Ilmenau University of Technology

Institute of Economics

Ilmenau Economics Discussion Papers, Vol. 27, No. 150

Attention Economics of Instagram Stars: #Instafame and Sex Sells?

Sophia Gaenssle

May 2021

Institute of Economics

Ehrenbergstraße 29
Ernst-Abbe-Zentrum

D-98 684 Ilmenau

Phone 03677/69-4030/-4032
Fax 03677/69-4203

https://www.tu-ilmenau.de/wth

ISSN 0949-3859

Attention Economics of Instagram Stars: #Instafame and Sex Sells?

Sophia Gaenssle*

Social media stars create stardom with uploads on social media pages like YouTube, TikTok or Instagram. One of the most popular platforms, especially designed to upload picture contents, is the service "Instagram" owned by Facebook. The growing social, cultural and economic power of social media star phenomenon raises the question about key drivers of success. Does body exposure drive Instagram success? Is there a difference between male and female content in this regard? This paper empirically analyses 500 top Instagram stars within the categories (1) fashion and beauty, (2) fitness and sports, (3) music, (4) photo and arts, (5) food and vegan. The unbalanced panel data set consists of 100 stars within each category over an observation period of five months. The data provides information on popularity measurements, such as subscribers, likes and comments, and most importantly, price estimates per post. Since influencers are not paid by the platform, but mainly by advertisers for promotion of their products, the estimated price per upload combined with the posting frequency serve as a valid proxy for weekly revenue and economic success. Mean comparison tests show that accounts with focus on female accounts have a significantly higher degree in body exposure, while the price per picture is higher for male content. Weekly revenues do not significantly diverge. Furthermore, using panel regressions, I estimate the effect of body exposure and sex on advertising revenue. The results show that body exposure has a positive effect, whereas the sex has no significant influence in the regression estimations. Eventually, this raises the question of a gender pay gap in social media.

Keywords: cultural and creative industries, attention economics, superstar theory, social media stars, influencers, Instagram, gender pay gap

---

* Researcher, Chair for Economic Theory, Institute of Economics, Ilmenau University of Technology, Germany, email: sophia.gaenssle@tu-ilmenau.de.
This research was funded by the *Department of Economic Science and Media* of the Ilmenau University of Technology. It was part of a young researcher funding and there is no conflict of interest.

1. Introduction

Popular content providers on social media, so-called influencers, represent a novel star-type of the digital era. The fame of social media stars (SMS) is native to social media platforms (Marwick, 2016). With self-produced content, they build their audiences on pages like YouTube, TikTok, Instagram, Twitch, etc. In contrast to stars of traditional media, there are no gatekeepers who manage audience access (Budzinski & Gaenssle, 2020; Gräve, 2017). One of the main tasks of traditional gatekeepers is the promotion of content and generating audience attention. Content providers on Instagram & Co are able to control upload frequencies and audience access themselves, without middlemen like editors or producers. Digital developments decrease specific technological barriers to enter creative industries, such as high-quality cameras to take pictures or shoot videos and the possibility to make them publicly available on your social media page. So from a technological point of view, it is possible to create content and put it online for the world to see, yet, it is (still) very difficult to gain consumer attention. The process of audience building can be explained using attention economics (AE), the concept of attention as a scarce resource (for an overview on AE see: Taylor & Greg, 2014). Since attention is scarce, it is difficult to gain even initial consumer access. To stand out and draw attention, nudity is a common way and the idea of "sex sells" has been subject to various studies (Wirtz et al., 2018). Nudity in media is not only of social and ethnical interest, but also from an economic point of view. This paper empirically studies if body exposure (BE) is beneficial for Instagram success. Therefore, I raise the following research questions: Does body exposure drive Instagram success? Is there a difference between male and female content in this regard?

The service "Instagram" owned by Facebook is one of the most popular platforms, and is especially designed to upload picture contents. I empirically analyse 500 top Instagram stars (IS) within the categories (1) fashion and beauty, (2) fitness and sports, (3) music, (4) photo and arts, (5) food and vegan. The panel data set consists of 100 stars within each category over an observation period of approximately five months (see Section 3.1 for details on sampling). The data set contains information on popularity measurements, such as followers, likes and comments, and most importantly, price estimates per post. Since IS are not paid by the platform, but mainly by advertisers for promotion of their products (see Section 3.2 for details on SMS income), the estimated price per upload is a valid proxy for economic success. The combination of weekly post frequency and price per post gives the estimated weekly revenue for each IS. Using panel regression, I statistically analyse the influence of body exposure, sex, and popularity measurements on revenue. The results show that BE positively influences advertising revenue, while impact of sex is more complex and needs careful interpretation. Therefore, further statistical methods are used to examine differences between sexes.

The paper is structured as follows. Section 2 provides an overview on theoretical aspects such as attention economics and the role of stars. Section 3 contains information on the data set, sample, and variables. In the following Section 4 the data is empirically analysed and discussed. Section 5 gives concluding remarks, limitations and implications.

2. Stars in Attention Economics

The concept of limited consumer attention is not a new phenomenon of the digital age, but it excessively increased due to its' developments. Simon (1971) first pointed out the problem of scarcity in an information-rich society, since information "consumes the attention of its recipients" (Simon, 1971, p. 40). With the shift to digital economy, the importance of information drastically increased, since former tangible goods could be digitised. Shapiro and Varian (1999) explain (way ahead of their time) that information goods can be all sorts of goods which can be digitised, such as films or books. The rise in available information shifted the focus; not information access, but information overload becomes prevalent in modern society (Shapiro & Varian, 1999; Taylor & Greg, 2014). Limited attention needs to be efficiently allocated dynamically over different sources and platforms (Che & Mierendorff, 2019). Therefore, limited consumer attention becomes the de facto barrier to entry in a lot of digital markets, among them social media platforms.

Budzinski and Gaenssle (2020) apply attention economics to the field of social media. This paper extends their work and theoretical idea of *audience building*. Audience building is separated in two economic effects, which take place simultaneously but can be distinguished analytically: audience *attraction* and audience *maintenance*. The former, translates into first contact and creating initial attention – an eye-catcher and first connection with consumers. A common way to gain consumer attention is the paradigm "sex sells". The exposure to sexual appeals for advertising, brand recognition/memory and purchase intentions has been subject to many scientific studies (for detailed meta-analyses see: Wirtz et al., 2018; or: Lull & Bushman, 2015). Nudity and ads with sexual appeal produce mixed results and disagreement among researchers regarding their effects on buying intentions of consumers; nudity not always increases sales (inter alia, Dudley, 1999; Mittal & Lassar, 2000; Severn et al., 1990). This study seeks to analyse the influence of *body exposure* and its' influence on Instagram success, regarding the star income. Franck (2019) analyses the "economy of attention" and refers to celebrity income as "attention income". In the following nudity serves as variable of audience attraction and means to increase attention income.

The second aspect of audience building is audience maintenance. For sustainable success it is not only necessary to generate one-time attention, but to keep followers on board. The concept of consumption capital and "building of taste" can be applied here (Stigler & Becker, 1977). According to the superstar theory of Adler (1985, 2006) there are three ways to acquire consumption capital:

(1) Direct consumption of content: When consumers are exposed to content they build specific knowledge, e.g. about the star, the type of content, and all other details and knowledge which is transmitted. A food account, for instance, can serve as information on health and cooking advice, and additionally the fans get used to the content provider and her type of presentation and communication. As Adler puts it in his seminal paper on superstars: "The more you know, the more you enjoy" (Adler, 1985, pp. 208–209). The more videos are available on an Instagram account, the better the possibility to acquire consumption capital. Fans can get to know the content provider, scroll through her page and build specific knowledge. Therefore, in this study the *number of total posts* on the account serve as proxy for the possibility to acquire consumption capital.

(2) Communication about content (communality effects): Consumers not only build specific knowledge and derive utility from consuming the content itself, but also through communications with others (commonality effect), i.e. exchanging information with others and learning even more. Consumption capital, thus, drives bandwagon effects (Leibenstein, 1950).- The communicational aspect gained importance in the digital environment. Cost of communication drastically lowered on the demand and the supply side (Gaenssle & Budzinski, 2020). Fans can easily comment on posts of their favourite stars and connect among each other; emojis and likes even simplify this process and further reduce costs of communication. It is very easy to find like-minded people and forward content to friends and family. This leads to considerable network effects (Katz & Shapiro, 1985, 1994). Jung and Nüesch (2019) find that popularity serves not only as a quality signal, but the mere number of historical views on a YouTube video generates utility itself. Consumers perceive these videos as popular; they can share and talk about it. There are different popularity indicators; the most common ones are views, followers, likes, and comments (Burgess & Green, 2018). To operationalise the

popularity concept in this paper, I use the total number of *followers*, and the average of recent *likes* and *comments*.

(3) Media coverage (availability): According to Adler (1985, 2006), the cost of consumption arise from (1) actual cost of consumption, i.e. watching videos, looking at pictures, reading captions, and (2) search cost of finding suitable content and conversation partners. If content availability is necessary to lower cost of consumption and drive social media success, *multihoming* strategies have to be taken into account. Multihoming could lower search costs for consumers and make the star's content broadly available. An IS might decide to post a video on Tiktok and also share it on Instagram. The variable multihoming will serve as another input factor for audience maintenance.

Both theoretical parts of audience building deal with scarce attention; attraction and maintenance need the consumers' time and focus. The second part, however, pertains to superstar theory, which is very well researched. A lot of empirical evidence can be found focusing on ideas of Adler and his concept of snowballing into superstardom.[1] This paper aims to contribute to filling the research gap and analyse the first part, the initial attraction of audience attention, using body exposure as a proxy.

3. Data and Variables

3.1 Sample

The data is retrieved from Heepsy.com and Instagram. Heepsy.com primarily provides data for companies, who want to find influencers for ads on Instagram. Therefore, the service includes prices per post. To retrieve data from Heepsy a professional account with payment is needed. The funding of the paper allowed a time series of 5 month and 500 influencers, with observations approximately every ten days (translating into 15 observations per account on average). Consequently, I have an unbalanced data set (unbalanced due to availability issues und cleaning of duplicates), with 7,362 observations in total.

[1] A literature overview on economics of superstars can be found in: Budzinski and Gaenssle (2020). Empirical papers testing Adler's concepts: Budzinski and Pannicke (2017); Candela et al. (2016); Crain and Tollison (2002); Ehrmann et al. (2009); Filimon et al. (2011), Franck and Nüesch (2008, 2012), Giles (2006); Hofmann and Opitz (2019); Jung and Nüesch (2019); Lehmann and Schulze (2008); Lucifora and Simmons (2003); Meiseberg (2014); Salganik et al. (2006).

It is possible to select the IS according to specific settings on Heepsy. Only accounts which stated their mail address on Instagram are included in the sample. Adding a mail address to the profile can be interpreted as interest in further contact, apart from direct messages within Instagram. It can be expected that stars with email address want to be contacted and show business interest. Five popular but distinct categories are selected: (1) beauty & fashion (Fashion); (2) fitness and yoga (Fitness); (3) food and health (Food) (3) music (Music); (4) photo and arts (Photo). The choice was influenced by the popularity of the categories and their distinctiveness (Hypeauditor, 2020). Some categories are broadly overlapping (e.g. sports and fitness). In case of doubt and considering double sampling, only the more popular one was chosen for the final sample. Within each category the top 100 accounts are sampled. Table 1 shows the final sample and observations per category. The data varied depending on the updates of the page Heepsy.com. Within the data cleaning process duplicates were eliminated.

Table 1 Overview observations per category

IG Category	Freq.	Percent	Cum.
Fashion	1,501	20.39	20.39
Fitness	1,501	20.39	40.78
Food	1,510	20.51	61.29
Music	1,504	20.43	81.72
Photo	1,346	18.28	100
Total	7,362	100	

3.2 Dependent Variable

The dependent variable for this study is the star factor income of advertisement, i.e. the advertising revenue. There are different ways to generate revenue as a content provider. In the following, a general overview shows the different possibilities to earn money on different social media platforms.

Types of platform immanent payments:

(i) Share of advertising revenue: This is the case, inter alia, on YouTube. Content providers agree to embed advertising before, during or/and after their videos and get paid per view – the more ads are consumed the better the payment.

(ii) Direct donations (tips): It is possible to directly send money to the content providers i.e. tip them. This is (among other payment methods) possible on Twitch.

(iii) A payment barrier to access content: The content provider can establish a paywall, for instance, a monthly flat rate (all you can eat) system or pay per view (à la carte) system, e.g. Patreon.

Types of external payments:

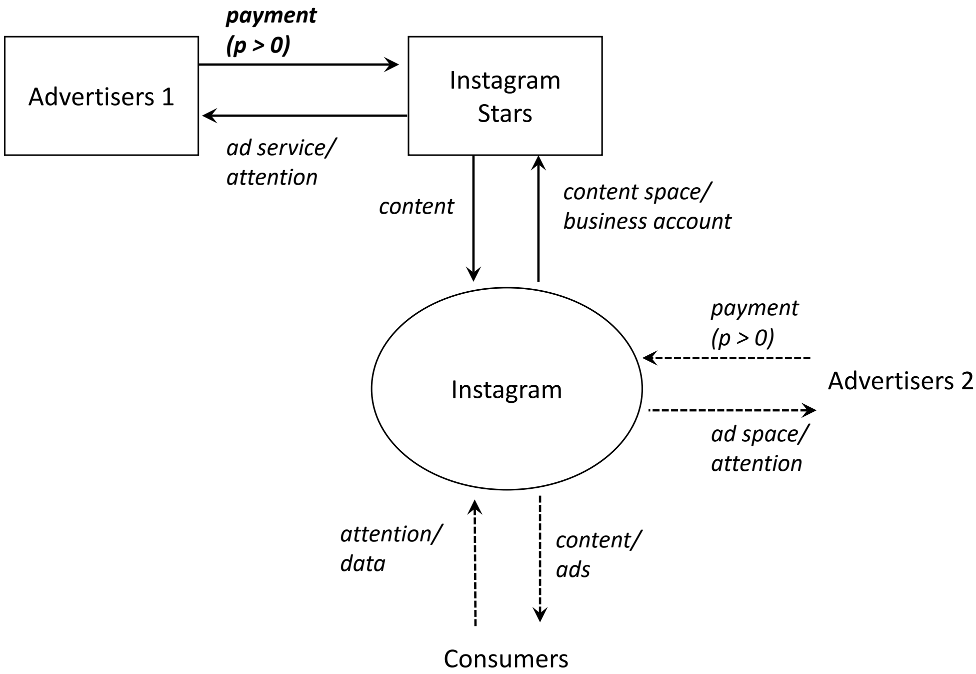
(iv) Own sponsored content or own brands: With growing reach content providers often start their own business or sell and promote their own products. A baker for example sells baking equipment, a makeup artist own makeup products. This is broadly used on WeChat in connection with Taobao shops in China; content providers have their own shop and products connected to the social media page. New options of Instagram enable similar functions.

(v) Commission and affiliated links: It is possible to embed affiliate links (e.g. Amazon cooperates with many retailers) or use discount codes to get a commission for sales. The latter is also popular on Instagram.

(vi) Ad financed (or sponsored) content: This can start very small with product placements and free samples. Content providers include products in their content and promote them. Very successful SMS are able to earn vast amounts of money to include ads in their posts. This payment strategy is predominant on Instagram.

Version (vi) is used within this study. It is a valid proxy for IS income on Instagram, since most of the top stars use ad financing and Instagram does not offer platform immanent payments. Figure 1 shows the Instagram payment system for deeper understanding. There are two advertising parties, those directly paying Instagram for placing ads in user chronics (Advertisers 2) and those financing IS, i.e. transmitting ads indirectly via the star (Advertisers 1). The consumers pay with their personal data and attention as they consume ads.

Figure 1 Multisided platform Instagram

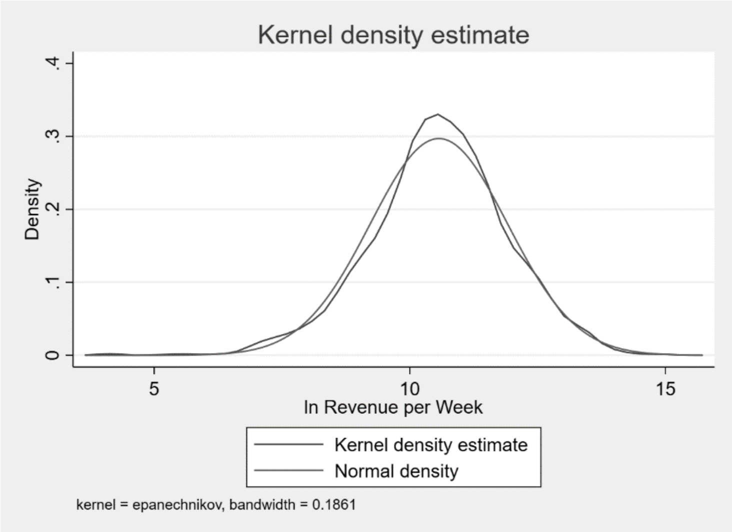


The stream between Advertisers 1 and IS is operationalised in this paper. The price per picture is the price an advertiser needs to pay for one sponsored picture on the respective account. For instance, the price for makeup artist Patrickstarrr end of January 2020 was USD 6.100 per picture. This data is offered by Heepsy.com, who have market based information and complement those values with estimated values (data interpolation).[2] To calculate the dependent variable, the price per picture is combined with the posting frequency, hence, a weekly revenue can be estimated.

The factor income proxy "revenue per week" varies between USD 46 and 5,635,000, with a mean at USD 90,461.32. Since the data is very right skewed and, thus, residuals have a skewed distribution, the data is transformed to obtain symmetrically distributed values. The logarithm of the income proxy provides a good fit, compared to the log-normal distribution (see Figure 2). A similar approach is used in other studies on superstars, measuring income or market value effects (inter alia, Franck & Nüesch, 2008; Lucifora & Simmons, 2003).

[2] Further details of data collection etc. are business secrets and not publicly available. This information can be obtained only through personal contact. As correctness and reliability is essential for Heepsy to calculate accurate costs for their customers, it can be expected that the proxy is valid.

Figure 2 Density allocation of logarithm of factor income



3.3 Independent Variables and Controls

I use two sets of independent variables. The ones for audience attraction and those for audience maintenance. Body exposure is used as a proxy for audience attraction. The information on BE is collected directly from Instagram. This is a time invariant variable, since the coding is very extensive, i.e. the process was only performed once. The last 12 pictures of the account and their respective degree of nudity are analysed.[3] Different types of nudity can be defined theoretically, as in everyday dresses ("demure"), mini-skirts or shorts ("suggestive"), bathing suits/shorts ("partially clad"), without clothes ("nude") (Reichert, 2002; Wirtz et al., 2018). Instagram's guidelines restrict nudity to a certain degree.[4] For this study the category "partially clad" is defined more closely into the degree of nudity. Therefore, the degree of nudity within the last active pictures posted (12 pics per account) are analysed. If a picture shows 50 per cent or more naked skin (excluding portrait pictures), the BE is coded as 1. If there is less nudity in the picture it is coded as 0. To account for the degree of suggestiveness, if 50 per cent or more focus lie on "dressed" primary sexual characteristics (breasts, bottom, genitals), this is also coded as 1 (see examples in the appendix). I operationalise the degree of nudity on the account

[3] Heepsy uses 12 pictures for their analyses and displays them for customers. Those 12 pictures are also used for further manual coding in this paper. Instagram Stories are not part of the analysis.

[4] Community guidelines by Instagram (as in spring 2021): "Post photos and videos that are appropriate for a diverse audience: We know that there are times when people might want to share nude images that are artistic or creative in nature, but for a variety of reasons, we don't allow nudity on Instagram. This includes photos, videos, and some digitally-created content that show sexual intercourse, genitals, and close-ups of fully-nude buttocks. It also includes some photos of female nipples, but photos in the context of breastfeeding, birth giving and after-birth moments, health-related situations (for example, post-mastectomy, breast cancer awareness or gender confirmation surgery) or an act of protest are allowed. Nudity in photos of paintings and sculptures is OK, too." Facebook (2021)

by summing up the “nude pictures”, i.e. accounts with BE = 12 have a very high degree of nudity, accounts with BE = 0 have no nude pictures. The percentage of BE pictures is calculated for every account, to improve transparency and understanding in the descriptive analysis. Since the coding process is sensitive to subjective perception, a second person evaluated the pictures for inter-coder reliability. Moreover, to ensure intra-coder reliability, a second test was performed, i.e. the same coder rechecked the pictures a few months later.

The second set of independent variables are the ones for audience maintenance: followers, likes, comments, total posts, and multihoming. They are summarised in Table 2

Table 2 Independent Variables: Audience Maintenance

Variable	Obs	Mean	Std. Dev.	Min	Max
Followers	7,362	6,474,005.00	6,587,006.00	1,436,180	65,800,000
Avg Likes	7,362	162,385.10	258,043.00	91	3,234,545
Avg Comments	7,362	1,497.38	3,813.10	2	85,580
Number of Posts	7,362	2,968.96	4,278.14	12	57,048
Multihoming	7,362	1.88	0.82	0	4

The total number of followers are all followers of the account at the time of observation, with a mean of 6.4 million. There are huge differences for followers, likes, and comments, which is why logarithmic values are used for the regression model. Likes and comments (there are no dislikes on Instagram) are the so-called audience engagement, the engagement of followers with the star. Average likes and are calculated by Heepsy according to the last 12 pictures posted. This gives the active engagement of the audience at the moment (i.e. calculating over the whole sample does not reflect the accurate engagement at that very moment. Historical outliers may bias results). For this study the average number of likes and comments over the last 12 pictures is a good proxy for the active engagement, influencing the IS success.

The number of posts is the number of total uploads on the account, i.e. total content available. The mean number of posts is 2968.96 pictures with a standard deviation of 4278.14; there are huge differences between accounts. Some post a lot more (higher frequency) then others. The age of the account is unknown, hence, it is not possible to control how much time the IS spend to upload content. For this variable I also use log values in the regression model.

Multihoming is a generated variable. I have information on secondary accounts of every IS, if they have a (a) website, a (b) Facebook, (c) YouTube, (d) Twitter or (e) Snapchat account. At maximum this variable can be 5 (all five channels are used), at a minimum 0 (nothing other than Instagram is used). No account has more than 4 channel next to Instagram. The sample has 1.88 other channels with a standard deviation of 0.82. For the last observation period in June 2020, 404 had a website, 45 had Facebook, 295 had YouTube, 63 had Twitter, 55 had Snapchat.

More complex is the information on the type of content on the account. The measurement of sex refers to the type of content and what the focus of the account is, i.e. is there a focus on male, female or no specific focus on the account. Therefore, all accounts are analysed individually. For decades researchers have carefully studied the terms sex (biology/physiology) and gender (social/sexual identity) (Lorber, 1996, 2005). An external identification of the sex is only possible as "read as" female or male, according to visible features. I coded five different variables (1) female (clearly female features, one or more women), (2) male (clearly male features, one or more men), (3) mixed (clearly male and female, if more than one person in the picture), (4) ambivalent (sexual characteristics recognizable, but not clearly attributable to a man or a woman, e.g. transvestite or similar), (5) no identification (no characteristics visible). Paintings, statues of humans are also coded accordingly. This goes hand in hand with the body exposure analysis; 12 pictures per account are analysed and coded. If all 12 pictures show a woman this is coded as 12-0-0-0-0, if there are 6 pictures of women and 6 pictures of men, this is coded as 6-6-0-0-0 (see example in the appendix). Thus, it is possible to implement a proxy, the degree of female or male pictures of every account. On average there is more female content in the sample with 51.88 per cent versus 21.6 per cent male content. The rest is even lower with 13.05 per cent mixed, 12.8 per cent no identification, and 0.27 per cent ambivalent.

Lastly, this paper uses a set of *control variables*: The percentage of branded posts means the number of posts with a mention of a brand in the caption in the last 12 posts. The mean is 26.50 brand mentions with a standard deviation of 21.68. Consequently, on average more than two brands are mentioned in a post. In the regression model I also control for the category of the respective IS.

4. Empirical Analysis of Instagram Stars

4.1 Descriptive Analysis of Audience Building

The analysis of the top 20 (Table 3) overall and the top 10 (Table 4) per category already gives some insights in the data. They are ordered by the dependent variable revenue – the top accounts according to mean revenue over all observation periods. Half of the top 20 are music accounts, followed by Fashion, Fitness, and Food. There is no Photo account in the top 20. The average

BE is 23 per cent, which could be interpreted as low. The majority of content shows women with 54.58 per cent. However, there are two accounts with female focus with a BE of 83 per cent.

Table 3 Sex and BE for the Top 20 (according to mean revenue)

Categories	Sex [per cent]		BE [per cent]
10 Music	Female	54.58	23.33
5 Fashion	Male	20.00	(min 0, max 83.33)
3 Fitness	Mixed	16.67	
2 Food	No Identification	9.17	
	Ambivalent	0.00	

Looking at the top 10 per category, the majority of contents display women, followed by men. In Fashion and Fitness more than half of the contents show pictures of women. Music has the highest amount male pictures. Also, mixed pictures of male and female can be found in all categories, varying between 13 and 18 per cent. The category Food shows the highest proportion of "No Identification", evidently with food pictures. Expectantly, the BE is also lowest in Food. The highest BE is in Fitness with more than 50 per cent. It can be argued that BE seems common among popular accounts, yet, is does not seem to be a necessary variable for success.

Table 4 Sex and BE for the Top 10 (according to mean revenue)

Category	Sex [per cent]					BE [per cent]
	Female	Male	Mixed	No Ident.	Ambiv.	
Fashion	63.33	17.50	15.83	3.33	0	40.83
Fitness	55.83	15.83	18.33	10.00	0	52.50
Food	45.83	20.00	16.67	18.33	0	0.83
Music	47.50	30.83	14.17	7.50	0	13.33
Photo	45.83	28.33	13.33	12.50	0	12.50

When analysing body exposure the question of sex is ubiquitous. The differences between male and female accounts are of interest. There are some accounts in the total sample, which do not have a clear focus on either male or female content. I exclude those accounts to study whether there is a difference between accounts with focus on male content and accounts with focus on female content. I restrict the observations to those accounts with "clear focus" (more than 50 per cent male/female content). This excludes accounts with diverse uploads, i.e. mixed accounts with females and males, non-human accounts (like memes, landscapes or pets), and non-focus accounts (a little bit of everything). This leaves 348 accounts.

With this sample, I perform mean-comparison tests (t-tests) to see if there are differences between women and men. The results show that accounts with focus on female contents have significantly higher BE than accounts with focus on male contents (p-value 0.0000). As such, women appear to show more nudity. While there is no statistically significant dissimilarity in posting frequency (p-value 0.9023), i.e. they seem to upload comparable amounts of pictures, there is a difference in price per picture (p-value 0.0017). Male contents achieve significantly higher price per picture. Yet, this difference is not reflected for the mean revenue, where no significant difference can be found (p-value 0.6385). Both groups earn similar advertising revenue on average. Since revenue *(R)* is price *(p)* times frequency *(q)* ($R = pq$) and prices diverge, but revenue does not, it seems that women actually upload somewhat more than men (even if not statistically significant; mean men = 7.69 pics per week, mean women 7.77 pics per week). To sum up, accounts with female contents show a higher degree in nudity and upload slightly more pictures, while they earn less per picture and on average the same amount as their male counterparts.

4.2 Analytic Analysis of Audience Building

If BE actually positively influences revenue is studied in the following analytical analysis using random effects regression estimations:

$$Y_{it} = \alpha + \beta x_{it} + u_{it} + \varepsilon_{it}$$

where α is a constant, β is the coefficient, u is the between-entity error and ε is the within entity error. Y is the dependent variable of star i in observation period t. In a random effects model differences across entities (in this case BE and sex) have influence on the dependent variable. In contrast to fixed effects, time invariant variables can be included in the analysis. This is necessary, since BE and sex do not change over time. Moreover, a Hausman test was performed to test between random effects and fixed effects and to confirm this choice.

To obtain symmetrically distributed residuals, the dependent variable revenue per week is logged, as well as the values for the number of posts, followers, likes, and comments. Since followers like and comment on pictures of their stars, the variables are correlated. Therefore, I implement a time lag for comments and likes. This reduces the number of observations to n =

5,978 and number of accounts to *498*. To check the specification and robustness, I estimated OLS regressions and tested the restrictions. There is no problem of multi-collinearity, as variance inflation factors are below 5. Standard errors are robust in all models, to control for heteroscedasticity. The values for BE and sex are logged to improve transparency and means of interpretation.[5]

The results are listed in Table 5. Model 1 includes the percentage of female content and model 2 the percentage of male content. The results do not change notably when controlling for the different sexes.

Table 5 Regression Results: ln Revenue per Week

VARIABLES	(1) ln Revenue per Week	(2) ln Revenue per Week
ln Body Exposure	0.131***	0.157***
	(0.040)	(0.040)
ln Female	0.033	
	(0.037)	
Multihoming = 1	-0.092	-0.084
	(0.195)	(0.197)
Multihoming = 2	-0.083	-0.078
	(0.195)	(0.197)
Multihoming = 3	-0.016	-0.011
	(0.205)	(0.208)
Multihoming = 4	-0.074	-0.065
	(0.233)	(0.237)
ln Number of Posts	0.173***	0.175***
	(0.028)	(0.028)
ln Followers	0.693***	0.700***
	(0.070)	(0.070)
ln Average Likes = L,	0.255***	0.254***
	(0.034)	(0.034)
ln Average Comments = L,	0.158***	0.158***
	(0.026)	(0.026)
Percentage of Branded Posts	-0.001	-0.001
	(0.001)	(0.001)
IG Category = 2, Fitness_Sports	0.266**	0.236**
	(0.104)	(0.105)
IG Category = 3, Food_Vegan	0.253**	0.253**
	(0.119)	(0.120)
IG Category = 4, Music	0.207**	0.181*
	(0.094)	(0.095)
IG Category = 5, Photo_Arts	0.311**	0.297**
	(0.128)	(0.129)

[5] Estimations without logged values were performed to cross-check results. They deliver very similar results, which can be interpreted as indicator of robustness.

ln Male		0.025
		(0.038)
Constant	-5.522***	-5.624***
	(1.057)	(1.073)
Observations	5,978	5,978
Number of IG_Handle	498	498

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Main results on BE and sex: BE has a significantly positive influence on advertising revenue in both models. The logged values can be interpreted as follows. An increase of one per cent BE leads to 0.131 per cent higher weekly revenue. Accordingly, one more nude picture increases revenue by 1.09 per cent.[6] For the mean revenue over the whole sample (91,535.48 USD) this means posting one more naked picture increases the weekly advertising income by 997,73 USD. In contrast, the type of content i.e. female or male content does not seem to have an impact. Additional estimations with interaction terms between sex and BE (not reported) fail to deliver insights on differences between content types. The effects are not significant. Although women show a higher degree in nudity (see Section 4.1), the interaction between sex and BE does not significantly influence the revenue in the sample. Therefore, it is not specifically profitable to be female and show naked skin. Rather, across all sexes, BE seems to have a positive effect. If revealing parts of your body is interpreted as cost or investment into success (since BE has a positive effect on income), accounts with female focus invest more into their success. It seems that, according to the results, females have to invest more to achieve the same income.

Further results are: Multihoming is not significant in any model, while the popularity indicators are (expectantly) highly significant. Further control variables are not interpreted, since they only serve as additional information against omitted variable bias. These results are in line with past studies (Budzinski & Gaenssle, 2020; Jung & Nüesch, 2019), which can be seen as a quality indicator and shows reliability of the data set.

[6] One picture equals 8.33 per cent.

5. Discussion and Conclusion

This paper empirically studies the effects of body exposure on Instagram success. Stars need to invest heavily into audience building, by drawing attention to themselves (audience attraction) and managing attention in the long run (audience maintenance). BE was studied as part of audience attraction within this paper. To answer the research question *"Does body exposure drive Instagram success?"* it can be said that BE positively influences advertising revenue of IS. A descriptive study of the data shows that a high level of BE is not exclusively necessary for top income positions, but is still common among the big ones. A more detailed statistical analysis shows that more BE is significantly better than no BE. The second question was: *"Is there a difference between male and female content in this regard?"*. There was no significant effect of female or male content on advertising revenue in the regression model. Hence, the focus on a specific type of content does not have significant influence on advertising revenue. Yet, looking at the differences of female and male content, a T-test shows that BE is significantly higher for accounts with focus on female content. However, it does not directly translate into monetary success of advertising revenue. There is no significant difference in revenues between the groups. These results raise a number of questions: Do women need to invest more to earn the same money? Is there a gender pay gap in social media?

The results can only be interpreted carefully and used as a first indicator. More research is needed to study differences in income, between sexes, categories, platforms etc. There are some limitations to this study, which open possibilities for further studies. As mentioned in the beginning, there are no traditional gatekeepers in social media markets (although agencies like multi-channel-networks established themselves during the last years (Budzinski & Gaenssle, 2020)). Yet, there are new gatekeepers, first and foremost the platform immanent algorithms. Sophisticated recommendation services manage scarce consumer attention and pre-select content according to individual preferences (Budzinski et al., 2021). A study by Richard et al. (2020) shows indicators that Instagram biases content allocation and favours nude content. According to their results, Instagram prioritises contents with high BE over others and pushes those posts. Since the algorithms are business secrets and ever-changing, it is not possible to subtract its' influence on income in my study. However, if this is the case, the gap between male and female income is expected to be even bigger – with females' higher degree in BE, further algorithmic support of the platform and, yet, no difference in payment. In any case, algorithm management and upload behaviour matter, as already pointed out by Budzinski and Gaenssle (2020) and Gaenssle and Budzinski (2020).

Nonetheless, it has to be considered that this study only focuses on the top group in five categories, which are dominated by female content (51.9 per cent female content; 21.6 per cent male content). A specific sampling according to sex would be interesting, to compare representative groups. From an economic point of view, scarcity for male content is higher than for female content, which is why it can be argued that it is more costly to advertise with them.

There are multiple sources of income for social media stars (see Section 3.2). In this paper, only the advertising revenue is observable. It serves as a good proxy, since it is common practice to earn money from ads and brand communication on Instagram. However, especially for nudity, there might be other sources of income. The website Onlyfans became very popular over the last years, featuring predominantly adult entertainment content. For very popular accounts with high BE, this might be a source of income, with Instagram merely being a marketing platform. Popular accounts link to Onlyfans, where a payment barrier is established to access further contents. However, the average of advertising revenue in this sample (USD 90.5k) shows a high degree of ad business and professional interactions between stars and advertisers. While the income proxy of this paper is legitimate, further studies on other sources of income would be interesting (if data is available).

There are limits to the data used in this paper. I use estimations of revenue, the exact numbers are not available. The data seems very reliable, conforming effects of past studies (see Section 4.2). Lastly, there is no classification of sex appeals within this data set. I do not differentiate e.g. between sportswear and lingerie. The sexual appeal of the pictures varies. Yet, sexual appeals are very subjective and leave room for further biases in coding.

References

Adler, M. (1985). Stardom and Talent. *The American Economic Review*, *75*(1), 208–212.

Adler, M. (2006). Stardom and Talent. In V. A. Ginsburgh & D. Throsby (Eds.), *Handbook of the Economics of Art and Culture* (Vol. 1, pp. 895–906). Elsevier. https://doi.org/10.1016/S1574-0676(06)01025-8

Budzinski, O., & Gaenssle, S. (2020). The economics of social media (super-)stars: an empirical investigation of stardom and success on YouTube. *Journal of Media Economics*, *31*(3-4), 75–95. https://doi.org/10.1080/08997764.2020.1849228

Budzinski, O., Gaenssle, S., & Lindstädt-Dreusicke, N. (2021). Data (R)Evolution – The Economics of Algorithmic Search and Recommender Services. In S. Baumann (Ed.), *Handbook of Digital Business Ecosystems* (forthcoming). Elgar.

Budzinski, O., & Pannicke, J. (2017). Does Popularity Matter in a TV Song Competition? Evidence from a National Music Contest. *Ilmenau Discussion Papers*, *21*(106).

Burgess, J., & Green, J. (2018). *Youtube: Online Video and Participatory Culture* (2nd ed.). *Digital Media and Society*. Polity Press.

Candela, G., Castellani, M., Pattitoni, P., & Di Lascio, F. M. L. (2016). On Rosen's and Adler's hypotheses in the modern and contemporary visual art market. *Empirical Economics*, *51*(1), 415–437. https://doi.org/10.1007/s00181-015-1002-3

Che, Y.-K., & Mierendorff, K. (2019). Optimal Dynamic Allocation of Attention. *American Economic Review*, *109*(8), 2993–3029. https://doi.org/10.1257/aer.20171000

Crain, W. M., & Tollison, R. D. (2002). Consumer Choice and the Popular Music Industry: A Test of the Superstar Theory. *Empirica*, *29*(1), 1–9. https://doi.org/10.1023/A:1014651130414

Dudley, S. C. (1999). Consumer Attitudes Toward Nudity in Advertising. *Journal of Marketing Theory and Practice*, *7*(4), 89–96. https://doi.org/10.1080/10696679.1999.11501854

Ehrmann, T., Meiseberg, B., & Ritz, C. (2009). Superstar Effects in Deluxe Gastronomy - An Empirical Analysis of Value Creation in German Quality Restaurants. *KYKLOS*, *62*(4), 526–541. https://doi.org/10.1111/J.1467-6435.2009.00449.X

Facebook. (2021). *Instagram Community Guidelines*. Facebook. https://www.facebook.com/help/instagram/477434105621119/

Filimon, N., López-Sintas, J., & Padrós-Reig, C. (2011). A test of Rosen's and Adler's theories of superstars. *Journal of Cultural Economics*, *35*(2), 137–161. https://doi.org/10.1007/s10824-010-9135-x

Franck, E., & Nüesch, S. (2008). Mechanisms of Superstar Formation in German Soccer: Empirical Evidence. *European Sport Management Quarterly*, *8*(2), 145–164. https://doi.org/10.1080/16184740802024450

Franck, E., & Nüesch, S. (2012). Talent and/or Popularity: What does it take to be a Superstar? *Economic Inquiry*, *50*(1), 202–216. https://doi.org/10.1111/j.1465-7295.2010.00360.x

Franck, G. (2019). The economy of attention. *Journal of Sociology*, *55*(1), 8–19. https://doi.org/10.1177/1440783318811778

Gaenssle, S., & Budzinski, O. (2020). Stars in social media: new light through old windows? *Journal of Media Business Studies*, 1–27. https://doi.org/10.1080/16522354.2020.1738694

Giles, D. E. (2006). Superstardom in the US popular music industry revisited. *Economics Letters*, *92*(1), 68–74. https://doi.org/10.1016/j.econlet.2006.01.022

Gräve, J.-F. (2017). Exploring the Perception of Influencers vs. Traditional Celebrities. In Association for Computing Machinery (Ed.), *Proceedings of the 8th International Conference on Social Media & Society - #SMSociety17* (pp. 1–5). ACM Press. https://doi.org/10.1145/3097286.3097322

Hofmann, K. H., & Opitz, C. (2019). Talent and publicity as determinants of superstar incomes: empirical evidence from the motion picture industry. *Applied Economics*, *51*(13), 1383–1395. https://doi.org/10.1080/00036846.2018.1527452

Hypeauditor. (2020). *The State of Influencer Marketing 2020: Influencer Fraud Dynamics*. https://hypeauditor.com/blog/state-2020/

Jung, C., & Nüesch, S. (2019). The more others care, the more you share? – Social contagion as a stardom trigger of social media superstars. *Applied Economics*, *51*(9), 881–888. https://doi.org/10.1080/00036846.2018.1497849

Katz, M. L., & Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *The American Economic Review*, *75*(3), 424–440. http://www.jstor.org/stable/1814809

Katz, M. L., & Shapiro, C. (1994). Systems Competition and Network Effects. *Journal of Economic Perspectives*, *8*(2), 93–115. https://doi.org/10.1257/jep.8.2.93

Lehmann, E. E., & Schulze, G. G. (2008). What Does it Take to be a Star? – The Role of Performance and the Media for German Soccer Players. *Applied Economics Quarterly*, *54*(1), 59–70. https://doi.org/10.3790/aeq.54.1.59

Leibenstein, H. (1950). Bandwagon, Snob, and Veblen Effects in the Theory of Consumers' Demand. *Quarterly Journal of Economics*, *64*(2), 183–207.

Lorber, J. (1996). Beyond the Binaries: Depolarizing the Categories of Sex, Sexuality, and Gender. *Sociological Inquiry*, *66*(2), 143–160. https://doi.org/10.1111/j.1475-682X.1996.tb00214.x

Lorber, J. (2005). *Breaking the bowls: Degendering and feminist change*. WW Norton New York.

Lucifora, C., & Simmons, R. (2003). Superstar Effects in Sport: Evidence From Italian Soccer. *Journal of Sports Economics*, *4*(1), 35–55. https://doi.org/10.1177/1527002502239657

Lull, R. B., & Bushman, B. J. (2015). Do Sex and Violence Sell? A Meta-Analytic Review of the Effects of Sexual and Violent Media and Ad Content on Memory, Attitudes, and Buying Intentions. *Psychological Bulletin*, *141*(5), 1022–1048. https://doi.org/10.1037/bul0000018

Marwick, A. E. (2016). You May Know Me from YouTube: (Micro-)Celebrity in Social Media. In P. D. Marshall & S. Redmond (Eds.), *A companion to celebrity* (pp. 333–350). Wiley Blackwell.

Meiseberg, B. (2014). Trust the artist versus trust the tale: performance implications of talent and self-marketing in folk music. *Journal of Cultural Economics*, *38*(1), 9–42. https://doi.org/10.1007/s10824-012-9196-0

Mittal, B., & Lassar, W. M. (2000). Sexual Liberalism as a Determinant of Consumer Response to Sex in Advertising. *Journal of Business and Psychology*, *15*(1), 111–127. https://doi.org/10.1023/A:1007723003376

Reichert, T. (2002). Sex in Advertising Research: A Review of Content, Effects, and Functions of Sexual Information in Consumer Advertising. *Annual Review of Sex Research*, *13*(1), 241–273. https://doi.org/10.1080/10532528.2002.10559806

Richard, É., Duportail, J., Kayser-Bril, N., & Schacht, K. (2020). *Undress or fail: Instagram's algorithm strong-arms users into showing skin*. https://algorithmwatch.org/en/instagram-algorithm-nudity/

Salganik, M. J., Dodds, P. S., & Watts, D. J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*, *311*(5762), 854–856. https://doi.org/10.1126/science.1121066

Severn, J., Belch, G. E., & Belch, M. A. (1990). The Effects of Sexual and Non-Sexual Advertising Appeals and Information Level on Cognitive Processing and Communication Effectiveness. *Journal of Advertising*, *19*(1), 14–22. https://doi.org/10.1080/00913367.1990.10673176

Shapiro, C., & Varian, H. R. (1999). *Information rules: A strategic guide to the network economy*. Harvard Business School Press.

Simon, H. A. (1971). Designing organizations for an information rich world. In M. Greenberger (Ed.), *Computers, communications, and the public interest* (pp. 37–72). Johns Hopkins P.

Stigler, G. J., & Becker, G. S. (1977). De Gustibus Non Est Disputandum. *American Economic Review*, *67*(2), 76–90.

Taylor, & Greg. (2014). Scarcity of Attention for a Medium of Abundance. In M. Graham & W. H. Dutton (Eds.), *Society and the Internet: How Networks of Information and Communication are Changing Our Lives* (pp. 257–271). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199661992.003.0017

Wirtz, J. G., Sparks, J. V., & Zimbres, T. M. (2018). The effect of exposure to sexual appeals in advertisements on memory, attitude, and purchase intention: a meta-analytic review. *International Journal of Advertising*, *37*(2), 168–198. https://doi.org/10.1080/02650487.2017.1334996

Appendix

Coding BE: 0-12

Coding Sex: 0-12, in (female, male, mixed, ambivalent, no identification)

Example 1:

BE: 8 *(1 = 1; 2 = 1; 3 = 1; 4 = 1; 5 = 1; 6 = 0; 7 = 1; 8 = 1; 9 = 0; 10 = 1; 11 = 0; 12 = 0)*

Sex: 0-12-0-0-0 *(all male)*

Example 2:

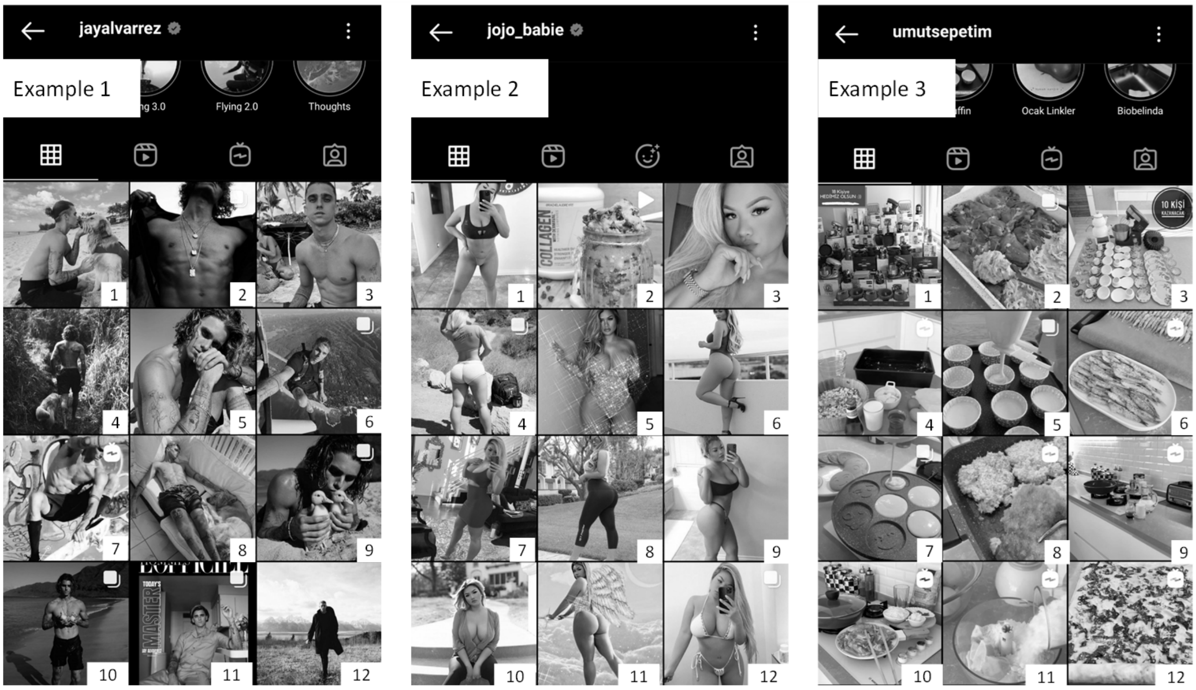
BE: 10 (*1 = 1; 2 = 0; 3 = 0; 4 = 1; 5 = 1; 6 = 1; 7 = 1; 8 = 1; 9 = 1; 10 = 1; 11 = 1; 12 = 1)* with picture 7 and 8 dressed, but 50 per cent or more focus is on primary sex characteristics

Sex: 11-0-0-0-1 *(all female, except second picture "no identification")*

Example 3:

BE: 0 *(no nudity in any picture)*

Sex: 0-0-0-0-12 *(all "no identification", no human characteristics)*



Diskussionspapiere aus dem Institut für Volkswirtschaftslehre

der Technischen Universität Ilmenau

Nr. 69 *Budzinski, Oliver:* Empirische Ex-Post Evaluation von wettbewerbspolitischen Entscheidungen: Methodische Anmerkungen, Januar 2012.

Nr. 70 *Budzinski, Oliver:* The Institutional Framework for Doing Sports Business: Principles of EU Competition Policy in Sports Markets, January 2012.

Nr. 71 *Budzinski, Oliver; Monostori, Katalin:* Intellectual Property Rights and the WTO, April 2012.

Nr. 72 *Budzinski, Oliver:* International Antitrust Institutions, Juli 2012.

Nr. 73 *Budzinski, Oliver; Lindstädt, Nadine:* Newspaper vs. Online Advertising - Is There a Niche for Newspapers in Modern Advertising Markets?, Juli 2012a.

Nr. 74 *Budzinski, Oliver; Lindstädt, Nadine:* Newspaper and Internet Display Advertising - Co-Existence or Substitution?, Juli 2012b.

Nr. 75 *Budzinski, Oliver:* Impact Evaluation of Merger Control Decisions, August 2012.

Nr. 76 *Budzinski, Oliver; Kuchinke, Björn A.:* Deal or No Deal? Consensual Arrangements as an Instrument of European Competition Policy, August 2012.

Nr. 77 *Pawlowski, Tim, Budzinski, Oliver:* The (Monetary) Value of Competitive Balance for Sport Consumers, Oktober 2012.

Nr. 78 *Budzinski, Oliver:* Würde eine unabhängige europäische Wettbewerbsbehörde eine bessere Wettbewerbspolitik machen?, November 2012.

Nr. 79 *Budzinski, Oliver; Monostori, Katalin; Pannicke, Julia:* Der Schutz geistiger Eigentumsrechte in der Welthandelsorganisation - Urheberrechte im TRIPS Abkommen und die digitale Herausforderung, November 2012.

Nr. 80 *Beigi, Maryam H. A.; Budzinski, Oliver:* On the Use of Event Studies to Evaluate Economic Policy Decisions: A Note of Caution, Dezember 2012.

Nr. 81 Budzinski, Oliver; Beigi, Maryam H. A.: Competition Policy Agendas for Industrializing Countries, Mai 2013.

Nr. 82 *Budzinski, Oliver; Müller, Anika:* Finanzregulierung und internationale Wettbewerbsfähigkeit: der Fall Deutsche Bundesliga, Mai 2013.

Nr. 83 *Doose, Anna Maria:* Methods for Calculating Cartel Damages: A Survey, Dezember 2013.

Nr. 84 *Pawlowski, Tim; Budzinski, Oliver:* Competitive Balance and Attention Level Effects: Theore-tical Considerations and Preliminary Evidence, März 2014.

Nr. 85 *Budzinski, Oliver:* The Competition Economics of Financial Fair Play, März 2014.

Nr. 86 *Budzinski, Oliver; Szymanski, Stefan:* Are Restrictions of Competition by Sports Associations Horizontal or Vertical in Nature?, März, 2014.

Nr. 87 *Budzinski, Oliver:* Lead Jurisdiction Concepts Towards Rationalizing Multiple Competition Policy Enforcement Procedures, Juni 2014.

Nr. 88 *Budzinski, Oliver:* Bemerkungen zur ökonomischen Analyse von Sicherheit, August 2014.

Nr. 89 *Budzinski, Oliver; Pawlowski, Tim:* The Behavioural Economics of Competitive Balance: Implications for League Policy and Championship Management, September 2014.

Nr. 90 *Grebel, Thomas; Stuetzer, Michael:* Assessment of the Environmental Performance of European Countries over Time: Addressing the Role of Carbon Leakage and Nuclear Waste, September 2014.

Nr. 91 *Emam, Sherief; Grebel, Thomas:* Rising Energy Prices and Advances in Renewable Energy Technologies, July 2014.

Nr. 92 *Budzinski, Oliver; Pannicke, Julia:* Culturally-Biased Voting in the Eurovision Song Contest: Do National Contests Differ?, December 2014.

Nr. 93 *Budzinski, Oliver; Eckert, Sandra:* Wettbewerb und Regulierung, März 2015.

Nr. 94 *Budzinski, Oliver; Feddersen, Arne:* Grundlagen der Sportnachfrage: Theorie und Empirie der Einflussfaktoren auf die Zuschauernachfrage, Mai 2015.

Nr. 95 *Pannicke, Julia:* Abstimmungsverhalten im Bundesvision Song Contest: Regionale Nähe versus Qualität der Musik, Oktober 2015.

Nr. 96 *Budzinski, Oliver; Kretschmer, Jürgen-Peter:* Unprofitable Horizontal Mergers, External Effects, and Welfare, October 2015.

Nr. 97 *Budzinski, Oliver; Köhler, Karoline Henrike:* Is Amazon The Next Google?, October 2015.

Nr. 98 *Kaimann, Daniel; Pannicke, Julia:* Movie success in a genre specific contest: Evidence from the US film industry, December 2015.

Nr. 99 *Pannicke, Julia:* Media Bias in Women's Magazines: Do Advertisements Influence Editorial Content?, December 2015.

Nr. 100 *Neute, Nadine; Budzinski, Oliver:* Ökonomische Anmerkungen zur aktuellen Netzneutralitätspolitik in den USA, Mai 2016.

Nr. 101 *Budzinski, Oliver; Pannicke, Julia:* Do Preferences for Pop Music Converge across Countries? - Empirical Evidence from the Eurovision Song Contest, Juni 2016.

Nr. 102 *Budzinski, Oliver; Müller-Kock, Anika:* Market Power and Media Revenue Allocation in Professonal Sports: The Case of Formula One, Juni 2016.

Nr. 103 *Budzinski, Oliver:* Aktuelle Herausforderungen der Wettbewerbspolitik durch Marktplätze im Internet, September 2016.

Nr. 104 *Budzinski, Oliver:* Sind Wettbewerbe im Profisport Rattenrennen?, Februar 2017.

Nr. 105 *Budzinski, Oliver; Schneider, Sonja:* Smart Fitness: Ökonomische Effekte einer Digitalisierung der Selbstvermessung, März 2017.

Nr. 106 *Budzinski, Oliver; Pannicke, Julia:* Does Popularity Matter in a TV Song Competition? Evidence from a National Music Contest, April 2017.

Nr. 107 *Budzinski, Oliver; Grusevaja, Marina:* Die Medienökonomik personalisierter Daten und der Facebook-Fall, April 2017.

Nr. 108 *Budzinski, Oliver:* Wettbewerbsregeln für das Digitale Zeitalter – Die Ökonomik personalisierter Daten, Verbraucherschutz und die 9.GWB-Novelle, August 2017.

Nr. 109 *Budzinski, Oliver:* Four Cases in Sports Competition Policy: Baseball, Judo, Football, and Motor Racing, September 2017.

Nr. 110 *Budzinski, Oliver:* Market-internal Financial Regulation in Sports as an Anticompetitive Institution, October 2017.

Nr. 111 *Bougette, Patrice; Budzinski, Oliver; Marty, Frédéric:* EXPLOITATIVE ABUSE AND ABUSE OF ECONOMIC DEPENDENCE: WHAT CAN WE LEARN FROM THE INDUSTRIAL ORGANIZATION APPROACH?, December 2017.

Nr. 112 *Budzinski, Oliver; Gaenssle, Sophia:* The Economics of Social Media Stars: An Empirical Investigation of Stardom, Popularity, and Success on YouTube, Januar 2018.

Nr. 113 *Gaenssle, Sophia; Budzinski, Oliver; Astakhova Daria:* Conquering the Box Office: Factors, influencing Success of International Movies in Russia, Mai 2018.

Nr. 114 *Budzinski, Oliver; Stöhr, Annika:* Die Ministererlaubnis als Element der deutschen Wettbewerbsordnung: eine theoretische und empirische Analyse, Juli 2018.

Nr. 115 *Budzinski, Oliver; Kuchinke, Björn A.:* Modern Industrial Organization Theory of Media Markets and Competition Policy Implications, September 2018.

Nr. 116 *Budzinski, Oliver; Lindstädt-Dreusicke, Nadine:* The New Media Economics of Video-on-Demand Markets: Lessons for Competition Policy, Oktober 2018.

Nr. 117 *Budzinski, Oliver; Stöhr, Annika:* Competition Policy Reform in Europe and Germany – Institutional Change in the Light of Digitization, November 2018.

Nr. 118 *Budzinski, Oliver; Noskova, Victoriia; Zhang, Xijie:* The Brave New World of Digital Personal Assistants: Benefits and Challenges from an Economic Perspective, December 2018.

Nr. 119 *Bougette, Patrice; Budzinski, Oliver & Marty, Frédéric:* EXPLOITATIVE ABUSE AND ABUSE OF ECONOMIC DEPENDENCE: WHAT CAN WE LEARN FROM AN INDUSTRIAL ORGANIZATION APPROACH? [Updated Version 2018], December 2018.

Nr. 120 *Bartelt, Nadja:* Bundling in Internetmärkten - Ökonomische Besonderheiten, Wettbewerbseffekte und Regulierungsimplikationen, Dezember 2018.

Nr. 121 *Budzinski, Oliver; Feddersen, Arne:* Measuring Competitive Balance in Formula One Racing, März 2019.

Nr. 122 *Budzinski, Oliver; Kohlschreiber, Marie; Kuchinke, Björn A. & Pannicke, Julia:* Does Music Quality Matter for Audience Voters in a Music Contest, März 2019.

Nr. 123 *Gaenssle, Sophia; Budzinski, Oliver:* Stars in Social Media: New Light Through Old Windows?, April 2019.

Nr. 124 *Stöhr, Annika; Budzinski, Oliver:* Ex-post Analyse der Ministererlaubnis-Fälle - Geminwohl durch Wettbewerbsbeschränkungen?, April 2019.

Nr. 125 *Budzinski, Oliver; Lindstädt-Dreusicke, Nadine:* The New Media Economics of Video-on-Demand Markets: Lessons for Competition Policy (Updated Version), May 2019.

Nr. 126 *Stöhr, Annika; Noskova, Victoriia; Kunz-Kaltenhäuser, Philipp; Gaenssle, Sophia & Budzinski, Oliver:* Happily Ever After? – Vertical and Horizontal Mergers in the U.S. Media Industry, June 2019.

Nr. 127 *Budzinski, Oliver; Stöhr, Annika:* Der Ministererlaubnis-Fall Miba/Zollern: Europäische Champions statt Wettbewerb?, Juni 2019.

Nr. 128 *Budzinski, Oliver; Gaenssle, Sophia & Kunz-Kaltenhäuser, Philipp:* How Does Online Streaming Affect Antitrust Remedies to Centralized Marketing? The Case of European Football Broadcasting, Rights, July 2019.

Nr. 129 *Budzinski, Oliver; Haucap, Justus:* Kartellrecht und Ökonomik: Institutions Matter!, Juli 2019.

Nr. 130 *Budzinski, Oliver & Stöhr, Annika:* Public Interest Considerations in European Merger Control Regimes, August 2019.

Nr. 131 *Gaenssle, Sophia; Budzinski, Oliver & Astakhova:* Daria: Conquering the Box Office: Factors Influencing Succes of International Movies in Russia (Update), October 2019.

Nr. 132 *Stöhr, Annika; Budzinski, Oliver & Jasper, Jörg:* Die Neue E.ON auf dem deutschen Strommarkt – Wettbewerbliche Auswirkungen der innogy-Übernahme, November 2019.

Nr. 133 *Budzinski, Oliver; Grebel, Thomas; Wolling, Jens & Zhang, Xijie:* Drivers of Article Processing Charges in Open Access, December 2019.

Nr. 134 *Gaenssle, Sophia; Kuchinke, Björn, A.:* Die Hörspielserie „Die drei ???" – Der wirtschaftliche Erfolg und Gründe dafür, Januar 2020.

Nr. 135 *Budzinski, Oliver:* The Economics of International Competition Policy: New Challenges in the Light of Digitization?, January 2020.

Nr. 136 *Dittmann, Heidi & Kuchinke, Björn A.:* Die Theorie mehrseitiger Marktplätze in der US-amerikanischen und deutschen Zusammenschlusskontrolle: Eine empirische Untersuchung für den Mediensektor, Januar 2020.

Nr. 137 *Budzinski, Oliver; Gaenssle, Sophia & Lindstädt-Dreusicke, Nadine:* The Battle of YouTube, TV and Netflix – An Empirical Analysis of Competition in Audio-visual Media Markets, April 2020.

Nr. 138 *Gaenssle, Sophia & Kunz-Kaltenhäuser, Philipp:* What Drives Binge-Watching? An Economic Theory and Analysis of Impact Factors, April 2020.

Nr. 139 *Budzinski, Oliver; Grusevaja, Marina & Noskova, Victoriia:* The Economics oft he German Investigation of Facebook's Data Collection, May 2020.

Nr. 140 *Budzinski, Oliver; Gaenssle, Sophia & Stöhr, Annika:* Der Entwurf zur 10. GWB Novelle: Interventionismus oder Laissezfaire?, Juni 2020.

Nr. 141 *Budzinski, Oliver & Kunz-Kaltenhäuser, Philipp:* Promoting or Restricting Competition? – The 50plus1-Rule in German Football, June 2020.

Nr. 142 *Budzinski, Oliver; Gaenssle, Sophia & Stöhr, Annika:* The Draft for the 10th Amendment of German Competition Law: Towards a new Concept of „Outstanding Relevance across Markets"?, June 2020.

Nr. 143 *Budzinski, Oliver & Stöhr, Annika:* Ministererlaubnis für Kartellfälle: Kooperation im Sinne des Gemeinwohls?, August 2020.

Nr. 144 *Gaenssle, Sophia:* Big Data Comes to Hollywood – Audiovisuelle Medienmärkte im Digitalen Zeitalter, August 2020.

Nr. 145 *Zhang, Xijie; Grebel, Thomas & Budzinski, Oliver:* The Prices of Open Access Publishing: The Composition of APC across Different Fields of Sciences, Oktober 2020.

Nr. 146 *Huppert, Caroline:* Die Fairsten werden die Letzten sein? Herausforderungen für die deutschen Wettbewerbsregeln durch die digitale Wirtschaft, Oktober 2020.

Nr. 147 *Budzinski, Oliver; Gaenssle, Sophia & Lindstädt-Dreusicke, Nadine:* Wettbewerb und Antitrust in Unterhaltungsmärkten, Januar 2021.

Nr. 148 *Budzinski, Oliver; Gaenssle, Sophia & Lindstädt-Dreusicke, Nadine:* Data (R)Evolution – The Economics of Algorithmic Search and Recommender Services, January 2021.

Nr. 149 *Kunz-Kaltenhäuser, Philipp:* Is the NFL´s Pro Bowl Broken? Considering the Players´ Perspective, April 2021.