around the estimated average utilities (β and α). The population standard deviation of the mean popularity of platform series (0.688) is much larger than that of prices (0.058) and popularity standard deviation (0.0005). This indicates that individuals vary much more in the utility they derive from mean series popularity, whereas the utility derived from prices and the range of series popularity is more consistent across individuals.

We modify our baseline regression to look at a SVOD platform's percentage of superstar series, termed in the table as *superstars*. As previously discussed, superstars are series which have an average popularity measure in the top 1% of all series for each quarter. Table 3 regression (2) presents these results. The estimates of the coefficients for prices, Mean, and SD are very similar to regression (1). However, the magnitude of the coefficient for Mean is somewhat smaller, 0.39 versus 0.57. Additionally, standard errors are much larger, indicating this estimate is much less sharp when superstars are included. The coefficient on Superstars is positive, however, it is not different from zero at the 10% level. Finally, the estimates of the standard deviation of individual preferences are also consistent with that of regression (1). The standard deviation of individual preferences regarding superstars is quite large, indicating that some individuals highly value superstar series, whereas other individuals derive little utility. Combined with the fact that the coefficient on Superstars is positive is not different from zero at the 10% level, we can deduce that the utility derived from superstar series by consumers is very heterogeneous.

With these results, we answer our first research question: how much do consumers care about superstar (i.e., highly popular) series, the average popularity of a SVOD platform's catalog, and the variance of this popularity (RQ1). These results suggest that consumers do care about the average popularity of a SVOD platform's catalog, and to a lesser extent superstar series. These results also suggest that consumers dislike it when there is a large variation in popularity. Together, these results imply that consumers obtain the most value from a streaming catalog where most series are decently popular rather than a catalog with only a few exceptionally popular series.

Robustness

How robust are these results to the measure of market share? In regressions (3) and (4) of Table 3, we define market share by the share of total subscribers. These results show that when the total subscriber share is used, the estimates of average utility derived from prices, the mean popularity of a platform's series, and the standard deviation of popularity actually take on the opposite signs. Particularly, we obtain upward sloping demand curves. These opposite signs reflect the nature of using total subscriber data. As previously discussed, this measure captures a different type of consumer decision: the existing consumer's decision to *stay* subscribed to a particular SVOD subscriber. There is likely to be persistence over time in the mass of subscribers for a given platform and an existing subscriber may be more willing to put up with a price hike - in fact, a price hike might be indicative of a platform investing in highly popular platforms or series. Prices may need to change by a large amount to prompt consumers to actively go and cancel a platform. As is shown in Figures 4 and 5, there are very few large price hikes in the time period we consider from Q3 of 2021 to Q2 of 2022. Further, the extant price hikes were implemented by Netflix and Hulu who, as the first movers in the SVOD market, have the largest number of subscribers. Therefore, an upward sloping demand curve using this definition of subscriber share is not wholly unexpected. Further, Netflix and Hulu also have lower mean series popularity and higher standard deviation in series popularity, driving the opposite signs for these coefficients.

Additionally, these atypical results may be driven by the underlying data used. First, we are missing total subscriber share data for Amazon Prime, which has the largest *new* subscriber share by a large lead. We are also unable to acquire Q2 2022 subscriber information, so we have even less observations than our already small initial sample. Lastly, there is very little variation in the total subscriber count over time as discussed previously. For these reasons, we prefer the specification using subscriber shares as defined by new subscribers. From now on, we will refer to baseline regression (1) using new subscriber shares as our preferred specification.

Lastly, the results presented in regressions (1) and (2) in Table 3 rely on the average price measure. These results are robust to the use of the median price measure (not presented), although they are slightly smaller in magnitude.

Popularity elasticities

We now present and discuss the estimated popularity elasticities of demand for our 6 SVOD platforms. Using the demand estimates from the BLP model, we are able to obtain how responsive consumer demand for a specific SVOD platform is to changes in either the (1) average popularity of or (2) the percentage of superstar series contained in a given SVOD platform’s catalog. We are also able to capture how consumer demand for a specific SVOD platform responds given a change in their own catalog (referred to as an own-elasticity), or another SVOD platform’s catalog (referred to as a cross-elasticity).

Average popularity elasticities. Table 4 presents the average own- and cross- popularity elasticities for each SVOD platform using the estimates from our preferred specification. We construct the bootstrapped mean elasticities for each SVOD platform for each quarter using 2000 draws from the data, and take the average of all four quarters in our sample period. As is shown in Table 4, own-elasticities of popularity are positive. That is, an increase in the average popularity of a platform's series increases demand for that platform. The estimates of cross popularity elasticities are negative: a SVOD platform that manages to increase the average popularity of their catalog reduces the demand for other SVOD platforms.

Overall, there are no large differences in the average popularity elasticities between SVOD platforms. Own-elasticities range from 0.44 to 0.58, and cross-elasticities range from -0.03 to -0.15. All elasticities are less than 1, indicating inelastic demand: a rise in the mean popularity of a SVOD platform's catalog increases consumer demand by *less* than the change in average popularity. Lastly, own-elasticities are larger in magnitude than cross-elasticities.

[Table 4 about here]

Superstar elasticities. We use the specification of regression (2) in Table 3 to estimate the elasticities of demand with respect to the percentage of superstar series on a platform. These elasticities are presented in Table 5 (in the appendix). Again, we construct the bootstrapped mean elasticities for each SVOD platform for each quarter using 2000 draws from the data, and take the average of all four quarters. Similar to the mean popularity elasticities, own super star elasticities are positive and the cross super elasticities are negative. That is, when a SVOD platform has a higher percentage of superstar series, all else equal, consumer demand for that platform increases and demand decreases for all other platforms. Additionally, demand is relatively inelastic to superstar series. Lastly, own-elasticities are larger in magnitude than cross-elasticities.

Unlike the mean popularity elasticities, however, the magnitudes are not the same across all platforms. Disney+ and Netflix have larger own superstar elasticities than other platforms. That is, when the percentage of superstar series increases for Disney+ or Netflix, the demand for that platform increases more so for a similar rise in superstar series for Amazon Prime Video, Apple TV+, HBO Max, and Hulu.

These results help answer our second research question surrounding how much consumer demand for a SVOD provider changes if they do improve the overall popularity of their catalog or increase the amount of superstar series (RQ2). In summary, consumer demand does not change greatly. We find that consumer demand is relatively inelastic to changes in the average popularity and the percentage of superstar series of a SVOD platform's catalog. However, consumer demand is much less responsive to changes in the percentage of superstar series compared to changes in average popularity.

Counterfactual simulations

In this subsection, we present two counterfactual simulations to explore how consumer surplus, SVOD prices, and new subscriber shares change in response to increases in average series popularity and the percentage of superstar series for each SVOD platform. To do so, we first build for each time period in our sample a counterfactual dataset in which the relevant measure (e.g., average series popularity, percentage of superstar series) is increased by 10% for the specified SVOD platform(s). We then use the estimates from our baseline model in Table 3 regression (1) to find new equilibrium prices and market shares that are consistent with the new counterfactual dataset. From these new prices and market shares, we can calculate the percentage change in various SVOD market features such as consumer surplus.

10% increase in average popularity. To understand the effect that series popularity has on the nature of competition among SVOD platforms and consumer welfare, we conduct counterfactual simulations in which a given SVOD platform experiences a 10% increase in the average popularity of their catalog. Tables 7 and 8 present the average changes in SVOD platform prices and new subscriber shares, respectively, given a 10% increase in a certain platform's average popularity. When a platform is able to increase the average popularity of their catalog, they are able to both raise their prices and increase their new subscriber share. This comes at a cost to the other SVOD platforms who do not experience a rise in popularity: they lower their prices, but still experience a loss in their new subscriber share. The magnitudes of changes in prices are not large: At most, prices can change up to 1.09% (Amazon Prime) in response to a 10% change in average popularity. Changes in new subscriber shares are higher, ranging from 3.22% (Disney+) to 5.45% (Hulu).

Now consider the case where *all* SVOD platforms increase the popularity of the SVOD catalogs by 10%. When the series of all platforms become 10% more popular on average, we see that Amazon Prime benefits the most regarding prices as they can increase their prices 0.24%. Hulu and Netflix suffer slightly, reducing their prices by less than .1%. Looking at new subscriber shares, when all SVOD platforms increase their average popularity, they all are able to increase their new subscriber shares (percentage increases ranging from 0.82% to 1.79%). That is, the SVOD market attracts new previously unsubscribed consumers to the market and all platforms benefit.

Lastly, consider the benefits to consumers of streaming platforms. Table 6 (in the appendix) presents the change in *consumer surplus,* or the economic gain consumers enjoy, given a 10% increase in average series popularity. On average, a 10% increase in the average popularity of Amazon Prime's catalog results in the highest increase in consumer surplus, 0.9%. Disney+ is the second leader, resulting in an increase of 0.73%. These small percentages are driven by the small elasticities of popularity shown in Table 4. However, if we increase the average popularity of all platforms in our sample - that is, all platforms experience a 10% boost in the average popularity of their content - consumer surplus rises 3.21%.

10% increase in the percentage of superstar series. We conduct a second exercise in which now there is a 10% increase in the percentage of superstar series. For this simulation, we use the estimates from our baseline regression (2). Tables 10 and 11(in the appendix) present the average changes in SVOD platform prices and new subscriber share, respectively, given a 10% increase in a certain platform's percentage of superstar series in their catalog. These results are quite similar to that of the previous experiment - the platform with more superstar series is able to charge higher prices and gain new subscribers, whereas the platforms that do not experience a rise in superstar series lower their prices and experience a decline in their new subscriber share. However, the magnitudes of these changes are smaller than the changes seen in the first simulation following an increase in average popularity. Percentage changes in prices range from 0.06% (Amazon Prime) to 0.51% (Disney+), and percentage changes in new subscriber shares range from 0.30% (Amazon Prime) to 1.98% (Disney+).

Table 9 presents the change in consumer surplus given a 10% increase in superstar series. On average, a 10% increase in the superstar series of Disney+'s catalog results in the highest increase in consumer surplus, 0.31%, followed by Netflix at 0.14%. Unlike average popularity, however, if we increase the percentage of superstar series for all platforms in our sample, consumer surplus only rises 0.66%. This result is consistent with the demand estimates presented in Table 3. As was discussed, the average utility derived from superstar series was not different from zero, and showed considerable heterogeneity among individuals. Average popularity, however, results in an average increase in utility across the population. Therefore, it follows that the overall impact of consumer surplus of a change in average popularity is larger than the impact of a change in superstar series.

With these counterfactual simulations, we are able to answer our third research question regarding how the landscape of the streaming market changes if a SVOD platform increases the average popularity of their catalog or the percentage of superstar series (RQ3). In the context of such a highly competitive and saturated market, these simulations uncover how prices, subscriber shares, and even the benefit to consumers change if SVOD platforms are able to make changes to the popularity of their catalog. In summary, we find that SVOD platforms are able to charge higher prices, garner a larger share of new subscribers when they increase either the average popularity of their catalog or the percentage of superstar series. Additionally, we find that both strategies are also beneficial to consumers. However, we find that increases in a SVOD platform's average popularity of their catalog have a higher impact than increases in the percentage of superstar series.

Discussion

Our results suggest that consumers are interested in SVOD platforms that have highly popular content, and are disinclined to embrace high variance in a platform's content (RQ1). Further, some consumers highly value superstar series more than others. This affirms past research on possessing highly valued content for greater revenue returns (Chan-Olmsted & Li, 2002) along with how important it is to limit content popularity variation (Hiller, 2017). Additionally, possessing a large subscriber share is not consistently correlated with possessing a high percentage of superstar series. This study found that consumers prize low popularity variance across content, deriving greater utility from less vacillation (RQ2). Lower-priced SVOD platforms offer consumers affordable options, reducing the risk associated with trying out the SVOD platforms. However, a low price may convey less popular content, leading to consumer churn. Differently, SVOD platforms with higher prices may struggle to attract more subscribers, but are well-suited to retain them. Consumer demand for a SVOD platform, however, did not fluctuate much based on price changes to other SVOD platforms. It is important for SVOD platforms to figure out consumer demand first, which will illustrate the leverage they have to increase prices and maintain market share (RQ3). From the perspective of the superstar effect, this study demonstrates that while having superstar series is helpful in marketing SVOD platforms to consumers, it is not a singular panacea for attracting and retaining consumers in perpetuity. SVOD platforms that are able to increase consumer demand are able to raise prices and stanch churn, including potentially raising content popularity. Based on the superstar effect (Rosen, 1981), which helps explicate the resulting inequalities in consumer demand, and therefore in SVOD platform demand, this phenomenon exists in the SVOD marketplace. For vastly popular SVOD platforms such as Disney+ and Netflix, an increase in their superstar series led to a notably greater increase in demand for these SVOD platforms compared to Amazon Prime Video, Max, Hulu, or Apple+. Together, these results demonstrate that there is a clear winner-take-all dynamic, as observed in previous studies that applied the superstar effect (Rosen, 1981; Gabaix & Landier, 2008; Koenig, 2023).

From this, there are numerous managerial implications to consider. There may be several different types of strategies embraced by these SVOD platforms, dependent upon their market share in the SVOD industry. Larger, widely embraced SVOD platforms are able to increase prices with less risk of churn, and may be able to further capitalize on content production. Smaller SVOD platforms may do well to cut down on the amount of content produced, and instead work to focus on limiting popularity variance across content. This may help stoke consumer demand, and allow these SVOD platforms to gradually raise their prices over time. Of course, some consumers may be less interested in less popular content, which aids SVOD platforms in building out the bulk of their respective content libraries, instead electing to migrate from superstar series to superstar series across SVOD platforms. This can throw into flux how content licensing and revenue splits are determined among different media parties, as well as future SVOD consumer utilization rates, both of which are major economic drivers (Rizzuto & Wirth, 2002). Understanding how superstar series demand can inform SVOD platform subscription and competition is massively important in the wake of new ad-tiered SVOD platforms offered by Netflix and Disney+ (Forristal, 2022). Audience measurement platforms that incorporate external data sources that are part of the consumer journey, such as online searches and social media postings and interactions, offer more sincere evaluations of SVOD content and platform demand. The introduction and use of Parrot Analytics data in this study validates the power behind granular assessment and investigation of daily demand for content. Functioning like individual daily stock tickers, consumer demand scores empower researchers and practitioners to anticipate and understand how this demand varies over time, rather than at singular engagement points. Moreover, this challenges traditional methods of audience measurement, which solely rely on measuring audiences at content viewing points. Of course, based on the superstar effect, this may further illustrate the wide disparities between superstar and non-superstar series. The combination of imperfect substitutes and technological prowess has helped elevate particular content at the expense of other content, which may be even more suitable for many consumers. Consumers are able to consume all accessible series at any time, and, with so much choice and finely attuned recommendation systems, may be less interested in self-driven discovery of content. If demand is relatively inelastic for SVOD platforms, this may also constitute thinking about diversifying revenue streams. Netflix and Disney+ now have ad-supported tiers, and Netflix is aiming to further diversify its revenue streams through its nascent video game department to further exploit, at the very least, proprietary intellectual properties (Spangler, 2022; Weprin, 2023). The exploitation of internal intellectual property across other owned SVOD platforms can serve as a way for these SVOD platforms to further exploit superstar series.

Conclusion

In this paper, we used a novel Parrot Analytics audience demand dataset to create a new measure of series popularity and used a structural demand estimation model to establish three key results regarding how series popularity plays a role in consumer demand for SVOD platforms. We find that (1) consumers prefer streaming platforms with more uniformly popular content, indicating a catalog with high average popularity and low variance is more attractive than having a few extremely popular superstar series. We also find that (2) consumer demand for streaming platforms is relatively inelastic to changes in catalog popularity or the addition of superstar series. Additionally, we find that (3) increasing a streaming platform's catalog average popularity or the percentage of superstar series allows the platform to charge higher prices and gain more subscribers. However, improving average catalog popularity has a greater positive impact than increasing the percentage of superstar series.

This study has implications for not just content acquisition and original content production, but also strategic scheduling as well as distribution. How content might compete with superstar series debuts or season releases are ostensible considerations. Deliberation on content spend is also critical here, particularly in thinking about how to maintain consumer popularity across all content. Consumers are not able to fully realize the suite of available content in content libraries. Instead, it may behoove SVOD platforms to strive toward limiting variance in popularity across content, rather than solely targeting potential superstar series with additional marketing dollars, advertising support, and even production budgets. Disseminating an entire new season from an original SVOD platform may no longer be tenable, as consumers who quickly binge content may simply go elsewhere for the next superstar series. Therefore, careful consideration of content spend and content library curation can aid these SVOD platforms in slowing churn rates. The demand for content has compelled SVOD platforms to begin to license content to other rival firms, increasing the sizes of consumer bases and competition across SVOD platforms. In an attempt to cauterize the financial wounds left from persistent churn, this has created a new diversified and strategic revenue stream for SVOD platforms, which are often part of greater global media conglomerates (Chan-Olmsted & Chang, 2003), which seek to maintain attractive stock prices, cash flows, and revenue streams. Managers may need to re-consider frameworks for content acquisition, development, and curation. This also means thinking about why each piece of new content is necessary to produce, license, or outright purchase for a content library, and what its purpose is in customer relationship management. The content may be used to acquire consumers, or to maintain them as subscribers. Differently, content that is binge-able and may be repeatedly consumed by consumers may be strong candidates to be interspersed with advertisements, leading to greater cash flows over time. Simply adding more new content to content libraries can engender frustrated consumer experiences, and even harm the parent brand over time.

The evolving dynamics of the SVOD industry prompt a reconsideration of the conventional wisdom that once supported the tenability of exclusive content. Content exclusivity, to some extent, is likely responsible for preventing other content from reaching superstar levels, or, at the very least, gaining further notoriety among consumers and critics. It may also be an unnecessary strategy, as not all content warrants exclusivity on a platform (Lindbergh, 2024). SVOD content is reliant on pre-secured consumer bases that have access to it. Netflix has had a stronghold over popular original series, allowing it to cultivate a massive consumer base, and leading other SVOD platforms to license content to it to create alternative revenue streams for themselves (White, 2023; Jones, 2024). Second, consideration toward when content should be exclusive is also a key issue, as this has implications not just for content managers, but also advertisers, who are seeking out audiences with whom to engage. There may be further opportunities to exploit first and second screen marketing across television and screen devices for further engagement (Hoeck & Spann, 2019), and even interaction with content. This may be done in part alongside understanding personalities and lifestyles behind SVOD consumption (Palomba, 2020), as well as consumer sensitivities toward SVOD prices (Palomba 2021). Time spent is a particularly important metric, as more ad-supported tiers become available on SVOD platforms as well as through FAST channels. The transition from cable and satellite to streaming has left cable networks and broadcast stations without retransmission and carriage fees they often enjoyed from MVPDs (Wolk, 2022). The superstar effect in the SVOD marketplace has been realized, but perhaps undermines its commercial structure and overall health moving forward without strategic interventions from member SVOD platforms. Whether SVOD platforms elect to minimize volume of content and popularity variance across content will inform how this industry carves out a viable path for its future.

There are notable limitations and necessary future research directions to help tailor future work in this area for media economics researchers. First, this study only examines whether and how much streaming customers value popularity and superstar series, not why they value popularity. Second, this work does not explore in detail how exactly SVOD platforms can affect the popularity of their series, and what would be the most cost-effective way of doing so. Future research should examine the long-term effects of superstar series on the industry. If there are limits to how much superstar series can push consumer adoption and viewership, there may be other variables that are far more predictive of slowing churn rate. Scholars may also consider investigating how consumer engagement may be heightened on SVOD platforms during periods in which there are few or no new superstar series or seasons for consumers. Moreover, investigating whether desirability for minimal content variance also manifests in music streaming playlists and elsewhere across the media landscape may also prove to bear intellectual fruit. Scholars should also consider if there are particular kinds of consumer segments who prefer minimized content variation against access to superstar series. Price and demand elasticities may vary over time, and it may be helpful to understand when superstar series may elevate or harm these metrics. If all SVOD platforms race to put out highly-popular content (in various quantities), this can inspire a lot of risk in the SVOD marketplace. It is likely that this may fuel further pressures on SVOD platforms to partner or bundle together, stemming the tide of churn and preserving subscriber rates. This may very well create a regression to the mean for SVOD prices. Additionally, there are clear inequalities in the SVOD marketplace, as Netflix and Disney+ possessed greater superstar elasticities, meaning they were able to drive more demand for their superstar series against other SVOD platforms. How might this drive brand personality differentiation among these SVOD platforms, or aid them in harnessing brand equity? How is superstar series perceived across different consumer segments? Must particular consumers view select content as superstar series in order for said series to gain this level of notoriety? How might the superstar effect here impact future mergers and acquisitions in the SVOD industry? From a financial perspective, content libraries are viewed as asset portfolios among investors, though individual art is often viewed as a collectible. This schism can create tension among analysts, who attempt to estimate the value of content over time. Scholars should also consider investigating how to predict and understand content valuation, as this is a remarkably difficult exercise. Creating content acquisition frameworks that can help scholars evaluate why particular content is successful in particular markets can help advance media-oriented theoretical frameworks in a new light. Understanding just how well cash flows may be generated from content, based on consumer demand scores, may be another way to unlock further value. Studies that investigate these suggested paths can aid further scholarship and theoretical advancement surrounding the superstar effect and SVOD industry.

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Figures

Figure 1: Average mean series demand

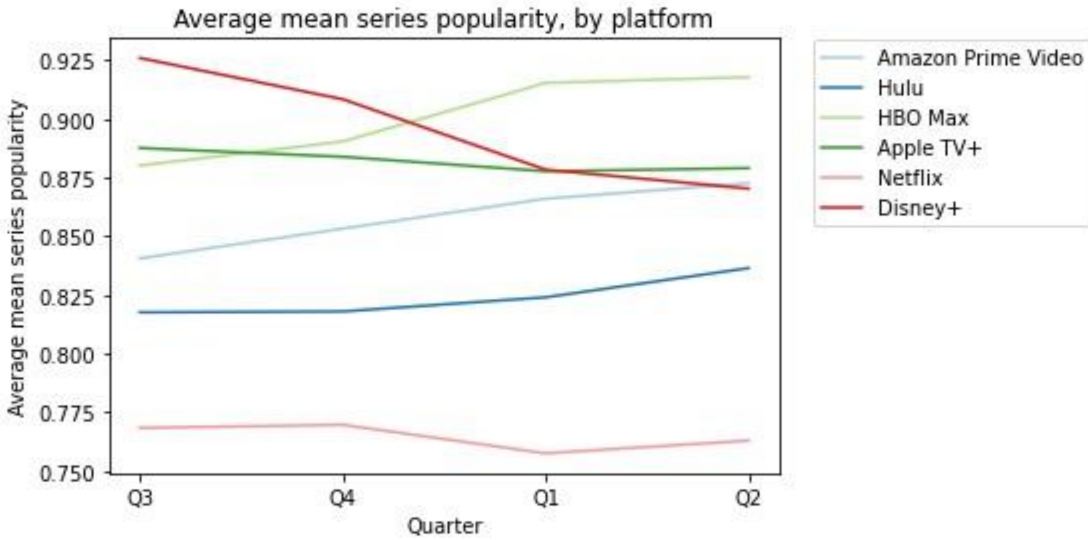


Figure 2: Average standard deviation of series demand

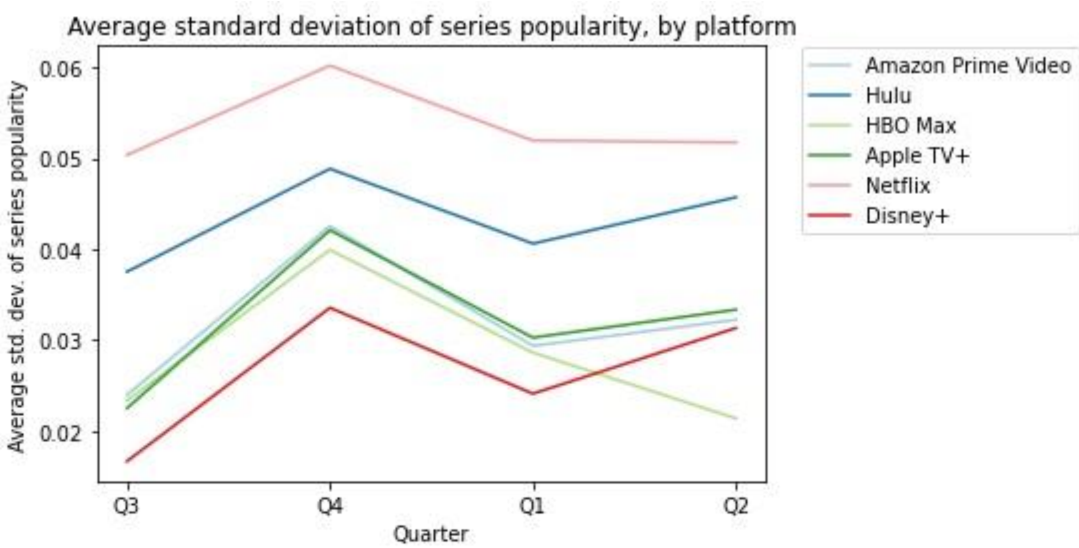


Figure 3: Superstars by platform

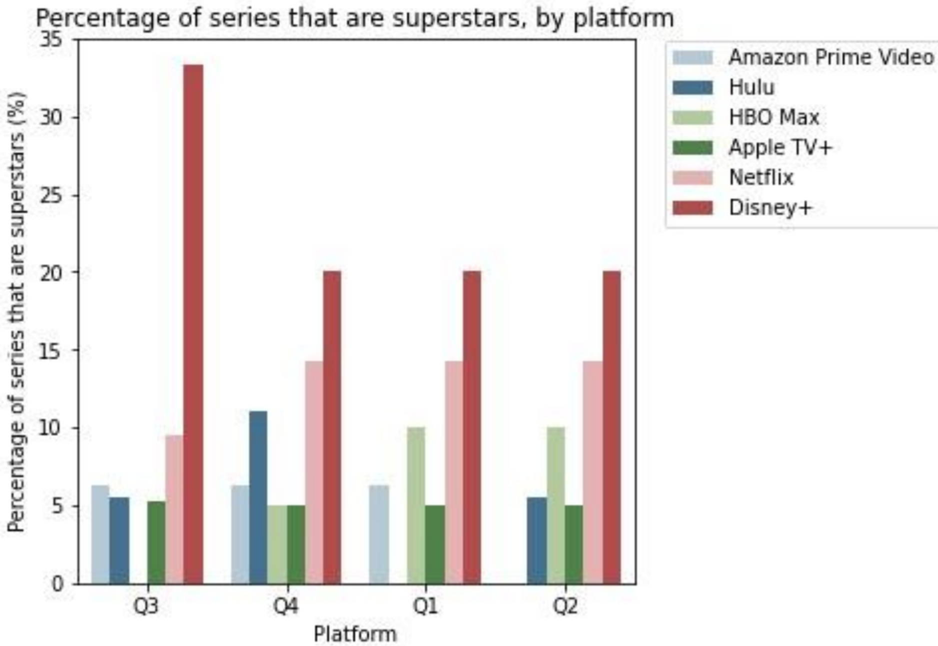


Figure 4: Average price measure

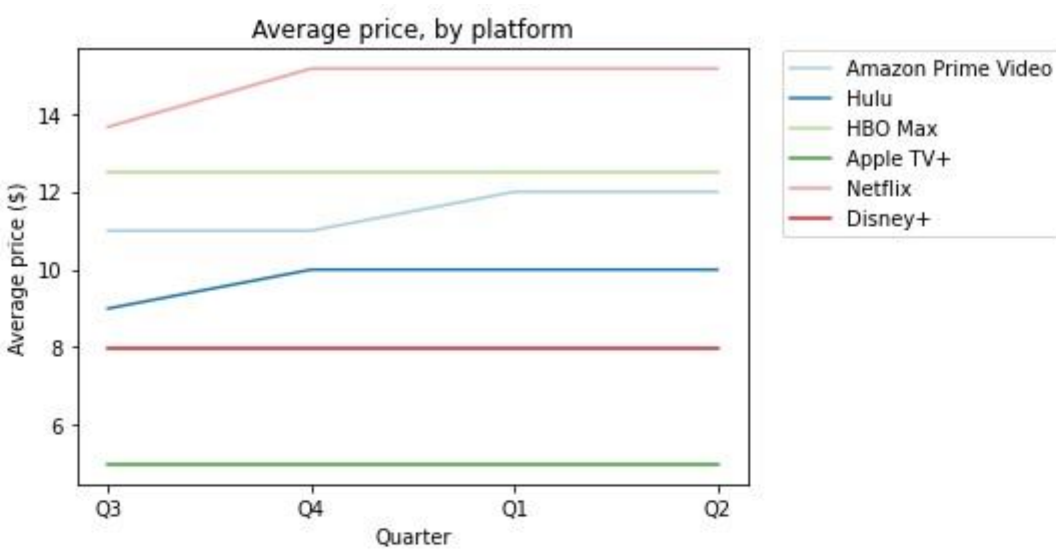


Figure 5: Median ad-free price measure

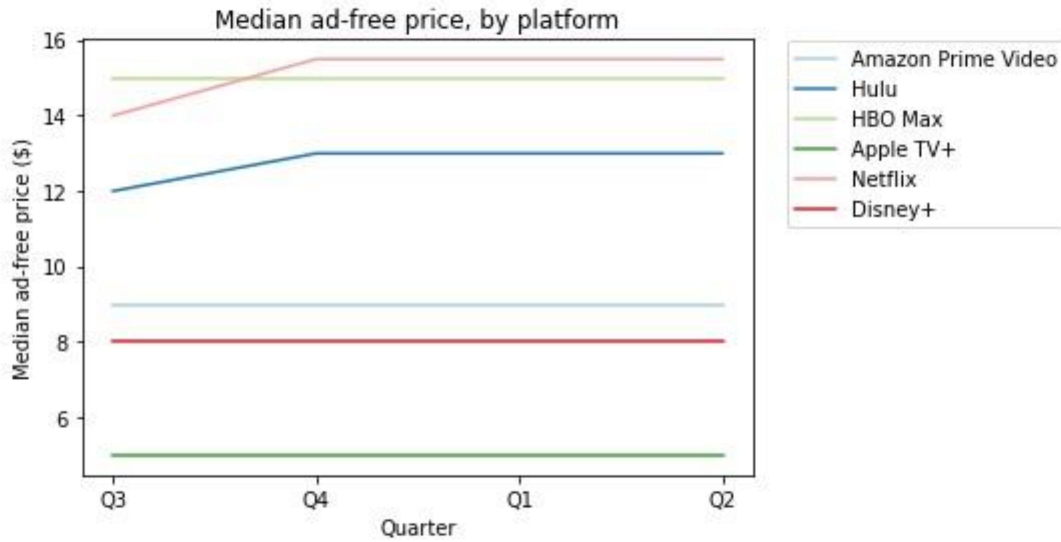


Figure 6: New subscriber share

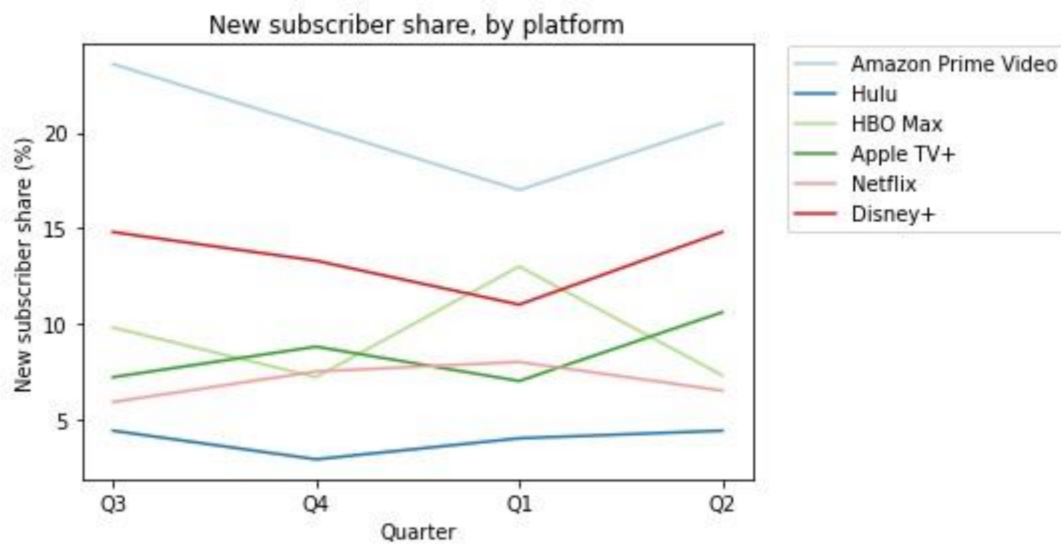
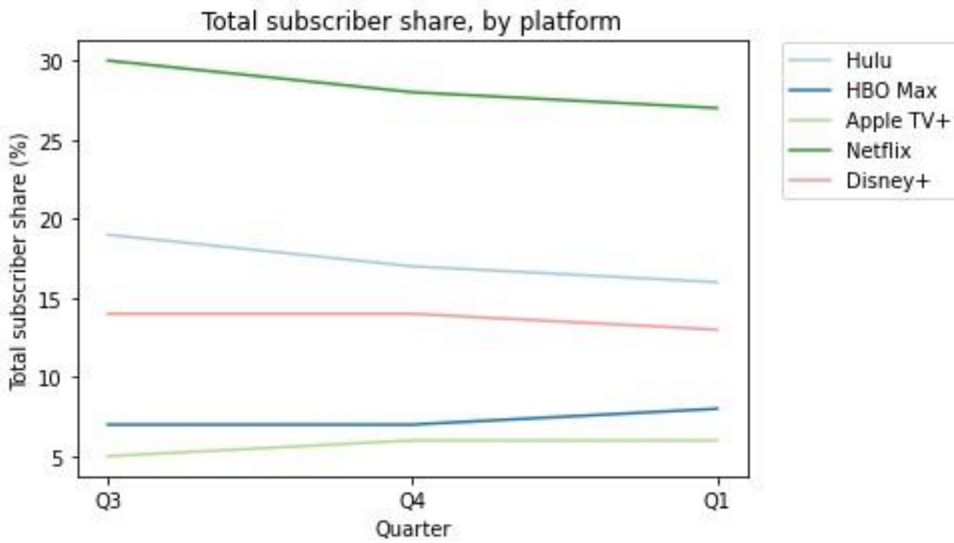


Figure 7: Total subscriber share



Tables

Table 1: Series popularity by platform, Q3 2021 to Q2 2022

Platform	No. Series	Min	Median	Mean	Max	Std. Dev.
Amazon Prime	16	0.08	0.86	0.86	1.00	0.11
Apple TV+	20	0.00	0.92	0.88	1.00	0.11
Disney+	15	0.00	0.94	0.89	1.00	0.12
HBO Max	20	0.11	0.95	0.90	1.00	0.12
Hulu	18	0.00	0.90	0.82	1.00	0.21
Netflix	21	0.00	0.89	0.76	1.00	0.28

Note: Popularity is measured at the series level; a popularity value of 1 indicates that a series was one of the most popular relative to the series in the sample on a given day according to the Parrot Analytics demand measure. This table presents the summary statistics for the popularity of all the series on a given platform in the entire sample period, Q3 2021 to Q2 2022.

Table 2: Series popularity by platform and by quarter

Q3 2021

Platform	No. Series	Min	Median	Mean	Max	Std. Dev.
Amazon Prime	16	0.13	0.86	0.84	0.99	0.16
Apple TV+	19	0.31	0.94	0.90	1.00	0.11
Disney+	15	0.34	0.97	0.93	1.00	0.12
HBO Max	20	0.24	0.94	0.88	1.00	0.16
Hulu	18	0.10	0.87	0.82	1.00	0.21
Netflix	21	0.00	0.87	0.77	1.00	0.27

Q4 2021

Platform	No. Series	Min	Median	Mean	Max	Std. Dev.
Amazon Prime	16	0.08	0.85	0.85	1.00	0.12
Apple TV+	20	0.00	0.92	0.88	1.00	0.11
Disney+	15	0.38	0.94	0.91	1.00	0.11
HBO Max	20	0.11	0.94	0.89	1.00	0.15
Hulu	18	0.03	0.89	0.82	1.00	0.22
Netflix	21	0.00	0.90	0.77	1.00	0.28

Q1 2022

Platform	No. Series	Min	Median	Mean	Max	Std. Dev.
Amazon Prime	16	0.59	0.85	0.87	1.00	0.08
Apple TV+	20	0.48	0.90	0.88	1.00	0.11
Disney+	15	0.36	0.91	0.88	1.00	0.12
HBO Max	20	0.30	0.95	0.92	1.00	0.09
Hulu	18	0.04	0.91	0.82	1.00	0.21
Netflix	21	0.00	0.89	0.76	1.00	0.28

Q2 2022

Platform	No. Series	Min	Median	Mean	Max	Std. Dev.
Amazon Prime	16	0.26	0.90	0.87	1.00	0.11
Apple TV+	20	0.00	0.91	0.88	1.00	0.10
Disney+	15	0.00	0.90	0.87	1.00	0.13
HBO Max	20	0.60	0.95	0.92	1.00	0.08
Hulu	18	0.00	0.90	0.84	1.00	0.20
Netflix	21	0.00	0.89	0.76	1.00	0.28

Note: Popularity is measured at the series level; a popularity value of 1 indicates that a series was one of the most popular relative to the series in the sample on a given day. This table presents the summary statistics for the popularity of all the series on a given platform for each quarter.

Table 3: Demand estimation results

	New subscriber share		Total subscriber share	
	(1)	(2)	(1)	(2)
α				
Prices	-0.1815	-0.1763	0.15105	0.1596
	(0.015)	(0.0305)	(0.0237)	(0.0202)
	[-0.201,-0.163]	[-0.2156,-0.1382]	[0.1197,0.181]	[0.1342,0.1860]
β				
Mean	0.57918	0.3914	-2.71008	-3.2119
	(0.022)	(0.2111)	(0.0506)	(0.0527)

	[0.565,0.616]	[0.1230,0.6673]	[-2.774,-2.642]	[-3.2790,-3.1466]
SD	-0.02105	-0.0281	0.0943	0.0705
	(0.0008)	(0.0216)	(0.0018)	(0.0038)
	[-0.022,-0.020]	[-0.0557,-0.0004]	[0.091,0.096]	[0.0658,0.0753]
Superstars		1.0736		3.4517
		(1.1021)		(0.5359)
		[-0.3323,2.4745]		[2.771,4.1367]
Σ				
Prices	0.058	0.0545	0.03109	0.0281
	(0.123)	(0.1668)	(0.1351)	(0.1372)
	[0,0.205]	[0,0.2611]	[0,0.202]	[0,0.2077]
Mean	0.688	0.7370	0.4063	0.3677
	(0.000667)	(0.0073)	(0.0025)	(0.0033)
	[0.685,0.687]	[0.7278.0.7464]	[0.402,0.4095]	[0.3634,0.37205]
SD	0.0005	0.0199	0.01419	0.0096
	(0.00000559)	(0.000096)	(0.000008)	(0.00002)
	[0.023936,0.023949]	[0.0197,0.02003]	[0.0141,0.0142]	[0.0095,0.0096]
Superstars		1.2490		0.5496
		(0.0194)		(0.0354)
		[1.0005,1.4965]		[0.5045, 0.5947]
N	24	24	15	15

Note: This table presents results from a random-coefficients logit model as described in the text. Robust SE's are included in parentheses and bootstrapped 90% confidence intervals are included in brackets. Estimates of α *refer to the average utility derived from the SVOD provider's price measure, estimates of* β *refer to the average utility derived from the corresponding product feature, and estimates of* Σ *refer to the standard deviation of the heterogeneous preferences.*

Table 4: Mean own and cross elasticities of demand with respect to mean series popularity

Platform	**Amazon Prime**	**Apple TV+**	**Disney+**	**HBO Max**	**Hulu**	**Netflix**
Amazon Prime	*0.46*	-0.06	-0.11	-0.07	-0.03	-0.05
Apple TV+	-0.15	*0.58*	-0.11	-0.07	-0.03	-0.04
Disney+	-0.15	-0.06	*0.54*	-0.08	-0.03	-0.05
HBO Max	-0.15	-0.06	-0.11	*0.58*	-0.03	-0.05
Hulu	-0.14	-0.06	-0.11	-0.07	*0.54*	-0.05
Netflix	-0.14	-0.05	-0.10	-0.07	-0.03	*0.44*

Note: Value in row j and column k is the elasticity of demand of SVOD provider j with respect to the average series popularity of SVOD provider k (i.e., the elasticity of demand of Apple TV+ with respect to the average series popularity of Amazon Prime Video is -0.15, whereas the elasticity of demand of Amazon Prime Video with respect to the average series popularity of Apple TV+ is -0.06)

Table 5: Mean own and cross elasticities of demand with respect to percentage of superstar series

Platform	**Amazon Prime**	**Apple TV+**	**Disney+**	**HBO Max**	**Hulu**	**Netflix**
Amazon Prime	*0.04*	-0.003	-0.05	-0.007	-0.002	-0.02
Apple TV+	-0.01	*0.05*	-0.05	-0.006	-0.002	-0.01
Disney+	-0.01	-0.005	*0.25*	-0.008	-0.003	-0.02
HBO Max	-0.01	-0.004	-0.05	*0.06*	-0.002	-0.02
Hulu	-0.01	-0.004	-0.05	-0.008	*0.06*	-0.02
Netflix	-0.01	-0.004	-0.05	-0.01	-0.003	*0.12*

Note: Value in row j and column k is the elasticity of demand of SVOD provider j with respect to the percentage of superstar series of SVOD provider k (i.e., the elasticity of demand of Apple TV+ with respect to the percentage of superstar series of Amazon Prime Video is -0.01, whereas the elasticity of demand of Amazon Prime Video with respect to the average series popularity of Apple TV+ is -0.003). These results rely on regression specification (2) of Table 3.

Table 6: Percentage change in consumer surplus given at 10% increase in average series popularity

Quarter	**Amazon Prime**	**Apple TV+**	**Disney+**	**HBO Max**	**Hulu**	**Netflix**	**All**
Q3 2021	0.89	0.35	0.63	0.50	0.24	0.32	2.87
Q4 2021	0.93	0.50	0.80	0.46	0.19	0.44	3.26
Q1 2022	0.85	0.40	0.66	0.77	0.25	0.46	3.32
Q2 2022	0.94	0.54	0.81	0.46	0.28	0.44	3.40
Average	**0.90**	**0.45**	**0.73**	**0.55**	**0.24**	**0.41**	**3.21**

Note: Each column corresponds to a 10% increase in the average popularity of the series of the SVOD provider to which the column refers; all values are in percentages.

Table 7: Percentage change in prices given at 10% increase in average series popularity

Platform	**Amazon Prime**	**Apple TV+**	**Disney+**	**HBO Max**	**Hulu**	**Netflix**	**All**
Amazon Prime	1.09	-0.15	-0.25	-0.19	-0.08	-0.14	0.24
Apple TV+	-0.20	0.73	-0.16	-0.11	-0.05	-0.09	0.07
Disney+	-0.21	-0.08	0.66	-0.12	-0.05	-0.10	0.07
HBO Max	-0.15	-0.05	-0.12	0.47	-0.04	-0.08	0.01
Hulu	-0.06	-0.01	-0.05	-0.04	0.12	-0.04	-0.08
Netflix	-0.08	-0.01	-0.06	-0.04	-0.02	0.15	-0.07

Note: Each column corresponds to a 10% increase in the average popularity of the series of the SVOD provider to which the column refers, and each row displays the percentage change in the price of the SVOD provider to which the row refers; all values are in percentages.

Table 8: Percentage change in new subscriber share given at 10% increase in average series popularity

Platform	Amazon Prime	Apple TV+	Disney+	HBO Max	Hulu	Netflix	All
Amazon Prime	3.22	-0.46	-0.62	-0.48	-0.21	-0.31	1.17
Apple TV+	-1.08	5.17	-0.84	-0.65	-0.28	-0.41	1.79
Disney+	-0.98	-0.55	4.15	-0.59	-0.25	-0.38	1.36
HBO Max	-1.09	-0.62	-0.85	4.90	-0.28	-0.42	1.55
Hulu	-1.17	-0.65	-0.91	-0.70	5.45	-0.46	1.37
Netflix	-1.07	-0.59	-0.84	-0.64	-0.28	4.36	0.82

Note: Each column corresponds to a 10% increase in the average popularity of the series of the SVOD provider to which the column refers, and each row displays the percentage change in the new subscriber share of the SVOD provider to which the row refers; all values are in percentages.

Table 9: Percentage change in consumer surplus given a 10% increase in the percentage of superstar series

Quarter	Amazon Prime	Apple TV+	Disney+	HBO Max	Hulu	Netflix	All
Q3 2021	0.09	0.03	0.44	0.00	0.02	0.04	0.63
Q4 2021	0.11	0.04	0.29	0.04	0.04	0.14	0.66
Q1 2022	0.11	0.02	0.23	0.22	0.00	0.26	0.84
Q2 2022	0.00	0.04	0.26	0.07	0.02	0.11	0.51
Average	**0.07**	**0.03**	**0.31**	**0.08**	**0.02**	**0.14**	**0.66**

Note: Each column corresponds to a one unit increase in the number of superstar series of the SVOD provider to which the column refers, and each row displays the percentage change in the consumer surplus of the SVOD provider to which the row refers; all values are in percentages. These results rely on regression specification (2) of Table 3.

Table 10: Percentage change in prices given a 10% increase in the percentage of superstar series

Platform	**Amazon Prime**	**Apple TV+**	**Disney+**	**HBO Max**	**Hulu**	**Netflix**	**All**
Amazon Prime	0.06	-0.01	-0.07	-0.01	0.00	-0.03	-0.07
Apple TV+	-0.01	0.05	-0.05	-0.01	-0.01	-0.02	-0.05
Disney+	-0.03	-0.01	0.51	-0.02	-0.01	-0.04	0.40
HBO Max	-0.01	0.00	-0.03	0.04	0.00	-0.02	-0.03
Hulu	-0.01	0.00	-0.02	0.00	0.01	-0.01	-0.03
Netflix	-0.01	0.00	-0.03	-0.01	0.00	0.06	-0.01

Note: Each column corresponds to a one unit increase in the number of superstar series of the SVOD provider to which the column refers, and each row displays the percentage change in the price of the SVOD provider to which the row refers; all values are in percentages. These results rely on regression specification (2) of Table 3.

Table 11: Percentage change in new subscriber share given a 10% increase in the percentage of superstar series

Platform	**Amazon Prime**	**Apple TV+**	**Disney+**	**HBO Max**	**Hulu**	**Netflix**	**All**
Amazon Prime	0.30	-0.03	-0.27	-0.05	-0.02	-0.08	-0.15
Apple TV+	-0.08	0.44	-0.34	-0.06	-0.02	-0.10	-0.16
Disney+	-0.08	-0.04	1.98	-0.06	-0.02	-0.11	1.66
HBO Max	-0.08	-0.04	-0.34	0.55	-0.02	-0.11	-0.04
Hulu	-0.09	-0.05	-0.37	-0.07	0.57	-0.11	-0.12
Netflix	-0.09	-0.05	-0.38	-0.07	-0.03	1.28	0.65

Note: Each column corresponds to a one unit increase in the number of superstar series of the SVOD provider to which the column refers, and each row displays the percentage change in the new subscriber share of the SVOD provider to which the row refers; all values are in percentages. These results rely on regression specification (2) of Table 3.

Appendix

Table A.1 Series by platform

Original Platform	Title	Origin Country
Amazon Prime Video	Invincible	United States
	The Expanse	United States
	Modern Love	United States
	Tom Clancy's Jack Ryan	United States
	Good Omens	United Kingdom
	The Marvelous Mrs. Maisel	United States
	Hanna	United States
	Tales From The Loop	United States
	Carnival Row	United States
	Upload	United States
	Them	United States
	The Wilds	United States
	Hunters	United States
	Undone	United States
	Alex Rider	United States
	Tell Me Your Secrets	United States
Apple TV+	Ted Lasso	United States
	See	United States
	For All Mankind	United States
	Mythic Quest	United States
	The Morning Show (US)	United States
	Servant	United States

	The Mosquito Coast	United States
	Schmigadoon!	United States
	Dickinson	United States
	Home Before Dark	United States
	Physical	United States
	Central Park	United States
	Truth be Told (2019)	United States
	Stillwater	United States
	Amazing Stories	United States
	Trying	United States
	Calls	United States
	The Snoopy Show	United States
	Acapulco	United States
	Invasion	United States
Disney+	Loki	United States
	Wanda Vision	United States
	The Falcon and the Winter Soldier	United States
	The Mandalorian	United States
	Star Wars: The Bad Batch	United States
	Marvel's What If?	United States
	Monsters at Work	United States
	Marvel Studios: Legends	United States
	High School Musical: The Musical: The Series	United States
	The Mysterious Benedict Society	United States

	Turner & Hooch	United States
	Big Shot	United States
	The Mighty Ducks:Game Changers	United States
	doogie kamealoha m.d.	United States
	The World According to Jeff Goldblum	United States
HBO	The White Lotus	United States
	Westworld	United States
	Euphoria	United States
	The Nevers	United States
	Insecure	United States
	Curb Your Enthusiasm	United States
	Barry	United States
	Industry	United States
	Perry Mason (2020)	United States
	In Treatment	United States
	My Brilliant Friend	United States
	The Righteous Gemstones	United States
	True Detective	United States
HBO Max	The Flight Attendant	United States
	Harley Quinn	United States
	Hacks	United States
	Search Party	United States
	Love Life	United States
	Gen:Lock	United States
	Gossip Girl	United States

Hulu	The Handmaid's Tale	United States
	Solar Opposites	United States
	Love, Victor	United States
	Animaniacs	United States
	Letterkenny	Canada
	Only Murders in the Building	United States
	The Great	United States
	Wu-tang: An American Saga	United States
	Pen15	United States
	Veronica Mars	United States
	Ramy	United States
	No Man's Land	United States
	The Hardy Boys	Canada
	Dollface	United States
	Y: The Last Man	United States
	Woke	United States
	Madagascar A Little Wild	United States
	The Mighty Ones	United States
Netflix	Stranger Things	United States
	The Witcher	United States
	The Umbrella Academy	United States
	Ozark	United States
	Record of Ragnarok	Japan
	Jurassic World Camp Cretaceous	United States
	Ragnarok	Norway

Warrior Nun	United States
Disenchantment	United States
The Dragon Prince	United States
Brand New Cherry Flavor	United States
Big Mouth	United States
Black Summer	Canada
Trese	Philippines
High-Rise Invasion	Japan
F is for Family	United States
Another Life	United States
B: The Beginning	Japan
Top Boy	United Kingdom
The Chair	United States
Squid Game	South Korea

A.1 Estimation method

To estimate our parameters of interest, practically we use the python package pyBLP. What follows is a brief description of the method the package uses. Define $\theta = (\alpha, \beta, \Sigma)$, the vector of our parameters of interest, where θ^* is the true value. We assume that platform features are mean independent of the unobserved platform characteristics ζ_{jt}, $E[\zeta_{jt}|X_{jt}] = 0, \forall j$. Let Z_{jt} be the vector of valid instruments. Therefore, we have the moment restrictions:

$E[Z'_{jt}\zeta_{jt}] = 0, \forall j$

Following BLP (1995) and as described in Nevo (2000), we estimate \theta by GMM using the following algorithm. Let the initial guess of θ^* be $\hat{\theta}^{(1)}$. For each guess $\hat{\theta}^{(i)}$, we do the following:

1. For each time t, we draw R observations of (α_i, β_i) from the multivariable normal distribution characterized by the guess $\hat{\theta}^{(1)}$.
2. We solve for the estimated mean utilities $\hat{\delta}_{jt}$ using the observed market shares, $\hat{s}_{jt}$. That is, for the guess $\hat{\theta}^{(i)}$ we find \hat{\delta}_{jt} such that for each market j in time t, the theoretical market share s_{jt} equals the observed market share $\hat{s}_{jt}$:
   $\hat{s}_{jt}(\hat{\delta}_{jt}) - \int_i P(j = J|i, t)dG(\alpha_i, \beta_i) = 0, \forall j$
   Where the R drawn observations from step 1 are used to approximate the integral.

3. Using the estimated mean utilities $\hat{\delta}_{jt}$, we construct the sample moment conditions that follow from equation (2)
   $m_t(\theta) = \frac{1}{J}\sum_{j=1}^{J}\left(\hat{\delta}_{jt} - X'_{jt}\beta + \alpha p_{jt}\right)Z_{jt}$
   Where $m(\theta) = \frac{1}{T}\sum_t m_t(\theta)$. We then estimate a new guess of θ^*, $\hat{\theta}^{(i+1)}$, using generalized method of moments (GMM) with positive-definite weighting matrix W_{JT}:
   $\hat{\theta}^{(i+1)} = argmin_\theta Q_{JT}(\theta) = argmin_\theta\left[m(\theta)\right]' W_{JT}\left[m(\theta)\right]$

We repeat the steps using each new guess $\hat{\theta}^{(i)}$ until we find the best guess $\hat{\theta}^*$ for which $Q_{JT}(\theta)$ is minimized.