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Abstract

New technological advancements such as Augmented Reality (AR) and Virtual Reality (VR) have introduced new hedonic products to the entertainment industry. Motivated by the growing popularity of AR-based games (e.g., such as Pokémon Go), the main objective of this study is to determine whether the success of AR-based games comes at the expense of more traditional hedonic products such as television or cinema. Therefore, we measure the impact of AR-based games on other classes of hedonic products (instantiated by products like e.g., television, cinema and online games) by studying rich, unique data sets which allow us to monitor the activity level of the different hedonic products before and after the introduction of AR-based games. Our results reveal that AR-based games have a high disruptive potential for the entertainment sector, and can both, substitute or complement the consumption of other hedonic products. We find that due to the AR-based games’ requirement for consumers to leave their home and be active outside, AR-based games will most likely substitute other hedonic products, except for those which (1) require the consumer to travel to a venue away from home, and at the same time (2) serve different entertainment needs as the needs satisfied by AR-based games (i.e., lean forward AR-games vs. lean back in cinema).

Keywords: Augmented Reality, Augmented Reality Games, Hedonic Products, Entertainment, Field Data
INTRODUCTION

The prevalence of powerful, camera-equipped smartphones with mobile Internet access enables technological advancements such as Virtual Reality\(^1\) (VR) and Augmented Reality\(^2\) (AR) to change the entertainment industry fundamentally, and introduce new types of hedonic products (such as VR news, VR documentaries or AR-based games) to the industry. While some of these new hedonic products are yet to be discovered by the masses (e.g. VR news and VR documentaries), AR-based games such as Ingress and Pokémon Go (PoGo) have already established a new class of entertainment products. Since their launch in November 2012 and July 2016 until the end of 2017, Ingress counts 20 million installations and PoGo approximately 750 million downloads (Tassi 2017). Within the first 90 days after release in mid-2016, PoGo earned $600 million in revenues (Smith 2018), and another $600 million throughout 2017, reaching a total of approximately $1.2 billion revenues by the end of 2017 (Smith 2018). This amount represents more than 1% of the global games total market value of 2016 (Newzoo Games 2016) and shows the economic potential of such products.

The success of Pokémon Go and Ingress represents, however, not outliers, but most likely the forefront of a completely new entertainment and service category: The revenue of VR and AR-based products is estimated to grow from $5.2 billion in 2016 to more than $162 billion in 2020 (IDC 2016). Recently, several companies announced the development of new AR-based games such as Harry Potter Wizards United (Niantic Inc. 2017) or Ingress Prime (Webster 2017) – a comprehensive overhaul of the AR-based game Ingress. In addition to their direct economic importance, AR-based games can affect competing entertainment

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\(^1\) The VR technology refers to a computer-generated environment, or a copy of the real world that is presented to the user via a headset.

\(^2\) The Augmented Reality technology can overlay digital elements atop the real environment (Daniels 2014) and “supplements the real world with virtual (computer-generated) objects that appear to coexist in the same space as the real world” (Azuma et al. 2001 p. 34).
products such as video games, cinemas and TV as well as other businesses by either attracting or deterring customers.

Traditionally, information systems research focuses on understanding the interaction of end user with technology from a cognitive and technology acceptance perspective, and focuses less on the economic implications of their behavior (Bapna et al. 2004). Similarly, the research on entertainment and media products does not focus on the economic impact of emerging hedonic products but rather on their adoption and consumer consumption behavior. Thus, it is not surprising that previous research on AR-based games focused primarily on their health and social impacts (e.g. Althoff et al. 2016; Howe et al. 2016; Tabacchi et al. 2017; Wong 2017), while research on the economic impact of AR-based games remains sparse. Pamuru, Khern-am-nuai and Kannan’s study (2017) which analyzes PoGo`s effect on the number of restaurant customers constitutes an exception. Yet, understanding the economic implications of the emerging sub-industry of AR-based games and in particular, understanding whether AR-based games have the capability to disrupt the entertainment industry, by capturing revenues from other prevalent hedonic products, such as TV, online games, and cinemas is crucial for business research.

To recognize opportunities or threats that emerging AR-based games bring along, managers must be able to fully understand the implications of AR-based games for their business. The goal of this study is to analyze the impact of AR-based games on prevalent hedonic products using behavioral field data.

We achieve our goal by studying the effect of the market introduction of PoGo as an instantiation for AR-based games on other existing hedonic products. For this purpose we employ knowledge from the theory of hedonic products\(^3\) (Hirschman and Holbrook 1982) and

\(^3\) The theory of consumer products differentiates between utilitarian and hedonic products. Utilitarian goods are consumed for their practical uses and based on real needs. On the contrary, hedonic products are "pleasure oriented" (Van der Heijden 2004) products which are consumed for luxury or enjoyment purposes. However, they must not be confused with
propose a conceptual framework to classify existing hedonic products into four classes. We measure the impact of AR-based games on the four classes of hedonic products by analyzing several unique data sets, which allow us to monitor the activity status of the hedonic products of interest before and after the introduction of PoGo. After presenting the results from the empirical analyses, this study concludes with a discussion of the theoretical and managerial implications of our main findings.

RELATED LITERATURE AND CONCEPTUAL FRAMEWORK

Related Work on Hedonic Goods Consumption

Previous research has extensively studied the interaction and interrelationships between different types of hedonic products (Adoni and Nossek 2001). Accordingly, there is a lot of research analyzing the interaction between emerging hedonic products and existing ones (e.g. Adoni and Nossek 2001; Coffey and Stipp 1997; Dutta-Bergman 2004; Lee and Leung 2008; Michel 2005; Nguyen and Western 2006).

However, this extensive research is inconclusive on the impact of new hedonic products on existent ones (Adoni and Nossek 2001): On one the hand, there are studies which find substitution effects between new hedonic products and older ones (e.g. Hong 2007; Michel 2005; Zentner 2006). These studies contend that due to specific characteristics of hedonic products, the consumption of newer products will ultimately always drive other existent hedonic products out of the market (Nguyen and Western 2006 p. 2): First, hedonic products suffer from decreasing marginal utility rates (Clement et al. 2006). These imply that the repeated consumption of a particular hedonic product yields decreasing enjoyment levels over time so that the consumption of a newer hedonic product will provide a consumer higher prestige goods and conspicuous consumption which are mainly consumed to show off a high social status (Hinz et al. 2015). Digitized hedonic products comprise all types of mobile, online and video games, interactive television, and movie streaming services. In the remainder of the paper, we refer to entertainment-related media and activities as prime examples of hedonic products.

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premise goods and conspicuous consumption which are mainly consumed to show off a high social status (Hinz et al. 2015). Digitized hedonic products comprise all types of mobile, online and video games, interactive television, and movie streaming services. In the remainder of the paper, we refer to entertainment-related media and activities as prime examples of hedonic products.
enjoyment levels than the consumption of an existent, previously consumed product. Second, a consumer’s demand for hedonic products is determined by her or his limited resources (e.g. time, money and attention). Because a consumer's decision to engage with a particular hedonic product will automatically diminish or replace the consumption of another hedonic product (Nguyen and Western 2006), all hedonic products are ultimately competing for the consumer's limited time, money, attention. A consumer's leisure time and budget for entertainment, for instance, are determined by her or his circumstances, such as work status, patterns of commuting (Taneja et al. 2012 p. 3), marital status, and number of kids. Similarly, a consumer's attention is another irreversibly depletable finite resource (Csikszentmihalyi 2014; Davenport and Beck 2001) which is determined by the consumer's capability to stay focused.

Further, this stream of literature promotes the concept that all types of hedonic products serve the same function (i.e. to provide entertainment to their consumer). Hence, consumers perceive different hedonic products as comparable and potential substitutes regardless of their price, quality or other factors. Because consumers in general try to satisfy and maximize their enjoyment levels (Bruton 2016; Cabanac 1992), while staying within their constraint boundaries with respect to limited amount of leisure time, money and attention, they will consume hedonic products that yield the highest utility level. Given the hedonic products’ declining marginal utility rates, individuals will consume hedonic products that are rather new to them, and thus eventually substitute older hedonic products with new ones.

On the other hand, there are several studies that find that new and existent hedonic products can exhibit complementarity effects between each other. These studies argue that different types of hedonic products cannot be seen as an absolute functional alternative to another. Because each hedonic product has its own distinctive features, they also serve different needs in different contexts. Accordingly, different hedonic products can complement each other in satisfying the diverse media-related needs of their consumers (Nguyen and
Western 2006). In economic theory, two products are complements for each other if the utility of consuming them together is greater than the combined utility of consuming them separately (Xu et al. 2014). For example, a mobile news websites and a mobile news app can be complements rather than substitutes, as the consumption of news via the app can increase the number of visits of the corresponding news website (Xu et al. 2014).

To understand the complementarity effects between new and existing hedonic products it is key to first understand consumer’s choice behavior for hedonic products. Consumers’ consumption of hedonic products is determined by their perceptions and expectations related to a particular product (Lichtenstein and Rosenfeld 1983; Ruggiero 2000). Up to now, research efforts aimed to understand how expectations and information diffusion determine the consumers’ choice behavior in favor or against a certain hedonic product (e.g. Hinz and Spann 2008; Hsu and Lu 2004; Jansz 2005; Merikivi et al. 2017; Vorderer and Klimmt 2004; Williams 2008; Yee and Caplan 2008). These studies postulate that expectations vary tremendously across consumers, and that “different users have always had different expectations and uses of the same media” (Williams et al. 2008 p. 998). Therefore, the impact of new hedonic products on existing is affected by the heterogeneity of different types and genres of hedonic products, as well as by consumers and their expectations.

In line with the theory of Use and Gratifications (Boyle et al. 2012), consumers have certain entertainment needs which need to be fulfilled. As different hedonic products serve different entertainment needs, a consumer aiming to satisfy her entertainment needs will consume a mix of hedonic products which will vary in the short term but will stay stable in the long run. For example, a consumer which inherently displays the need for more relaxing, at home entertainment (e.g. television, or reading books) can satisfy her needs only by consuming this type of hedonic products. The consumption of more active, away from home entertainment (e.g. sports activities) will not satisfy the needs for relaxing, at home
entertainment. Further, consumers who have experienced Csikszentmihalyi’s (2014) “flow” when consuming a certain hedonic product (Agarwal and Karahanna 2000) may try to repeat the flow experience by consuming the same product again and again (Agarwal and Karahanna 2000). Subsequently, the introduction of new hedonic products might not replace the consumption pattern of older hedonic products but rather motivate individuals to consume newer hedonic products in addition to their previous consumption.

Previous literature is thus in sum inconclusive on whether we should expect complementarity or substitution effects between AR-based games and existing hedonic products.

**Related Work on Media Consumption and AR**

Research on entertainment media also found both — the substitution of existing media by new (digital) media (e.g. Engel and Breunig 2015; esa 2016; Hinz et al. 2014), as well as evidence that new media products can complement existent ones (e.g. Gentzkow 2007; Nguyen and Western 2006; Xu et al. 2014). Research focusing on interaction effects between different types of media explains the occurrence of complementarity or substitution effects based on the relationship these have with each other. For example, media products which have a low level of overlap (and thus they serve different needs) are more likely to be complements.

By definition, the Augmented Reality technology can overlay digital elements atop the real environment (Daniels 2014) and enhances the real world with virtual objects that appear to coexist in the same space as the real world (Azuma et al. 2001 p. 34). AR, was first developed in late 1960’s (e.g. Greenwald et al. 2017; Merchant et al. 2014) and was originally used in education (e.g. Bower et al. 2014; Dunleavy and Dede 2014; Radu 2014; Wu et al. 2013), in medical training (e.g. Barsom et al. 2016; Hondori et al. 2013), or for military purposes (LaViola et al. 2015; Livingston et al. 2011; Oskiper et al. 2015). However, due to its capability to merge the virtual and real world and allow consumer interaction with digital elements in real-time and 3D (Azuma R. 1997; Bernardes et al. 2008) the AR technology
AR-based mobile games differ from any other existing hedonic products due to their location awareness and their requirement for constant consumer mobility. Most traditional hedonic products, such as music events, soccer games, cinema, TV or even video games are bound to a certain venue. Other hedonic products, which are installed on mobile devices, are not location-bound and can be played while at home and on the go. Nevertheless, these mobile hedonic products do not require their consumer to get out of their house in order to enjoy them.

In contrast to all these hedonic products, AR-based mobile games require their consumers to be physically mobile, walk around the streets, and actively search and visit different venues. They can be played only while the consumer is on the go since the AR-based mobile games experience is based on capturing the real environments and enhancing them with digital elements. In fact, the AR-based mobile games experience is designed to reward gamers who move around and go to remote places. Due to this characteristic, which makes AR-based games unique when compared to any other hedonic product, the overlap of AR-based with other hedonic products is relatively low, facilitating a potential complementary relationship between AR-based games and other products.

**Conceptual Framework**

Currently, a broad range of different hedonic products exists, which all vary with respect to content, location, timing, length, sensory input, consumer engagement type, consumer skills required, emotions invoked, or experience intensity. To structure our analyses on the effects of AR-based games on existing hedonic products, we classify hedonic products into four categories based on two dimensions.

The first dimension of our proposed hedonic products classification is based on the consumer’s engagement type with the product and distinguishes between "**lean back**" and
"lean forward" hedonic products (de Freitas and Griffiths 2010; Jansz 2005; Nakatsu 2005). The consumption of lean forward hedonic products, such as surfing the Web or playing games, require that the consumer has an active role in determining what is going on (de Freitas and Griffiths 2010). In contrast, the consumption of lean back hedonic products, such as watching a film on TV or at the cinema, implies that the viewer is passive and has no control over what happens (de Freitas and Griffiths 2010). Lean back hedonic products can also be understood as “passive" and lean forward as “active" hedonic products. Meanwhile, passive hedonic products relate to the predominantly passive consumption of information and require less concentration and attention; active hedonic products need consumer interaction and attention. A video game for instance "requires a constant exchange of messages between the game and its player" (Vorderer and Klimmt 2004) and is thus typically classified as a lean forward hedonic product.

As mentioned previously, AR-based games are different from any other existing hedonic products because they require their consumer to be mobile. To account for this distinctive characteristic of AR-based games we consider the location where a hedonic product is typically consumed as our second classification criteria and differentiate between hedonic products which are typically consumed "at home", and those which are usually consumed "away from home".

Based on these two dimensions we distinguish between four classes of hedonic products (see Fig. 1):

- **Class 1: lean forward & away from home** hedonic products such as sports activities (i.e. soccer or tennis), games for mobile devices⁴, but also AR-based games such as PoGo and Ingress.

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⁴ Games for mobile devices can be played technically while at home and away from home. AR-based games appertain to the group of games for mobile devices but require that the player is playing the game away from home. Accordingly, AR-based games are classified as lean forward & away from home games.
• **Class 2: lean forward & at home** hedonic products such as console games, board games and browser based online games.

• **Class 3: lean back & away from home** hedonic products like cinema, theater or music festivals.

• **Class 4: lean back & at home** hedonic products like television or reading books at home.

To study the economic impact of AR-based games on other hedonic products we select one prevalent (existing) hedonic product from each of the four classes and analyze the impact of a particular AR game (PG) on this existing product. Specifically, we evaluate the changes in the consumption patterns of the selected hedonic product from each class a priori and posterior to an AR-based game’s release. For this purpose we monitor the changes in the consumption of a competing AR-based game (Ingress), as a operationalization for the class of lean forward & away from home hedonic products (class 1); browser based online games as a proxy for the lean forward & at home hedonic products (class 2); cinemas as a proxy for the class of lean back & away from home hedonic products (class 3); and television consumption as a proxy for the class of lean back & at home hedonic products (class 4), before and after the introduction of PoGo – the AR-based game released by Niantic in Germany on the 13th of July 2016.
Concluding, we note that the literature discussed in this section presents evidence and arguments for the existence of both — substitution and complementarity effects between new hedonic products and available ones. Thus, the interaction between the different types of hedonic products and particularly the impact of the emerging genre of AR-based games on prevalent hedonic products can not be explained conclusively on the basis of previous literature. Ultimately, to determine the real effect of AR-based games on the four classes of hedonic products, it is necessary to follow an empirical, data-based approach.

**DATA AND METHODOLOGY**

This section presents our methodological approach including the data collection methods as well as measures for identification to determine the economic impact of AR-based games on other classes of hedonic products.

**Data**

We collected five data sets which reflect the activity levels in the focal AR-based game as well as one other hedonic product in each of the four classes. Further, we collected information for additional control variables.
For our study, we focus on a geographic area located in the middle of Germany that covers the State of Hesse – a state comparable to the size of the US state Vermont (i.e. the size is approximately 25,000 km²). Hesse has a population of 6.2 million and comprises densely-populated urban areas (the Frankfurt Rhine-Main metropolitan area) as well as less-populated rural areas in the north of the state.

The data related to our focal AR-based game – PoGo (e.g. exact location of Pokestops and -gyms) – was collected via crawlers, from two different websites (www.pokemonradar.de, www.pokemongomap.info). Striving for a complete data set with all Pokestops and gyms in the area of interest we merged the two data sources, removed all duplicates so that the final data record comprises a precise list of all existing Pokestops and gyms in the area of interest.

The data related to the competing AR-based game – Ingress⁵ – was gathered directly from the official Ingress Intel Map (www.ingress.com/intel). The map shows all the user activities in Ingress on a Google Map, but for our purpose, we observed only the area of interest. We collected highly granular data on the actions made in the game, including GPS positions and a time stamp of each action performed, from the 1st of January 2016 to the 09th of October 2016. This observation period of 283 days is the maximum period that is covered by this dataset and all other dataset which we will describe in the following.

The activity in online games was provided by a popular platform with more than 60 different online games. Note that this platform is not optimized for mobile operating systems and playing the games makes online sense on a desktop PC. The data set records the number of games started and finished per day, during the period from the 1st of January 2016 to the 9th

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⁵ Ingress is a location-based AR game based on a science fiction story where a user can appertain to one of two opposing groups (factions) of players. Consumers are usually walking or driving around and try to hack so called Portals, which are public locations or buildings. Portals which are owned by gamers appertaining to the same team can be linked (under certain circumstances) into control fields. The aim of the game is to create numerous and vast control fields for your team.
of October 2016. Based on this information we computed the number of active games per day – the variable measuring the activity levels on that platform.

The **cinema attendance** in the area of interest was provided by seven multiplex cinemas, from 1st of January 2016 to the 09th of October 2016. For reasons of confidentiality, we cannot disclose the names and exact locations of the movie theaters and indexed the absolute numbers of cinema visitors per day and standardized the data such that for each cinema the day of the year with the lowest number of visitors was set to 1. The remaining days of the year have been put in relation to the visitor numbers of the weakest business day. Thus, this standardization of the data accounts for different numbers of visitors between cinemas.

The number of **TV viewers** in Hesse was provided by MediaControl – a German market research company measuring TV audiences in Germany. The dataset comprises the number of TV viewers (in millions) per hour, from the 1st of January 2016 to the 09th of October 2016. The number of TV viewers contains the whole population aged 3 and above.

In addition to the above-mentioned main data records, we also gathered **additional control variables**, especially location-dependent weather data which was collected from the archives of the German weather agency (Deutscher Wetter Dienst – DWD).

**Identification strategy**

To estimate the effect of AR-based games on the previously presented hedonic product classes, we use the release date of PoGo in Germany (13th of July 2016) as the decisive intervention to capture the effect of the AR-based games on other hedonic products. Accordingly, we monitor the activity levels of Ingress, browser based online games and the number of cinema visitors and television viewers before and after the introduction of PoGo in Germany.
In all models we control for potential factors influencing the activity levels in the hedonic products such as the weather conditions (e.g. temperature, rain) and time controls (weekday effects and time of the day effects).

Besides using the temporal effect of the introduction of PoGo into the market, we use two additional measures for identification. First, we use PoGo server outages as an additional measure to identify the causal impact of AR-based games on other hedonic products, and test if during the PoGo server outages consumers turn their attention to Ingress, online games, cinema or TV. Since the PoGo server outages were unpredictable, they represent exogenous random shocks which can be leveraged for a quasi-experimental setting for our analysis.

Second, we use geospatial information which is available for the “away from home” entertainment products, i.e. we have location information on the different movie theaters and for the Ingress portals. Fortunately, these data come with variation such that some movie theaters are also Pokéstops and others are not. The same holds true for Ingress portals which are sometimes also Pokéstops and some are not. If PoGo has an impact on the different classes of hedonic products, we could also expect a marginal activity difference between movie theaters / Ingress portals that are also Pokéstops and which are not.

Below, we present the base model estimated for each of the four previously introduced hedonic product classes:

$$DV_i = cons + \beta_1 \cdot PokemonReleased_i + \beta_2 \cdot ServerDown_i + \beta_3 \cdot Temperature_i$$
$$+ \beta_4 \cdot Temperature^2_i + \beta_5 \cdot Rain_i + \gamma \cdot TimeControls_i + \epsilon_i$$ (1)

The model estimates the effects caused by the release of PoGo ($PokemonReleased$) on a specific other hedonic product as dependent variable (DV) (e.g. number of actions in Ingress, number of online games, number of TV viewers, number of visitors in cinema) while controlling for weather effects ($Temperature$ in °C, $Temperature^2$ in °C, $Rain$ in mm) and time effects.
In addition to this base model described in equation (1), we employ – for the “away from home” products – additional analyses to tease out the causal effect. Based on the heterogeneity and the characteristics of the different datasets, we exploit the geospatial variation in the data and conduct a Difference-in-Difference (DID) analyses where the treated item is directly linked or related to PoGo (movie theater is Pokéstop / Ingress portal is Pokéstop). The Ingress portals and movie theaters that do not constitute Pokéstops serve as control group. The treatment intervention is PoGo’s release date in Germany – the 13th of July 2016. Prior to the DID analysis we checked our treated and control group for the parallel trend assumption (see Table A1 in Appendix).

**EMPIRICAL ANALYSES**

**Impact of AR-Based Games on Lean Forward & Away From Home Products**

**Setting**

To analyze the impact of AR-based games on lean forward products that are consumed away from home we created a panel data set comprising the number of actions per Ingress Portal per day. In total, we analyzed the daily activity levels of 49,110 Ingress Portals prior to and after the introduction of PoGo in Germany (see Table 1 panel a). Given that PoGo utilizes large parts of the portal database and infrastructure built in Ingress, each of the Ingress Portals can also be simultaneously a Pokéstop or a –gym. In fact, approximately 88% of the analyzed Ingress portals are simultaneously Pokéstops or –gym (see Figure 2). We exploit this variance to monitor the activity levels of the Ingress Portals pre- and post- PoGo’s release, and between Ingress Portals which are Pokéstops and those that are not. We use a classical difference-in-difference approach and let the interaction isPokéstop*PokemonReleased capture the relevant between-subject variation. We estimate our empirical base model from equation (1) on a panel data set which consists of the daily activity level for each of the
49,110 analyzed Ingress Portals by employing a regression model with cluster-robust standard errors (with day as cluster variable).

*Table 1: Descriptive statistics of different hedonic products, period: 01 Jan. 2016 to 09 Oct.*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. AR Games (Ingress)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actions per portal and day (all portals (i.e. 49,110 portals))</td>
<td>13,898,130</td>
<td>1.037</td>
<td>3.451</td>
<td>0</td>
<td>1,070</td>
</tr>
<tr>
<td>Actions per portal and day (only Ingress portals (i.e. 6,017 portals))</td>
<td>1,702,811</td>
<td>1.225</td>
<td>3.965</td>
<td>0</td>
<td>925</td>
</tr>
<tr>
<td>Actions per portal (Ingress portals and Pokestops (i.e. 43,093 portals))</td>
<td>12,195,319</td>
<td>1.011</td>
<td>3.372</td>
<td>0</td>
<td>1,070</td>
</tr>
<tr>
<td>b. Online board games</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active Games per day</td>
<td>283</td>
<td>31,521.96</td>
<td>499.207</td>
<td>30,142</td>
<td>32,920</td>
</tr>
<tr>
<td>c. Cinema attendance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indexed number of visitors per cinema and day (all 7 cinemas)</td>
<td>1,981</td>
<td>10.113</td>
<td>8.837</td>
<td>1</td>
<td>75.333</td>
</tr>
<tr>
<td>Indexed number of visitors per cinema and day (no Pokestop (5 cinemas))</td>
<td>1,415</td>
<td>11.262</td>
<td>9.809</td>
<td>1</td>
<td>75.333</td>
</tr>
<tr>
<td>Indexed number of visitors per cinema and day (is Pokestop (2 cinemas))</td>
<td>566</td>
<td>7.240</td>
<td>4.615</td>
<td>1</td>
<td>23</td>
</tr>
<tr>
<td>d. TV viewers</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of viewers per hour, per day (in thousands)</td>
<td>6,792</td>
<td>4,344.993</td>
<td>2,537.885</td>
<td>1</td>
<td>8,783</td>
</tr>
<tr>
<td>Number of viewers during primetime (in thousands)</td>
<td>849</td>
<td>2,542.06</td>
<td>955.759</td>
<td>625</td>
<td>4,684</td>
</tr>
</tbody>
</table>


Estimation Results

Table 2 shows the estimation results for the different datasets. Model (1a) illustrates that the introduction of PoGo had a negative effect on the competing AR-game (Ingress). According to our estimations the activity levels per Ingress portal per day drop by c.p. 0.279 (p<.01), actions per day (or 27%) after PoGo’s release. We thus observe a substitution effect for this lean forward product that is typically “consumed” away from home. This finding is supported by the fact that the PoGo server outages led to a significant increase in Ingress activity (p<.05). Obviously some of the players come back to Ingress if PoGo is not playable.

The DID analysis in model (1b) makes use of additional geospatial information and shows that the treated portals, i.e. the portals that serve simultaneously as Pokéstop and Ingress portal, at least experience a lesser drop in activity. The interaction effect isPokestop*PokemonReleased is positive (p<.01) but the coefficient is not high enough to mitigate the overall substitution effect that PoGo has on Ingress.

With respect to the covariates we find in both models that rain decreases the number of actions in Ingress (p<.01) and that too cold and too hot temperatures lead to a lower number

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6 Computed based on the mean actions per portal per day of 1.037 actions
of actions in Ingress (p<.01). Both results are plausible for an away from home hedonic product.

Impact of AR-Based Games on Lean Forward & at Home Hedonic Products

Setting

To estimate the impact of AR-based games on the consumption of lean forward & at home hedonic products we investigate the effect of the intervention on online games, in particular a website where visitors can play typical board games online. This website is not optimized for mobile usage and players have to use a browser to play a game; hence we can safely conclude that the large majority of games are played from desktop PCs. We analyze a time series with active games per day as unit of observation. We estimate an OLS regression with cluster-robust standard errors with the dependent variable active games. Table 1 panel b shows the descriptive statistics of the activity levels on the online games website in question.

Estimation Results

Model (2) in Table 2 shows that the release of PoGo had a significant negative effect on the numbers of played games on this platform (p<.01). According to our estimations the number of active games per day drop by c.p. 773 (p<.01) games per day after PoGo’s release. Though the absolute decline in the number of active games per day might appear significant, in relative terms, the decrease in activity levels of online games amounts only approximately 2.4%. At the same time, the results show that PoGo server outages do not alter the consumption of online games in a statistically significant way. Thus, in summary, we record that PoGo’s release exerts a small but significant negative influence on the consumption of online games, i.e. lean forward hedonic products that are typically consumed at home.

\[\text{Number of active games on a particular day (reference date) is computed as the difference between the number of active games on the reference date, and the number of games which have been finished on the reference date.}\]
Impact of AR-Based Games on Lean Back & Away From Home Products

Setting

To analyze the impact of AR-based games on lean back hedonic products which are typically consumed away from home we examine the impact of the intervention on cinema attendance, and assess the impact of PoGo on seven of the largest movie theaters in the area of interest by estimating cluster-robust OLS regression for the attendance of each one of the seven movie theaters. We create for this purpose a panel dataset that consists of attendance per cinema per day and estimate equation (1). In addition, as an additional measure for identification, we also exploit the fact that two of the seven movie theaters in the dataset serve also as Pokéstops (i.e. the other five are not related to PoGo) and perform a DID analysis where the two theaters which are also Pokéstops appertain to the treatment group. The DID analysis reveals the effect of the treatment (i.e. movie theater is a Pokéstop after the intervention) on the number of visitors. Table 1 panel c displays the indexed cinema attendance in the period in question.

Estimation Results

The results of the estimated models (3a) and (3b) in Table 2 show that the release of the AR-based game has a statistically significant (p<.01) positive effect on the cinema attendance across all seven cinemas. As our estimates show, the number of visitors after PoGo’s release increases c.p. by 2.84 times. Although this finding might be surprising at first, a certain degree of complementarity between PoGo and cinema attendance is in fact quite plausible, especially under the premise that consumers wanting to go to the movies can use their travel time between home and cinema, to play PoGo. This result also provides support for the findings presented by Pamuru, Khern-am-nuai and Kannan (2017), who show that restaurants can benefit from PoGo, and restaurants can be classified as lean-back away from home hedonic product.

On the other hand, it seems surprising that a person's decision to visit the cinema is dependent on the intent to play PoGo. Accordingly, in an attempt to verify our findings, we
perform additional tests by employing the DID technique. We find that movie theaters that serve also as Pokéstop have a higher number of visitors after the release of PoGo (p<.01). This result could serve as additional evidence for some complementarity between these classes of hedonic products.

The results also reveal that if people are already outside and the Pokémon servers go down, this leads to a higher number of cinema visitors (p<.01). Rain has a positive and significant impact on cinema attendance (p<.01) while higher temperatures lead to fewer visitors in general (p<.01).

Impact of AR-Based Games on Lean Back & at Home Hedonic Products

Setting
As still one of the most widespread mass media products, watching TV represents a relaxing entertainment activity, which consumers typically like to enjoy at home (Katz et al. 1973; Perse and Greenberg Dunn 1998). To estimate the effect of PoGo on the consumption of TV, we again estimate equation (1) but use the hourly consumption as unit of observation and focus on the primetime, i.e. the time between 7pm and 10pm as this is typically the most popular time to watch TV (see Table 1 panel d) for descriptive statistics.

Estimation Results
Model (4) in Table 2 shows that PoGo had a negative effect on the number of TV viewers who consume TV during primetime (p<.01). To be more specific, the number of TV viewers during the primetime decreased c.p. and on average by 220,424 thousand of viewers after PoGo’s release. Although this decrease might also capture some other effects (e.g. waning quality of the TV program, higher popularity of video on demand and other online services), it remains plausible that PoGo is one of the main factors inducing it as the results show face validity: According to Statista (2016), the PoGo player basis in Germany counted a total of 7.1 million active users in the observation period. If we assume that these players are more or less equally distributed across the 16 German states, the state of Hesse accounts for
approximately 532,000 players\textsuperscript{8}. This means that approximately 40% of the player base, who used to watch TV during primetime instead, is now striving to catch Pokémons during primetime.

In case of PoGo server outages, people tend to turn the TV on again (p<.01) which is another indicator for substitution effects. Model (4) also indicates that people tend to watch TV if it is raining (p<.01) and when it is rather cold outside (p<.01). Overall, the results have face validity.

**Instrumental Variable Regression as Robustness Check**

Although the results have face validity, we cannot fully rule out reverse causality or that some unobserved variance over time caused an omitted variable bias. We address this potential problem by estimating an instrumental variable regression. For this purpose we use another unique data source: Although the number of active Pokémon players is actually a classified piece of information, we have access to a large dataset provided by a firm that runs security software on over one million mobile devices. This software allows us to see, anonymously, how often different apps are used. We make the assumption that the security firm’s user base is representative for smart phone users in our area of interest. In this case we can use this information to proxy the number of Pokémon users over time. Since Niantic infrequently informed about active players per day, we can compare these pieces of information to our proxy, and found that our user estimate is consistent with the information provided in press releases. We thus need to find an instrumental variable that fulfills two requirements: First, the instrument needs to be correlated with the endogenous explanatory variables conditional on the other covariates (i.e., something that is correlated with the

\textsuperscript{8} Calculated based on the total population of Germany in 2016 (82.67 million), total population of Hesse in 2016 (6.2 million) and the number of PoGo players in Germany in 2016 (7.1 million).
number of active PoGo players). This requirement can easily be tested by examining the significance of the IV in the first stage of a two-stage model.
### Table 2: Impact of Pokémon Go Release on Prevalent Media

<table>
<thead>
<tr>
<th></th>
<th>(1a) AR Games</th>
<th>(1b) AR Games (+GeoSpatial Information)</th>
<th>(2) Online Games</th>
<th>(3a) Cinema</th>
<th>(3b) Cinema (+GeoSpatial Information)</th>
<th>(4) Prime-time TV Viewers in Thousands</th>
</tr>
</thead>
<tbody>
<tr>
<td>PokémonReleased</td>
<td>-0.279***</td>
<td>-0.357***</td>
<td>-773.255***</td>
<td>2.848***</td>
<td>2.374***</td>
<td>-220.424***</td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.028)</td>
<td>(70.836)</td>
<td>(0.677)</td>
<td>(0.508)</td>
<td>(67.002)</td>
<td></td>
</tr>
<tr>
<td>Server Down</td>
<td>0.100***</td>
<td>0.100**</td>
<td>-121.982</td>
<td>2.292**</td>
<td>2.292***</td>
<td>307.550***</td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.039)</td>
<td>(112.053)</td>
<td>(0.984)</td>
<td>(0.719)</td>
<td>(110.942)</td>
<td></td>
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<tr>
<td>Temperature in °C</td>
<td>0.013***</td>
<td>0.013***</td>
<td>56.547***</td>
<td>-0.255**</td>
<td>-0.255***</td>
<td>-20.993***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(10.971)</td>
<td>(0.120)</td>
<td>(0.081)</td>
<td>(8.722)</td>
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<tr>
<td>Temperature² in °C</td>
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<td>-0.001***</td>
<td>-1.462***</td>
<td>-0.008</td>
<td>-0.008**</td>
<td>-1.767***</td>
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<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.469)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.349)</td>
<td></td>
</tr>
<tr>
<td>Rain in mm</td>
<td>-0.012***</td>
<td>-0.012***</td>
<td>4.514</td>
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<td>0.164***</td>
<td>19.379***</td>
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<td>(0.070)</td>
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<td>(4.059)</td>
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<td>-0.245***</td>
<td></td>
<td></td>
<td>-4.545***</td>
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</tr>
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<td>(0.010)</td>
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<td>(0.341)</td>
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<tr>
<td>isPokéstop*PokémonReleased</td>
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<td>0.089***</td>
<td></td>
<td>1.661***</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td>(0.017)</td>
<td></td>
<td>(0.526)</td>
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<tr>
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<td>1.057***</td>
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<td>18.877***</td>
<td>20.176***</td>
<td>2744.151***</td>
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<td>(0.004)</td>
<td>(0.026)</td>
<td>(87.307)</td>
<td>(1.056)</td>
<td>(0.865)</td>
<td>(92.957)</td>
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</tr>
<tr>
<td>Time Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>F</td>
<td>2466.436</td>
<td>75.832</td>
<td>20.947</td>
<td>26.741</td>
<td>46.363</td>
<td>247.466</td>
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<td>R²</td>
<td>0.002</td>
<td>0.002</td>
<td>0.449</td>
<td>0.266</td>
<td>0.310</td>
<td>0.732</td>
</tr>
<tr>
<td>RMSE</td>
<td>3.481</td>
<td>3.480</td>
<td>378.055</td>
<td>7.591</td>
<td>7.364</td>
<td>559.873</td>
</tr>
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<td>N</td>
<td>13,603,470</td>
<td>13,603,470</td>
<td>283</td>
<td>1,981</td>
<td>1,981</td>
<td>849</td>
</tr>
</tbody>
</table>

Cluster Robust Standard Errors in Parentheses

* p < .1, ** p < .05, *** p < .01
Second, the IV should not correlate with the error term in the explanatory equation, which means that the instrument should not suffer from the same problem as the original predicting variable. However, it cannot be statistically tested whether this is true because the condition involves the unobservable residual. This condition has hence to be taken on faith, which is why theory or facts are very important for the analysis to be convincing.

A good IV should not be predictable so that no actor (i.e. consumer) driving the equation could anticipate and proactively change his behavior. Furthermore, the IV should not be influenced by the dependent variable (consumption of prevalent hedonic products) or the endogenous explanatory factor (number of PoGo players) to be truly exogenous. For our research question, an exogenous outage, i.e. an outage that is not caused by a high number of PoGo players but at the same time influences the number of PoGo players, could constitute a valid IV.

In our observation period one of the three large mobile network operators (Telefonica) in Germany suffered from technical problems for two days. These problems made it difficult for a larger number of individuals to play PoGo and can thus serve as exogenous, unpredictable shock on the number of active players on these given days. This impact can then be used to partial out the causal effect of PoGo on the consumption of prevalent hedonic products. We can rule out reverse causality, i.e. the consumption of TV, movies, online board games on a PC and other AR games did not cause the network problems because it was a result of a hardware problem.

Finally, we need to discuss whether the mobile network problems could impact the consumption of prevalent hedonic products above and beyond the effect that is caused by PoGo. Theoretically we could overestimate the effect to some extent if other mobile games that require a mobile data network (not wireless local area network) would be impossible to play. To assess the magnitude of this potential problem, we analyzed the Top 20 of games in Google’s Play Store and Apple’s App Store, and checked their dependency on a mobile
Internet connection. The analysis of the Google Store\(^9\) revealed that in September 2016, the daily Top 20 most popular apps in Germany featured 43 different apps. From these 43 apps 43% - i.e. 26 apps need only sporadic Internet access or are primarily used at fixed locations with Wi-Fi, and can thus compensate a missing mobile Internet connection. Furthermore, 38% - i.e. 16 apps do not require the use of Internet at all. Similarly, the analysis of the most popular apps in the Apple Store revealed that in September 2016, Germany’s Top 20 app charts featured 49 different apps. Amongst these, 84% - i.e. 41 apps need only sporadic Internet access, and 14% of them do not require an Internet connection at all. From all the apps analyzed, PoGo is the only one that requires a continuous mobile Internet connection. As alternative we could also extend the focus of our analysis and argue that we are actually interested in the impact of this game genre which constitutes a superclass of the AR games that we actually want to focus on. However, we certainly have to acknowledge that the competing AR-game is also be affected by the network problems, which may lead to an underestimation of the substitution effect of PoGo (and is thus a conservative test) while the other hedonic products should not be substantially affected above and beyond the effect through PoGo.

We estimate a 2SLS IV regression with cluster-robust standard errors (Table A2 in the Appendix presents the impact of the IV on the number of active Pokémon users per day). The results of the first stage of the regression reveal a significant decrease in the player base caused by the mobile network problems (p<.01). Based on this result we conclude that we present an IV that had an unexpected, unpredictable impact on the number of Pokémon players. To test the suitability of our instrument, we further run an under-identification test, which is an LM test of whether the equation is identified (i.e., that the excluded instruments are “relevant”), meaning it is correlated with the endogenous regressors. Because we dropped

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\(^9\) Analysis based on data provided by 42matters app database (42 matters AG 2017)
the i.i.d. assumption and use HAC statistics, we apply the Kleibergen and Paap (2006) rk LM statistic. We can reject the null hypothesis, which indicates that the matrix of regressors and instruments is of full column rank (i.e., the model is not underidentified \((p<.01))\). However, a rejection of the null hypothesis of this under-identification test does not rule out the possibility of weak instruments (Hall et al. 1996). This problem arises when the excluded instruments are correlated with the endogenous regressors but only weakly (see e.g., Stock and Yogo 2005 for further discussion). We thus apply a weak instruments test based on the Kleibergen-Paap Wald rk F statistic and compare the values with the corresponding critical values compiled by Stock and Yogo (2005). The Kleibergen-Paap rk Wald F statistic is 448.303, which clearly indicates that our IV is not within the set of weak instruments as defined by Stock and Yogo, in terms of both relative bias to OLS and bias in second-stage significance. In summary we conclude that an instrumental variable approach with the proposed instrument can serve as a valuable robustness check for the findings presented in the previous sections.

We use this shock to partial out the causal effect of the number of Pokémon users on the different DVs in the second stage of the regression. Table 3 presents the results which are completely in line with our previous analyses: PoGo substitutes hedonic products that are typically consumed at home and it replaces hedonic products that are consumed away from home and serve the same needs, but we observe a strong complementarity between PoGo and hedonic goods that are consumed away from home but a more leaned back (e.g. cinema attendance or eating out at restaurants) (all results \(p<.01\)). The DID analyses indicate moreover — and once again — that the coincidence of the same location leads to further complementarity effects \((p<.01)\).
Table 3: Impact of Pokémon Go Release on Prevalent Media, Instrumental Variable Regression (2nd Stage)

<table>
<thead>
<tr>
<th></th>
<th>(1a) AR Games</th>
<th>(1b) AR Games (+GeoSpatial Information)</th>
<th>(2) Online Games</th>
<th>(3a) Cinema</th>
<th>(3b) Cinema (+GeoSpatial Information)</th>
<th>(4) Prime-time TV Viewers in Thousands</th>
</tr>
</thead>
<tbody>
<tr>
<td>PokémonUsers</td>
<td>-0.016***</td>
<td>-0.032***</td>
<td>-46.802***</td>
<td>0.183***</td>
<td>0.161***</td>
<td>-12.679***</td>
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<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(5.068)</td>
<td>(0.040)</td>
<td>(0.045)</td>
<td>(3.900)</td>
</tr>
<tr>
<td>Temperature in °C</td>
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<td>0.008**</td>
<td>43.420***</td>
<td>-0.222*</td>
<td>-0.222*</td>
<td>-26.095***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(10.685)</td>
<td>(0.120)</td>
<td>(0.120)</td>
<td>(8.473)</td>
</tr>
<tr>
<td>Temperature² in °C</td>
<td>-0.000</td>
<td>-0.000</td>
<td>-0.720</td>
<td>-0.010*</td>
<td>-0.010*</td>
<td>-1.492***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.511)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.359)</td>
</tr>
<tr>
<td>Rain in mm</td>
<td>-0.011***</td>
<td>-0.011***</td>
<td>6.021</td>
<td>0.165**</td>
<td>0.165**</td>
<td>20.484***</td>
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<td></td>
<td>(0.002)</td>
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<td>(4.070)</td>
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<td>(0.021)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>isPokéstop*PokémonUsers</td>
<td>0.019***</td>
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<td></td>
<td>(0.003)</td>
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<tr>
<td>Constant</td>
<td>1.071***</td>
<td>1.350***</td>
<td>31398.402***</td>
<td>18.815***</td>
<td>20.086***</td>
<td>2759.097***</td>
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<td></td>
<td>(0.027)</td>
<td>(0.034)</td>
<td>(90.607)</td>
<td>(1.046)</td>
<td>(1.075)</td>
<td>(90.405)</td>
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<tr>
<td>Time Controls</td>
<td>yes</td>
<td>yes</td>
<td>Yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>F</td>
<td>27.800</td>
<td>65.740</td>
<td>18.998</td>
<td>28.659</td>
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<td>262.653</td>
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<td>R²</td>
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<td>0.002</td>
<td>0.306</td>
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<td>RMSE</td>
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<td>3.480</td>
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<td>7.339</td>
<td>553.565</td>
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<td>13,603,470</td>
<td>283</td>
<td>1,981</td>
<td>1,981</td>
<td>849</td>
</tr>
</tbody>
</table>

Cluster Robust Standard Errors in Parentheses
* p < .1, ** p < .05, *** p < .01
DISCUSSION

The goal of this study was to assess the impact of the new genre of AR-based games on prevalent hedonic products by measuring the change in consumption of selected hedonic products (i.e. Ingress, online games, cinema, and TV) before and after the introduction of a popular AR-based game (i.e. PoGo) in Germany. The results of the empirical studies (see Figure 3) indicate that AR-based games substitute lean back & away from home hedonic products (class 1), lean forward & at home (class 2) and lean back & at home hedonic products (class 4). Further, they also show that AR-based games can complement and contribute to a rise in consumption of lean back & away from home hedonic products (class 3) such as watching movies in a cinema or having dinner in a restaurant (Pamuru et al., 2017). This insight can be explained based on the special mobility characteristics of AR-based games and the potential factors influencing the consumers’ mobility patterns. According to Cho, Myers and Leskovec (2011), who studied the mobility patterns of people by exploiting location-based social networks and geo data from mobile phones, consumers usually move only within a limited region and visit remote places only if motivated to do so (e.g. because they have a friend in that area or another reason to go there). Given that AR-based games require their consumers to be mobile and go to remote areas, they are changing the consumers’ mobility patterns by giving them a reason to go to certain (more remote) venues – which can also be places with movie theaters.
The findings of our study have both — theoretical and managerial implications not only for the gaming industry but also for other industries.

From a scholarly point of view, this paper represents the first comprehensive study with the goal to reveal the economic impact of the product class of AR-based games on a range of other hedonic products. Based on the growing rates in games consumption, rapid development in AR technology and related products, as well as various ongoing efforts to develop further successful AR-based games sustains the expectation that the genre of AR-based games is an emerging and promising sub-industry in entertainment. Moreover, this study adds to the existing research by contributing to a deeper understanding of the impact of digital hedonic products on other hedonic products. In addition, this article also illustrates that the emergence of new hedonic products based on novel technologies (e.g. AR-based games) require the development of new explanatory frameworks, which can disentangle the interrelationships between the different classes and types of hedonic products. Our conceptualization of AR based games’ impact on other hedonic products extends the former perspective on hedonic products consumption, in which special characteristics of products emerging from innovative technologies are either considered insufficiently or not at all. As mentioned previously, prevalent hedonic products are location bound, while AR-based games require their consumer to be on the move. This mobility requirement or specific characteristic of AR-based games is
not only essential for the AR-based games’ experience but also unique to this type of hedonic product. As a result, the analysis of AR-based games requires frameworks that account for the typical characteristics of this type of hedonic products. This study introduced a novel classification framework for hedonic products, which classifies hedonic products based on two dimensions. The first dimension originates in the realm of media science and refers to the commonly used ‘lean back’ and ‘lean forward’ taxonomy, according to which hedonic products are group based on the consumer engagement type during the actual product consumption. The second dimension is the location where the hedonic product is typically consumed (i.e. at home or away from home). Although this classification framework is straightforward, we believe that the framework can become a useful tool in research on entertainment products. Due to the high heterogeneity of currently available hedonic products\textsuperscript{10}, the study of entertainment from a holistic angle requires appropriate frameworks or concepts, which facilitate the classification of heterogeneous hedonic products into researchable and comparable clusters.

Our study provides several managerial implications. First, this study reveals not only that AR-based game can threaten other prevalent hedonic products by attracting attention and ultimately may detract revenues from other prevalent hedonic products, but they also show that brick and mortar businesses might also profit from the new genre of AR-based games. The results of our empirical study corroborate that AR-based games benefit those hedonic products which are consumed away from home (i.e. hedonic products which require the consumer to leave their house) and do not satisfy the same or similar entertainment needs as AR-based games (i.e. they are not lean forward hedonic products). In contrast, hedonic products aimed at serving the consumers’ lean forward entertainment needs and those which

\textsuperscript{10}Currently, there exists a broad range of different hedonic products, which all vary with respect to content, location, timing, length, sensory input, user engagement levels, user skills required, emotions invoked, experience intensity, etc.
are consumed at home are at risk to be substituted. Thereof, companies can predict whether any of their products run the risk to be affected positively or negatively by AR-based games. In fact, our insights can be employed to predict the effect (at least the direction) of AR-based games on video games, restaurant visits, football games visits, concert visits, online streaming, public viewing events, shopping, and much more. Because managers can anticipate the potential impact of AR-based games on their business well in advance of their release, managers gain valuable time to develop suitable strategies. For instance, companies, which can predict a negative impact of AR-based games on their profits should focus on developing avoidance or counteracting strategies, which depend on the business in question, may entail one or several measures. These may, for instance, involve marketing and discount campaigns aimed at raising awareness of the brand and gaining new customers. Moreover, it can take the form of strategic decisions to re-focus or extend their business and target age groups that are not particularly active in AR-based games. Further, a diversification strategy could also be conceivable, as the loss in revenue due to AR-based games could be compensated by investing in businesses that remain either unaffected or even profit from positive developments in the AR technology.

On contrary, businesses for which AR-based games have a complementary effect can seize the opportunity arising from the popularity of AR-based games and actively seek to collaborate with the game developer, to be somehow present or involved in the AR game of interest. Restaurants, for instance, could engage into partnership programs (Pamuru et al. 2017), and may thereby benefit from a higher number of visitors (if the cost of the partnership does not outweigh the monetary benefits). This also applies for cinemas (as discussed in the empirical analysis section of this study), gas stations, shopping centers, or any other location-bound businesses.

In addition, our findings do not only provide an estimation of the AR-based games’ economic potential, but also insights towards more informed investment decisions.
Technology experts forecast that AR will be "transform[ing] the way individuals interact with each other and with software systems creating an immersive environment" (Panetta, 2016) as early as 2020. Thus, AR is one of the emerging technology trends which should not be ignored. Even if disregarding the expectations that AR-based games are a promising emerging entertainment genre, and sustaining the belief that PoGo might have been an exceptional game, the fact that it created $950 million in global revenues (Annie, 2016, p. 25) within only six months after its release in mid-2016, reveals the unexploited revenue potential which could be tapped by the new emerging genre of AR-based games. At the same time, it also reveals that it can be worthwhile to invest in companies building AR-based products.

Another implication can be derived for marketing budget allocation. We find that television attendance, especially during primetime, is declining because of AR-based games. Therefore, AR-based games may partially substitute TV as a marketing channel. Online advertising has been steadily increasing because of the advancements in information technology that allow companies to track and measure advertising outcomes and target advertisements (Chen and Stallaert, 2014). At the same time, more than half of the consumers believe that advertising is not relevant to them, and try to avoid traditional marketing instruments at all (Hinz et al. 2011). Thus, for successful and efficient marketing strategies marketers need new tools and techniques to attract the attention of relevant consumers. Our findings suggest that AR-based games can be powerful marketing tools, and indicate that marketing campaigns in cooperation with AR-based games might allow a more targeted and possibly more efficient and cost-effective marketing initiatives. Because AR-based games are constantly aware of the consumers’ location, targeted advertising in AR-based games can be more precise and thus more successful than (personalized) online ads issued otherwise (e.g. push Ads in Apps, Ads on websites, etc.). Up to date, there are already numerous businesses working with PoGo or Ingress (e.g. AXA insurance) to raise awareness of their brand and to ultimately increase their profits (e.g. Duncan, 2016; Taylor, 2016). As more AR-based games
will be developed and released to the market, we expect that this marketing channel will become increasingly popular.

Again, related to business strategy but now more from the perspective of game developing companies, it is noteworthy that also business leaders engaged in the development of AR-based games can profit from the findings of this study. Companies aspiring to gain market shares may employ a cannibalization strategy where new products or new improved versions of existing products are introduced to the market, despite the ex-ante certainty that the newly issued products will result in a reduction of sales volume of older products. As our study shows, this finding also holds in the context of AR-based games. However, game developers in this domain can exploit the geospatial data of previous games to build new ones atop and benefit twofold. Niantic, for instance, built PoGo upon the existing technology of Ingress, so that Ingress users were automatically also able to play PoGo and vice versa. Further, there is a high degree of overlap between important locations in both games, so that many of the locations in Niantic’s AR world are both: Ingress portals and Pokéstops (or gyms). Thus, players can practice “multihoming” and play both games when visiting only one location. In result, the cannibalization effect or substitution effect that occurs with the release of the new game (i.e. PoGo) is somewhat reduced with this multihoming option. As the empirical analysis on Ingress and PoGo discloses (see Table 2, Model (1b)), the cannibalization effect of PoGo on Ingress was c.p. and on average 25% weaker in multihoming capable locations than otherwise.

Further potential application of AR-based games could include the insurance and health service industries. The decline in TV viewers during the primetime hours, for instance, is a good example for the AR-based game’s motivational power to change peoples’ behavior. According to our estimates, AR-based games on the one hand manage to attract people to go outdoors and be active. Thus, the AR-based mobile games could indeed have the capability to combat obesity and other sedentary lifestyle related diseases, and thus, offer opportunities for
health services or health insurances. Yet, because our framework predicts that AR-based games could also substitute lean forward activities that are consumed away from home (i.e. AR-based games like PoGo could also deter people from going to the gym (Note: we mean here “real” gyms, not Pokémon gym) or football workouts), further analyses are required to understand the total effect of AR-based games on a population’s fitness.

Finally, we also have to acknowledge two main limitations, which provide avenues for future research. First, our identification strategy for revealing the impact of AR-based games on other hedonic products is based on monitoring any changes in consumption before and after the release of PoGo. As this particular game has managed to develop into a "social and cultural phenomenon" (Evangelho, 2016), lastly not because of vast media attention, our results might be somewhat biased. The media buzz around this AR-based game, for instance, could have biased the results by motivating consumers to break out their usual consumption pattern for hedonic products. If PoGo’s immense success was unique to the history of AR-based games and no other game will manage to be as popular as PoGo, the impact of AR-based games on other hedonic products might not be as salient as in our empirical analysis. Although the magnitude might be therefore somewhat upward biased, we expect the direction of the impact to be stable also for not so popular AR-based games. The second limitation of our work is that we dispose of data about consumers from Germany only. Given the cultural differences across the regions around the world, the handling and adoption of new technological hedonic products such as AR-based games might vary across the globe. Accordingly, consumer’s consumption patterns in Asia, the Americas, or Europe might differ from each other. Similarly, the impact of AR-based games on other hedonic products might also differ across regions.

We conclude that this study represents a unique effort to disentangle the economic impact of the new genre of AR-based games on prevalent hedonic products. As new technologies are transforming markets, industries but also the lives of consumers (Lucas et al.,
2013), and the number and diversity of technology based entertainment products are increasing at unprecedented rate (Han et al., 2016), the results presented in this study are probably just a first glimpse of AR-based gaming opportunities and threats within the entertainment industry. To be able to understand and meet the opportunities and challenges posed by the emergence of AR-based games it is pivotal that academics conduct more research in this area.
## APPENDIX

**Table A1: Test of Parallel-trend Assumption for AR Games and Cinema DID Analysis Data**

<table>
<thead>
<tr>
<th></th>
<th>AR Games Treated Portals</th>
<th>AR Games Control Portals</th>
<th>Cinema Treated Cinema</th>
<th>Cinema Control Cinema</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trend</td>
<td>-0.000***</td>
<td>-0.000</td>
<td>-0.021***</td>
<td>-0.020***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.801)</td>
<td>(0.008)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Temperature in °C</td>
<td>0.016***</td>
<td>0.018***</td>
<td>0.025</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.093)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>Temperature² in °C</td>
<td>-0.001***</td>
<td>-0.001***</td>
<td>-0.005</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Rain&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.011***</td>
<td>-0.017***</td>
<td>0.073</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.046)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Monday&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.062***</td>
<td>-0.199***</td>
<td>-7.163***</td>
<td>-6.774***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.029)</td>
<td>(0.872)</td>
<td>(0.788)</td>
</tr>
<tr>
<td>Tuesday&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.100***</td>
<td>-0.232***</td>
<td>-6.047***</td>
<td>-6.370***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.029)</td>
<td>(0.797)</td>
<td>(0.698)</td>
</tr>
<tr>
<td>Wednesday&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.097***</td>
<td>-0.109***</td>
<td>-3.678***</td>
<td>-3.434***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.033)</td>
<td>(0.878)</td>
<td>(0.764)</td>
</tr>
<tr>
<td>Thursday&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.094***</td>
<td>-0.172***</td>
<td>-6.360***</td>
<td>-5.314***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.032)</td>
<td>(0.840)</td>
<td>(0.781)</td>
</tr>
<tr>
<td>Friday&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.036***</td>
<td>-0.173***</td>
<td>-2.612***</td>
<td>-2.180***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.029)</td>
<td>(0.798)</td>
<td>(0.707)</td>
</tr>
<tr>
<td>Saturday&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.018*</td>
<td>-0.000</td>
<td>1.524*</td>
<td>1.415*</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.041)</td>
<td>(0.877)</td>
<td>(0.775)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.831***</td>
<td>1.199***</td>
<td>12.818***</td>
<td>12.069***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.036)</td>
<td>(0.810)</td>
<td>(0.754)</td>
</tr>
<tr>
<td>F</td>
<td>152.957</td>
<td>42.544</td>
<td>29.284</td>
<td>35.469</td>
</tr>
<tr>
<td>R²</td>
<td>0.001</td>
<td>0.001</td>
<td>0.636</td>
<td>0.666</td>
</tr>
<tr>
<td>RMSE</td>
<td>3.014</td>
<td>4.270</td>
<td>2.789</td>
<td>2.426</td>
</tr>
</tbody>
</table>

Cluster Robust Standard Errors in Parentheses

* *** p<0.01, ** p<0.05, * p<0.1

Variables with a b in superscript (<sup>b</sup>) are binary variables (0/1)
Table A2: First Stage Results – Impact of Mobile Network Problems on Number of Active Pokémon Users

<table>
<thead>
<tr>
<th>(1) First Stage: Pokémon Users</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PokemonReleased</td>
<td>16.704***</td>
</tr>
<tr>
<td></td>
<td>(0.621)</td>
</tr>
<tr>
<td>Mobile Network Problems</td>
<td>-9.526***</td>
</tr>
<tr>
<td></td>
<td>(0.804)</td>
</tr>
<tr>
<td>Temperature in °C</td>
<td>-0.296***</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
</tr>
<tr>
<td>Temperature² in °C</td>
<td>0.017***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Rain in mm</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.646</td>
</tr>
<tr>
<td></td>
<td>(0.541)</td>
</tr>
<tr>
<td>Time Controls</td>
<td>yes</td>
</tr>
<tr>
<td>F</td>
<td>203.36</td>
</tr>
<tr>
<td>R²</td>
<td>0.892</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.983</td>
</tr>
</tbody>
</table>

Cluster Robust Standard Errors in parentheses

* p < .1, ** p < .05, *** p < .01
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