TV's Dirty Little Secret:
The Negative Effect of Popular TV on Online Auction Sales

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Abstract

Timing online auctions to attract a large number of prospective buyers is important for sellers. This study examines whether online auction sellers need to account for exogenous effects like TV viewing when timing and predicting their auction results. An ongoing debate questions whether TV viewers can spread their attention across multiple devices while watching TV, for example, by concurrently shopping online or posting on social media. Recent research has focused on understanding cross-media effects; however, little attention has been given to TV viewership's relationship with a very important economic activity, namely participation in online auctions.

We examine this potential cross-media effect by analyzing the four-year sales history of a German online auction platform and addressing potential endogeneity problems with an instrumental variable approach. We use three different instrumental variables that have different advantages and disadvantages but can — in sum — be used for triangulation as they lead to the same result: The analyses reveal a significant negative cross-media effect between TV consumption and online auction sales, indicating that TV consumption and online auction sales might compete for the scarce attention of consumers and are thus substitutes for each other rather than complements.

Keywords: Cross-Media Effects, Online Auctions, Attention Economy, Instrumental Variable Approach, Second Screen, Electronic Commerce

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INTRODUCTION

Online auctions, whose dominant worldwide player is eBay (ebay.com), are extremely popular and play a tremendous role in online sales. eBay reports over 200 million active users on its online auction site, and in 2013, eBay’s gross merchandise volume (GMV) was $75.6 billion[1]. To put these numbers in perspective, Amazon, the United States’ largest electronic commerce retailer, had a GMV of approximately $100 Billion in 2013. These two popular websites—ebay.com and amazon.com—lead US e-commerce websites in the number of unique visitors per year.

On sites like eBay, drawing the attention of prospective visitors to obtain a preferably high number of online buyers by auction closing time is important for sellers. The larger the number of prospective buyers, the greater the chance of bidding wars and hence of a higher closing price (Milgrom and Weber, 1982). Anything that might draw buyers’ attention to an auction is thus advantageous for sellers; alternately, anything that could divert prospective buyers from an auction is particularly problematic due to auctions’ limited lifespans. This real-time aspect makes a better understanding of potential distraction effects crucial for timing online auctions.

Related research that focuses on the consequences of inattention previously addressed calendar effects (DellaVigna and Pollet, 2009; Fields, 1931; Jaffe and Westerfield, 1985), competitions (Bapna et al., 2010; Hausch, 1986; Simonsohn, 2010), and events (Eisensee and Strömberg,

[1] Last accessed 11-23-2014 https://www.internetretailer.com/2014/05/06/chinese-e-commerce-giant-alibaba-files-ipo

2007). We are the first to show whether and in which direction cross-media channels, namely TV viewing, affect the attention of prospective buyers for online auctions.

The idea is based on the concept of the *attention economy*, which suggests a need to efficiently manage attention allocation (Davenport and Beck, 2013; Simon, 1969). According to this concept, media channels compete for consumer attention; as some media divert consumer attention away from other media, one medium may tangibly affect another medium's relationship with consumers. With the public's ever-increasing use of an ever-increasing number of devices as an integral part of their daily activities, the potential for distraction is increasing for TV viewers and Internet users alike.

TV viewing habits and distractions have evolved in tandem with increased Internet use. The habit of engaging with multimedia devices while watching TV is on the rise, and both continue to be hugely prevalent as independent activities as well. More people are routinely using the Internet and various multimedia platforms while simultaneously watching TV, a practice known as second screening, as evidenced by TV-related Facebook and Twitter posts made in real time during the transmission of TV shows. In addition to posting on Facebook and tweeting about shows while watching TV, people are also making online purchases while viewing shows. An AdWeek/Harris poll from 2011 reported that of 2,309 Americans surveyed, 56% said they surf the Internet on a laptop and 18% use a smartphone device while watching TV. Nearly three out of ten respondents (29%) reported shopping online during TV viewing[2]. The second screen is one example of how TV has a direct relationship to Internet use.

However, it is unclear whether TV is a captivating force distracting viewers from online activity or whether TV instead reinforces such activity. Obviously, determining the relationship between

[2] Last accessed 1-27-2014 http://www2.technologyreview.com/article/418541/tr10-social-tv/

TV viewership and online purchases, especially the question of whether TV promotes or discourages participation in online auctions, would be of interest to many online retailers. This is particularly true for online auction sites, whose real-time sales are more directly vulnerable to distractions.

To answer this question, we studied a large German online auction firm. Our data consists of a time series from a two-sided auction platform that includes 78,066 transactions over a period of 211 weeks. In addition, we acquired two-hourly national TV viewership data over the same period. By applying an instrumental variable regression, we can estimate the spillover between TV viewing and Internet sales for the German online auction site. Our goal is to reveal cross-media effects and their directions. If TV viewing significantly impacts buyers' attention, sellers should incorporate this effect when forecasting sales and timing auctions. Given the scheduled and hence predictable nature of TV, knowledge of this effect will allow them to optimize the start and end dates of their time-dependent online auctions.

PREVIOUS RESEARCH

Previous research on auction design has put a strong focus on endogenous design parameters that can be used by sellers to optimize profits or sales probability. Such practically endless parameters (Schwind et al., 2008) are controlled directly by sellers and are thus essential from their perspective. For example, some researchers have focused on the ability to set (secret) price thresholds in auctions (Bajari and Hortacsu, 2003; Hinz et al., 2011; Myerson, 1981; Vincent, 1995), and others have addressed the issue of whether to allow a buy-it-now option (Budish and Takeyama, 2001; Wang et al., 2008).

With respect to exogenous parameters, economists and researchers in Information Systems and Marketing have analyzed the competition factor. Bapna et al. (2010), for example, studied a setting where a number of sellers simultaneously offer vertically differentiated Vickrey auctions for imperfect substitute goods to unit-demand buyers. Some papers have addressed the problem of sequential auctions (Elmaghraby, 2003) and compared simultaneous with sequential auctions (Hausch, 1986). Most relevant to our study is the work by Simonsohn (2010), who showed that inattention to competition during peak eBay hours can lead to excess supply and, ultimately, lower prices. Simonsohn (2010) found that a disproportionate share of online auctions end during peak bidding hours with lower selling rates and lower final prices than during non-peak hours. The author suggested that peak-listing is not an optimal timing strategy for all sellers because the goods sold on the auction platform (in this case, eBay have substitutes; more than one seller can offer the same DVD, for instance. This competition drives prices down at peak times.

Besides competition, research on inattention suggests that other exogenous parameters such as calendar effects or events may be important for timing of business strategies. While calendar effects haven't been studied extensively for auction sales, they have been studied in other digital sales domains. For example, Fields (1931) and Jaffe and Westerfield (1985) observed a calendar effect in both American and foreign exchanges. The Monday effect, also known as the day-of-the-week or weekend effect, can be seen when securities market returns on Mondays are lower, on average, than on other days of the week. DellaVigna and Pollet (2009) revealed another weekday effect by showing that limited attention among investors affects stock returns. Due to inattention on Fridays, compared to other days of the week, the authors found evidence of a less immediate and more delayed response to new information, which potentially results in abnormal returns in an investment portfolio in differential Friday drifts. Ariel (1987) and Lakonishok and Smidt (1988) observed the tendency of stock prices to increase during the last two days and the first three days of each month. This turn-of-the-month effect is most likely based on the timing of monthly pension fund cash flows that invest in the stock market at this time of each month. Lakonishok and Smidt (1988) also observed another calendar-related effect, termed the holiday effect.

Their empirical study revealed that investors can generate abnormal returns before an exchange-mandated long weekend or holiday such as Labor Day or Christmas. Other fundamental related anomalies are the small-cap effect (Roll, 1981), which describes the tendency of small-capitalization stocks to outperform the market, and the value effect (Fama and French, 1998), which refers to the positive relationship between security returns and the ratio of accounting-based measures of cash flow or value to the market price of the security.

Moreover, inattention to events may affect business outcomes. Eisensee and Strömberg (2007) studied the influence of mass media on US government responses to natural disasters. They found that relief depends on the extent of mass media reporting on a disaster. Inattention to a disaster due to competing events (such as the Olympic Games) can result in a lesser relief effort compared to disasters of a similar magnitude occurring without any competing events. Similarly, Hirshleifer et al. (2009) studied competition between the financial announcements of two firms and found that the immediate stock price and volume reaction to a firm's earnings is weaker, and post-earnings announcement drift stronger, when a greater number of earnings announcements by other firms are made on the same day. The distraction effect has been shown to be stronger in firms with positive rather than negative earnings surprises.

No research exists yet studying the cross-media effects that may affect online auction sales, such as the effect of TV viewing on online auction sales, which is a relationship based on the concept of *attention economy*. Attention economy (Simon, 1969) holds that a world rich in information leads to a scarcity of whatever that information consumes, in this case, human attention.

Therefore, attention and the information that demands our attention need to be managed efficiently to avoid information overload (Davenport and Beck, 2013; Goldhaber, 1997; Shapiro and Varian, 2013; Simon, 1969). One group of researchers and practitioners attempted to manage the problem of how to allocate information more efficiently by examining applications that better control or customize information (Huberman and Wu, 2008; Shapiro and Varian, 2013). Falkinger (2007) developed a theoretical model that describes the structure of competition for attention. Assuming a world rich with information, and thus with limited available attention, he found that international integration and progress in information technologies tend to decrease global diversity and subjects' attention levels.

From a marketing perspective, research in attention economics is essential to the struggle against the problem of information overload. Consumers today simply cannot process all incoming information. Decades ago, Krober-Riel (1987) had already found that only 5% of advertising reached its intended recipients. As a new communication channel, the Internet breaks the mold; consumers now have access to all kinds of easily-retrieved information such as news and advertising. Media channels face stiff competition for customer attention online, including on social media. For example, Lerman and Hogg (2010) and Hodas and Lerman (2012) described how limited attention affects information diffusion on social media. Attention given to the Internet also appears to affect other channels. Dimmick et al. (2004) showed the Internet has displaced traditional media in the daily news market, with the largest displacement found in newspapers and TV, resulting in decreased sales for print media. Liebowitz and Zentner (2012) examined the impact of the Internet on TV viewing. Using regression analysis, they found that its effect varies by age group; the greatest effect was on younger age groups while there was almost no effect on older age groups. This suggests that the Internet may be a substitute activity for television viewing for some people but not for others. Though this paper is based on the basic principle of attention economy, it opens the door to the possibility that Internet usage is not invariably a substitute for television viewing. The authors discuss the degree of substitutability of attention-consuming activities and how this plays a role in the degree to which participation in one activity constrains time spent engaged in other activities.

Recent research on second screening has demonstrated that alternative theories of attention may be applicable to TV viewing, supporting the idea that media channels are not negatively interrelated. Enoch and Johnson (2010) discussed the difference between cannibalization and convergence. Using a variety of data sources, the researchers found that the heaviest Internet users watched more TV than other groups while the heaviest TV viewers were above-average Internet users. The data showed that the use of additional forms of media had no effect on the amount of TV viewing or Internet usage. Rather, additional media use was incremental: the more platforms a group consumed, the greater their total amount of media use. Brasel and Gips (2011) examined concurrent Internet use and TV viewing and how people allocate their attention to two screens through direct behavioral observation. By exploring gaze duration between multiple screens and viewer recall of their behavior during a measured observational session, they found that television captured significantly shorter gazes than the computer and that participants had poor recall about how much switching between media they actually did compared to their observed behavior. Holmes et al. (2012) found while observing behavior in TV watchers with synchronized second-screen content that the second screen attracted around 30% of viewers' total attention as measured by eye movement patterns. The net effect of recent research on multimedia viewership demonstrates that considering TV viewing and Internet usage as substitution activities may be outdated and no longer accurately reflects the ways people engage with media (Benton and Hill, 2012; Hill, 2014; Hill and Ben-assuli, 2013; Hill and Benton, 2012; Hill et al., 2012). In fact, as discussed in the Introduction, simultaneous multimedia engagement was the norm for 74% of respondents to the AdWeek/Harris poll from 2011. However, it is important to note that while simultaneous engagement is prevalent for social interactions like tweeting and commenting, it is not yet as common for economic actions like auction participation that may possibly require more attention.

By analyzing different exogenous effects such as weather, prospective buyers' budgetary restrictions and the impact of TV viewing on online auction outcomes, we contribute to existing research on online auctions by offering an evaluation of the interplay between attention economy and online purchasing, focusing on the direction of influence from TV viewing. To retain the audience's attention, it is important that sellers consider all relevant factors on their end and do not let their own inattention sabotage their efforts.

EMPIRICAL SETTING AND MODELING APPROACH

We examined the sales of a German intermediary referred to as *Platform.com*. Platform.com was founded in 2005 as a startup and was valued in the two-digit million EUR range (based on investments by investors) at the end of our observation period. At that time, the platform had about 184k registered users and about 13k users who had been active within the last four weeks of the observation period. Platform.com has been featured in the media, but does not invest in costly marketing activities such as promotions or advertising. Every week about 1,000 new users registered at Platform.com in the observation period. However, compared to eBay Germany, with its approximately 14.5 million active users in the same year, *Platform.com* is quite small. The offered assortment has a broad range of products and includes consumer electronics, DVDs, furniture and garden equipment, perfumes and cosmetics, toys, sporting and fitness equipment, and watches and jewelry.

Platform.com applies a continuous double-auction type of pricing mechanism, where professional sellers offer their products to buyers. All products offered by sellers are new and in their original packaging. Prices include VAT and shipping costs. Professional sellers must use a nickname profile on Platform.com rather than disclosing their real identity so that there is no indication of the seller's location. The purpose of this rule is to avoid competition between the different channels used by the same seller. Platform.com charges sellers a 3% fee from the transaction price; there are no listing fees for sellers, and buyers can use the platform for free. All bids and requests for a particular product are listed in an order book (similar to a stock exchange), and both buyers and sellers can see how the price for each product has developed by viewing price diagrams for previous months.

A transaction occurs only if both sides agree on a specific price. Initially, a prospective buyer sees an order list for a specific product that shows which (anonymous) seller is offering what quantity of product at what price. Prospective buyers then have two options: they can either buy the product for the lowest available price (similar to eBay's buy-it-now option) or they can decline to buy the product for the stated price and leave an open bid that is submitted to the seller and is valid up to a certain date determined by the buyer. Then, all sellers offering the specific product can immediately sell it to the buyer at the open bid price; they can also decline to sell the product and ask for a new price, which is higher than the buyer's bid but lower than the initial asking price. Sellers usually set a secret threshold when setting up the offer and use the platform's proxy mechanism. This negotiation can continue for several rounds until both sides agree on the price or decide to terminate negotiations. It should be noted that, in contrast to auction houses, for example, the product is automatically sold to the buyer who places the highest bid if the bid surpasses the seller's threshold.

This continuous double-auction pricing mechanism makes Platform.com unique in the industry and comparable to stock exchanges. It is the unique selling proposition of Platform.com. Late bidding, as practiced by sophisticated bidders on eBay (Roth and Ockenfels, 2002), is not possible on Platform.com because there is no official time-determined end to auctions. The other major difference from eBay, aside from the double-auction pricing mechanism, is that Platform.com only hosts professional sellers (i.e., the same actor cannot switch roles and act both as a buyer and a seller).

Data

Our study comprises transaction data between buyers and sellers on Platform.com, covering the period between April 2005 and May 2009, as the first data source. The prices range between 0.70 EUR and 4,199.00 EUR, with a mean price of 106.18 EUR. Overall, 351 different sellers sold 25,677 unique product types, as identified by their unique European Article Number (EAN), in 78,068 transactions to 65,894 different buyers.

As these numbers indicate, the retention rate for sellers is high, whereas the retention rate for buyers is rather low. Most buyers only buy one product on Platform.com, a proportion the intermediary has to improve if s/he wants to capture a significant market share in the auction market. A nice feature of this platform is that all users must have a German delivery address. With respect to our analyses, this mitigates concerns that foreign shoppers, from, for example, Austria, might use Platform.com but have no access to German TV programs.

We also acquired two-hourly TV viewer information from one of the leading German media measurement companies. As available budget can influence spending behavior (Wilcox et al., 2011), we acquired as a third data source: the mean account balance per day from a representative savings bank, which can be used as a representative proxy for the yearly cash flow of the German population. In case the weather influences demand, we obtained weather data from Germany's National Meteorological Service (Deutscher Wetterdienst). We also controlled for time effects such as public holidays and for seasonal effects. Finally, we controlled for the effect of competition and acquired daily advertising spending levels of the main competitor, eBay Germany. These data were provided by another media measurement company.

Obviously, the data was examined at a highly aggregated level. However, we conducted some analyses to test whether the data sufficiently represents the German population and if there is a sufficient overlap with Internet users and TV viewers. Figure 1, for instance, shows that the number of units sold at the ZIP-code level, using the first two of five digits, is a linear function of the area population. To test this claim statistically, we compared whether the sales per 1,000 residents per ZIP code statistically differs from the average sales per 1,000 residents in the entire sample. According to this analysis, sales do not deviate significantly from the expected distribution ($p < .05$).

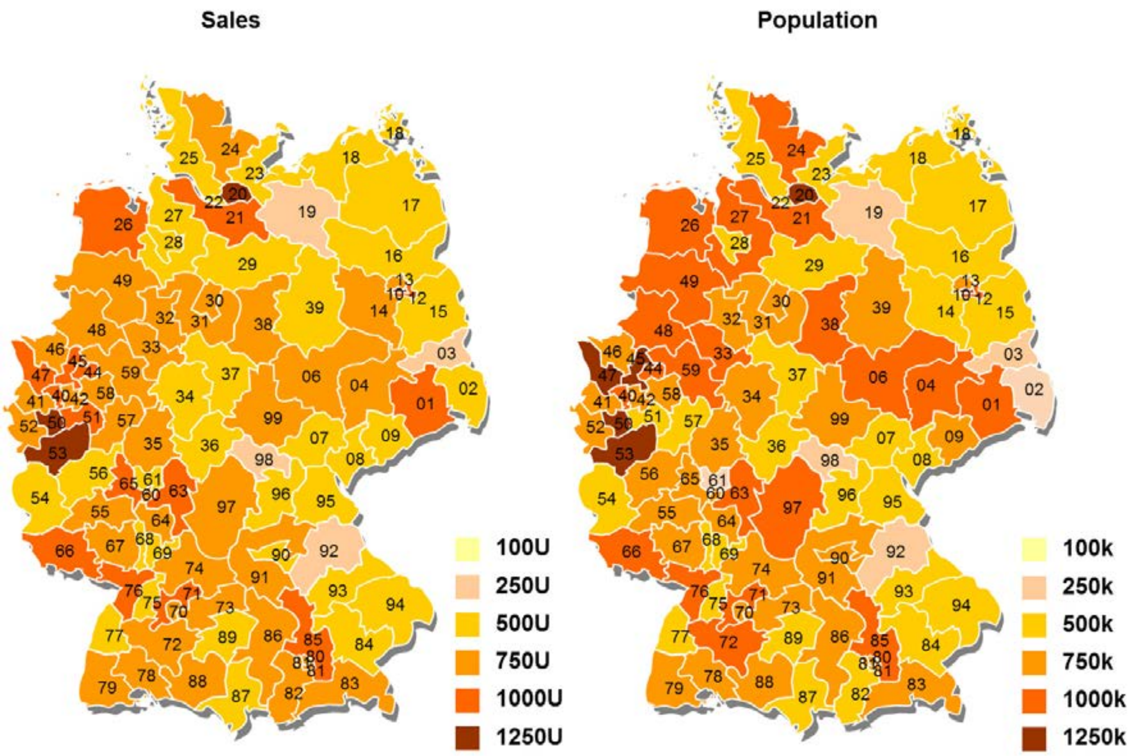

Figure 1: Sales and Population per ZIP.

To analyze the overlap of the user population at Platform.com and German Internet users, we examined their age. The average age of German Internet users during the observation period was between 40 and 41 years[3]. The average age of Platform.com users was 40.7 years. The distribution of Platform.com users and the Internet population with respect to age is, however, slightly different as very young and elderly people did not engage in auctions, as might be expected based on the characteristics of the Internet population.

However, we believe that these small differences should not significantly bias our results and that users of Platform.com and the average Internet user do not greatly differ. We further know that 97% of the German Internet population owns a TV[4]. Therefore, we believe that the overlap

[3] Last accessed 10-01-2014 http://www.ard-zdf-onlinestudie.de/index.php?id=421
[4] Last accessed 10-01-2014 http://www.ard-zdf-onlinestudie.de/index.php?id=398

between users of the focal platform and TV viewers is sufficient for our purposes and that the aggregated data can provide interesting evidence when examined.

Finally, we examined whether sellers already anticipated TV programs. The data reveal that 94% of sellers' offers are handled by a proxy system and sellers' offers run for an average of 292.5 days while TV program guides are typically not available for more than 30 days in advance. This indicates that sellers did not take into account the TV program when creating their offers. This is supported by the fact that the number of opened seller offers varied less than 0.06% over the run of a day. Different models thus logically revealed that there is no significant correlation between TV viewership and opened sellers' offers ($p > .6$).

Descriptives

Figure 2 illustrates monthly sales and shows that Platform.com benefits from a brisk Christmas trading period, whereas the number of sales is substantially lower during the summer months. The right-hand side of Figure 2 illustrates the mean TV audience per month, which is lower during the summer months and higher during the winter months, as one would expect for a country in the northern hemisphere.

With respect to weekday effects (Figure 3), we found that Mondays have the highest sales, whereas Saturdays have the lowest number of transactions. With respect to TV audience, we found — as expected — that the mean number of TV viewers is higher during the weekend. Plotting the frequency of sales by the days of the month (see Figure 4), we found that transactions increase during the first days of the month. The number of sales then decreases until the 25th day of the month and then begins to increase again. We found a similar pattern when we looked at the mean account balance (see Figure 4). The mean account balance typically drops over the month until the 26th day, when it begins to increase again.

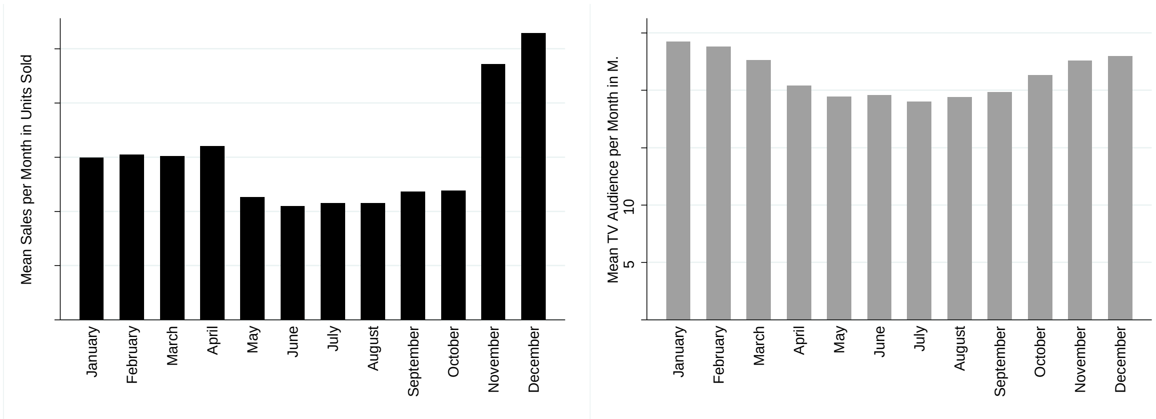

Figure 2: Mean Sales in Units Sold and TV Audience per Month in M.

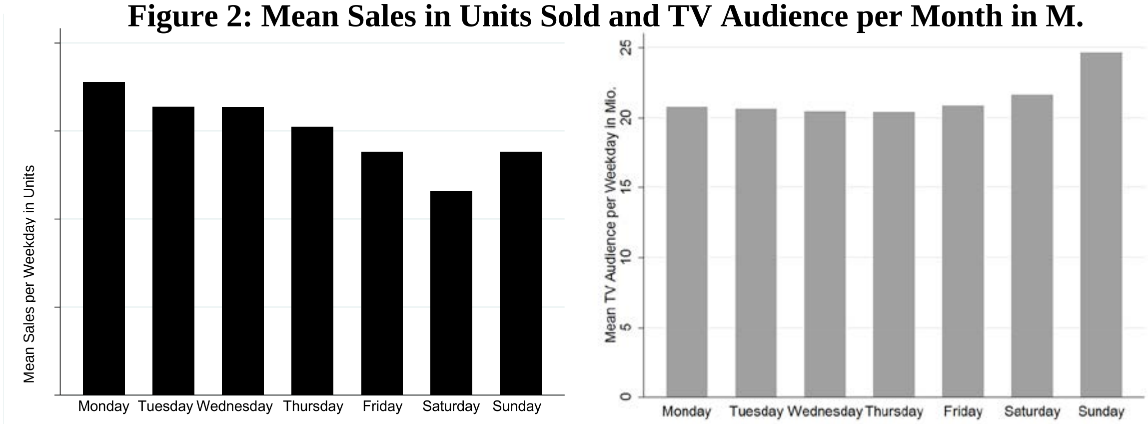

Figure 3: Mean Sales in Units Sold and TV Audience per Weekday in M.

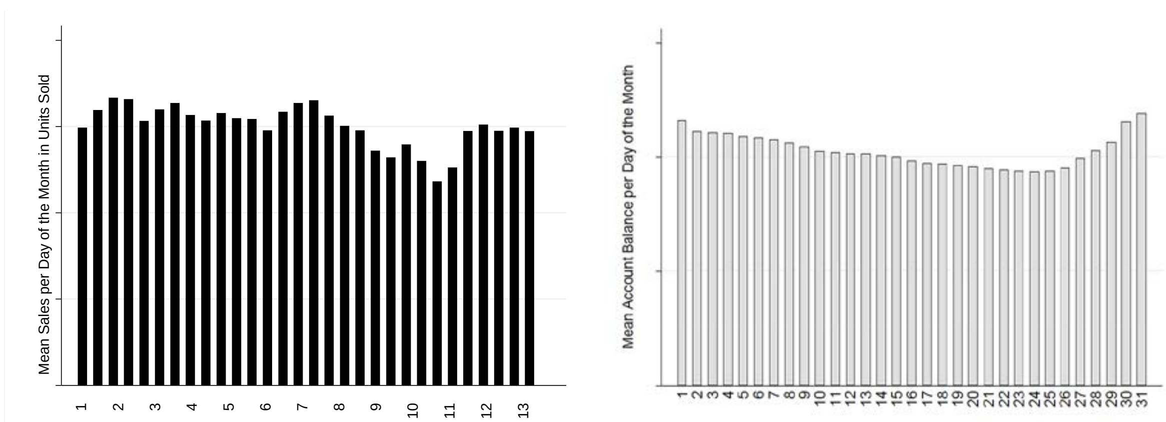

Figure 4: Mean Sales in Units Sold and Account Balance per Day of the Month.

Figure 5 illustrates sales and TV audience by time of day. We observed that sales are highest between 10:00 AM and 10:00 PM, which is also true for the number of TV viewers. Based on these data, one would expect a positive correlation between sales and TV audience, given that people are at home and are hence more likely to watch TV and/or shop online. Because we do not have access to this information, we had to address this endogeneity problem with an appropriate modeling approach that we describe in the following sections.

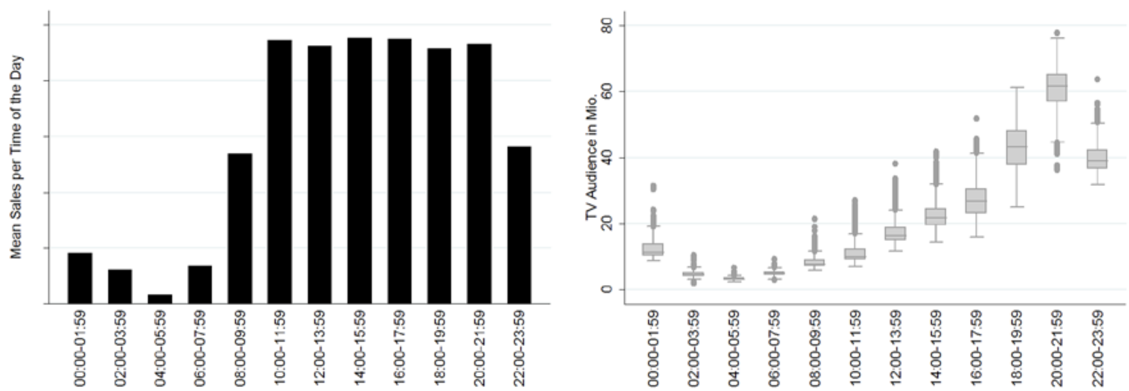

Figure 5: Mean Sales in Units Sold and TV Audience over the Course of the Day in M.

Model Specification

Our dependent variable is sales in units. We chose a two-hour period as the unit of observation, which yielded 17,023 observations. The two-hour period was pre-defined by the media control group that measures TV viewership and is advantageous because many movies run for about two hours. As the dependent variable, we use sales in terms of number of units sold, as sales in EUR would heavily depend on unit prices and hence introduce excessive variance. However, we additionally provide the results with sales in EUR as the dependent variable in the Appendix.

To examine the interplay between TV viewing and auction sales, we included the variable $TVViewer$ and use the number of TV viewers for the study period. As a proxy for consumer budget ($Budget$), we further collected data on the daily bank balance, for one year, of the German population from a representative savings bank. These data should reflect the bank balance of the German population over time.

To control for weather effects we used $Precipitation$ in mm and $Temperature$ in degrees Celsius. We further used eBay Germany's advertising expenditures ($CompetitiveAd$) to control for the general promotional level of the industry. We included time variables to control for $weekday$, $monthly$ and $timeofday$ effects and a linear trend over time. Equation (1) summarizes our basic Model 1:

$$
\begin{aligned}
(1)\ Sales_t = {} & \beta_0 + \beta_1 \cdot TVViewer_t + \beta_2 \cdot Budget_t + \beta_3 \cdot Precipitation_t + \beta_4 \cdot Temperature_t \\
& + \beta_5 \cdot CompetitiveAd_t + \beta_6 \cdot PublicHoliday_t + \beta_7 \cdot t + \sum_{i=1}^{7} \gamma_i \cdot Weekday_{i,t} \\
& + \sum_{i=1}^{12} \delta_i \cdot Month_{i,t} + \sum_{i=1}^{12} \epsilon_i \cdot TimeOfDay_{i,t} + \varepsilon_t
\end{aligned}
$$

Identification and Endogeneity

A common problem with time-series data is spurious correlation. With respect to technologically intensive goods, for example, price and cost generally decrease over time because of technological advances, whereas quantity increases over time. These correlations make it difficult to determine the extent to which increasing quantities result from a growing user base or are simply due to lower prices (Gowrisankaran and Stavins, 2002).

In our model, we emphasize that the problem is not econometric identification, which can always be achieved by choosing appropriately parsimonious functional forms, but the identification of causal effects on sales. In particular, the number of TV viewers may be endogenous. Therefore, we need to consider potentially omitted variables and the possibility that there may be some dependent variable (sales) effects on the independent variables that could cause a reverse causality bias.

An omitted variable bias results from correlations between omitted cause X_t and included variables (Liu et al., 2007). For example, in our model, X_t, the unobserved time spent at home, is likely to bias the results in a simple OLS. The situation of being at home could result in a greater likelihood of online shopping and, at the same time, is likely to be correlated with the number of TV viewers. This may bias our inference with respect to the effect of TV programs on sales. There may also be an effect of sales on the number of TV viewers ("I switch off the TV when I do online shopping") that could additionally bias the results.

We employed a combination of strategies to achieve causal identification. First, to control for unobserved changes over time that may correlate with sales, we introduced a linear time variable. We further included variables that capture seasonality as well as daily, weekly, and monthly patterns. However, there is a risk of the time dummies overly controlling system-specific factors that are a legitimate part of the complementarity system we are examining. Thus, the coefficient estimates from such models may underestimate the true effect of the complements if we do not introduce orthogonal variance (cf. Wu (2013)) for a detailed discussion).

Second, we used instrumental variables (IVs) to identify variation in the number of TV viewers orthogonal to the terms of our system. The instrument had to fulfill the main requirement of being correlated with the endogenous explanatory variables, conditional on the other covariates. The first requirement, that an exogenous shock has a significant impact on the number of TV viewers, can easily be tested (e.g., in the first stage of a two-stage model). However, the second requirement is that the IV is uncorrelated with the error term in the explanatory equation, meaning that the instrument does not suffer from the same problem as the original predicting variable. The validity of this last requirement cannot be tested because the condition involves an unobservable residual. Therefore, this condition has to be taken on faith, which is why theory or facts are very important for a convincing analysis. In this paper, we suggest three different IVs that are likely to be uncorrelated with the error term.

Lastly, IV models depend on a strong theoretical argumentation and not all assumptions can be tested empirically. Empirical models tend to mitigate this weakness of IV models by showing that alternative models (i.e., non-IV specifications) produce a similar relationship between the core variables of interest, albeit with different magnitudes. Therefore, we additionally suggest a proxy variable approach (Greene, 2003). A proxy variable is a variable used to measure an unobservable quantity of interest. Although a proxy variable is not a direct measure of the desired quantity, a good proxy variable is strongly related to the unobserved variable of interest. Proxy variables are extremely important and frequently used in the social sciences because of the difficulty or impossibility of obtaining measures of the quantities of interest[5]. In contrast to an IV, a proxy variable should be correlated with the error term as it should capture some variance generated by an omitted variable. In our case, we need a proxy for the likelihood of being at home, which is certainly an omitted variable with a high probability of biasing our estimates. Although alternative causal mechanisms are imaginable, we believe that the triangulation of three different IVs and the proxy variable approach — yielding similar results —help to build confidence in the results of our analysis.

(1) Disasters as Instrumental Variable. Disasters are unpredictable, not limited to a certain day of the week or time of day, and, in some cases, extensively covered by TV stations. They can thus serve as a truly exogenous, positive shock to the attention paid to TV, which should be reflected by an increase in the number of TV viewers. Our argument is that if the direct effects of disasters are limited to small areas (as in our case), it is unlikely that they will have any influence on online sales other than an effect caused by shifting attention to TV. If, however, broadcasts concerning a disaster cause strong feelings that alter behavior in this period, the results should be

[5] Last accessed 9-30-2014 http://srmo.sagepub.com/view/the-sage-encyclopedia-of-social-science-research-methods/n768.xml

interpreted with care. We revisit this point in detail and discuss potential confounding effects that may later influence our IV. We used all local disasters in the observation period that induced a program change by the main TV stations. In particular, we included the following events listed in Table 1:

		Special Broadcast	**Description**
1	Flood in Bavaria	08-23-2005; 6pm-10pm	http://www.quotenmeter.de/n/11018/hochwasser-in-bayern-interessiertfernsehzuschauer
2	Snow Storm in Germany	11-24-2005; 8pm-10pm	http://www.quotenmeter.de/n/12152/grosses-interesse-an-schnee-chaos-in-deutschland
3	Lathen Train Collision	09-22-2006; 12pm-4pm	http://en.wikipedia.org/wiki/Lathen_train_collision
4	Winnenden School Shooting	11-03-2009; 12pm-12am	http://en.wikipedia.org/wiki/Winnenden_school_shooting

Table 1: Disasters that Induced Special Broadcasts in the Observation Period

We set the dummy variable "*Disaster*" equal to '1' when the main German stations had special broadcasts on a disaster and equal to '0' otherwise. A similar dummy variable was also used by Bhattacharjee et al. (2007) as an instrumental variable. This leads us to the two-stage Model 2 summarized by Equations (2) and (3):

$$(2)\ TVViewerEst_t = \alpha_0 + \alpha_1 \cdot Disaster_t + \alpha_2 \cdot Budget_t + \alpha_3 \cdot Precipitation_t \\ +\alpha_4 \cdot Temperature_t + \alpha_5 \cdot CompetitiveAd_t + \alpha_6 \cdot PublicHoliday_t + \alpha_7 \cdot t \\ + \sum_{i=1}^{7} \zeta_i \cdot Weekday_{i,t} + \sum_{i=1}^{12} \eta_i \cdot Month_{i,t} + \sum_{i=1}^{12} \theta_i \cdot TimeOfDay_{i,t} + \varepsilon_t$$

$$(3)\ Sales_t = \lambda_0 + \lambda_1 \cdot TVViewerEst_t + \lambda_2 \cdot Budget_t + \lambda_3 \cdot Precipitation_t + \lambda_4 \\ \cdot Temperature_t + \lambda_5 \cdot CompetitiveAd_t + \lambda_6 \cdot PublicHoliday_t + \lambda_7 \cdot t \\ + \sum_{i=1}^{7} \mu_i \cdot Weekday_{i,t} + \sum_{i=1}^{12} \nu_i \cdot Month_{i,t}, + \sum_{i=1}^{12} \xi_i \cdot TimeOfDay_{i,t} + \varepsilon_t$$

(2) Soccer World Cup Games 2006 as Instrumental Variable. The soccer World Cup of 2006, held in Germany, constituted an exogenous shock on the number of TV viewers. When the German team faced an opponent, nearly 90% of the relevant target group for advertisements watched the matches[6], and nearly 30 million people watched the semi-final, which was a record high at that time. This event thus qualifies as an exogenous positive shock to the number of TV viewers. It is unlikely that alternative influences other than the attention given to the World Cup during the German team's playing hours influenced sales to such an extent, and it is unlikely that online auctions influenced the likelihood of an individual watching the German matches. We revisit this topic in detail and discuss potential confounding effects that may influence our IV. The instrument fulfills the main requirement of being correlated with the endogenous explanatory variables, conditional on the other covariates.

However, the second requirement is that the IV be uncorrelated with the error term in the explanatory equation so that the instrument does not suffer from the same problem as the original predicting variable. With respect to our IV, watching a soccer match is unlikely to be correlated with being at home because the World Cup 2006 was very different from other sporting events. Certain people watched the games at home as usual, others watched with friends, and some enjoyed the matches in 'fan fests' (also called 'public viewings' in Germany, which has a different meaning than the equivalent term in English). During the World Cup, dedicated locations were organized where the public could watch live games without entering the stadium or paying for admission. This was very popular, and many cities, beer gardens, universities, and

[6] Last accessed 10-01-2014: http://www.handelsblatt.com/unternehmen/management/strategie/leistungswerte-aus-media-sicht-ist-die-fussball-wm-2006-ein-erfolg/2678242.html

other institutions and organizations offered large TV screens so that supporters could meet and watch the matches together (see e.g., description of social climate[7]). We set the dummy variable *"WC2006"* equal to '1' when a match involving the German soccer team was broadcast during the World Cup 2006 and equal to '0' otherwise. This leads us to the two-stage Model 3 summarized by Equation (4) for the first stage; Equation (3) describes the second stage of the model:

$$(4)\ TVViewerEst_t = \pi_0 + \pi_1 \cdot WC2006_t + \pi_2 \cdot Budget_t + \pi_3 \cdot Precipitation_t \\ + \pi_4 \cdot Temperature_t + \pi_5 \cdot CompetitiveAd_t + \pi_6 \cdot PublicHoliday_t \\ + \pi_7 \cdot t + \sum_{i=1}^{7} \varpi_i \cdot Weekday_{i,t} + \sum_{i=1}^{12} \rho_i \cdot Month_{i,t} \\ + \sum_{i=1}^{12} \varrho_i \cdot TimeOfDay_{i,t} + \varepsilon_t$$

(3) United States Presidential Election 2008 as Instrumental Variable. The US presidential election of 2008 was held on Tuesday, November 4, 2008 and resulted in some special broadcasts in our study's focal country after the prime time news (8pm) and in the early morning hours of November 5th (due to time differences). While the previous two IVs may have strongly impacted the mood of spectators (disasters might have a direct negative impact on the viewer, and World Cup games have a positive or a negative impact depending on the outcome), coverage of the US presidential election was certainly interesting and exciting but of considerably less emotional character. Thus, the media coverage may have attracted some attention (a question we test in the first stage of the IV regression), but it is hard to imagine how the 2008 US presidential election might have changed shopping behavior above and beyond the distraction effect. Moreover, reverse causality effects are impossible (i.e., there is no way online

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[7] Last accessed 10-01-2014 http://www.spiegel.de/international/germany-s-world-cup-reinvention-from-humorless-to-carefree-in-30-days-a-426063.html

auctions in Germany can impact the timing of elections in another country). Again, we coded the observation periods and set the dummy variable *"USElection2008"* equal to '1' when the TV stations broadcast special reports on the election and '0' otherwise. This leads us to the first stage of Model 4 described in (5); Equation (3) describes the second stage of Model 4:

$$(5)\ TVViewerEst_t = \sigma_0 + \sigma_1 \cdot USElection2008_t + \sigma_2 \cdot Budget_t + \sigma_3 \cdot Precipitation_t \\ + \sigma_4 \cdot Temperature_t + \sigma_5 \cdot CompetitiveAd_t + \sigma_6 \cdot PublicHoliday_t \\ + \sigma_7 \cdot t + \sum_{i=1}^{7} \varsigma_i \cdot Weekday_{i,t} + \sum_{i=1}^{12} \tau_i \cdot Month_{i,t} \\ + \sum_{i=1}^{12} \upsilon_i \cdot TimeOfDay_{i,t} + \varepsilon_t$$

(4) Daylight Leisure Time as Proxy Variable. A major concern about simple OLS regression (Model 1) is that omitted variables can bias the estimates. Certainly, the likelihood of being at home is a very important variable as being at home increases the probability of concurrently shopping online and watching TV, making causal inference impossible. Unfortunately, we do not have access to this information and had to develop a proxy for this latent variable. Such a proxy variable can be used to extract some variance and arrive at unbiased or at least more reliable estimates. We expect that daylight increases the likelihood of people not spending time at home and instead going out for leisure activities, and we thus expect daylight to have a negative impact on auction sales. Using information on the number of daylight minutes per day, which varies over the year in central Europe, we considered leisure time only, using 6pm as cut-off, and defined our proxy variable *"Proxy"* as daylight minutes after 6pm. We further introduced the interaction effect between the daylight proxy and the number of TV viewers *"Proxy*TVViewers"* to allow for a different impact of TV viewership on sales over the run of the year, referred to as Model 5, which is described by Equation 6:

$$(6)\ Sales_t = \phi_0 + \phi_1 \cdot TVViewer_t + \phi_2 \cdot Budget_t + \phi_3 \cdot Precipitation_t + \phi_4 \cdot Temperature_t + \phi_5 \cdot CompetitiveAd_t + \phi_6 \cdot PublicHoliday_t + \phi_7 \cdot t + \sum_{i=1}^{7} \varphi_i \cdot Weekday_{i,t} + \sum_{i=1}^{12} \chi_i \cdot Month_{i,t} + \sum_{i=1}^{12} \psi_i \cdot TimeOfDay_{i,t} + \phi_8 \cdot Proxy_t + \phi_9 \cdot Proxy_t \cdot TVViewer_t + \varepsilon_t$$

RESULTS

Estimation Results

We estimated the base Model 1, the IV Models 2-4, and the proxy Model 5. We estimated the OLS models with robust standard errors and the IV models using extended instrumental variable regressions (see Baum et al. (2007)) with heteroskedastic and autocorrelation consistent (HAC) standard errors and covariance estimation. Table 2 summarizes the results based on n=17,023 observations. The F-values for all models allow us to reject the null hypothesis that the sets of coefficients are jointly zero ($p < .01$). We first report the OLS estimates for descriptive purposes then the estimates generated by the IV regressions, and, finally, the OLS model with the additional proxy variable plus the interaction effect.

To test the suitability of our IVs, we further ran an under-identification test, which is an LM test of whether the equation is identified (i.e., that the excluded instruments are ’relevant’, meaning correlated with the endogenous regressors). Because we dropped the i.i.d. assumption and used HAC statistics, we applied the Kleibergen and Paap (2006) rk LM statistic (Model 2: 5.311, $p < .05$; Model 3: 5.354, $p < .05$; Model 4: 2.899, $p < .1$).

For all IV models, we can reject the null hypothesis; this indicates that the matrix of regressors and instruments is of full column rank (i.e., all IV models are identified). However, rejecting the null hypothesis for this test should be done with caution because weak instrument problems may still be present (Hall et al., 1996). This problem arises when the excluded instruments are correlated with the endogenous regressors, but only weakly (see Stock and Yogo (2005) for further discussion). We accordingly applied a weak instruments test based on the Kleibergen-Paap Wald rk F statistic and compared the values with the corresponding critical values compiled by Stock and Yogo (2005).

The Kleibergen-Paap rk Wald F statistic is 10.135 for Model 2, 101.734 for Model 3, and 10.186 for Model 4. At these values, we can clearly reject the hypothesis that our instruments are within the set of weak instruments as defined by Stock and Yogo (2005), both in terms of relative bias to OLS and in terms of bias in the second-stage significance. The first-stage estimates (see Appendix) show that a disaster broadcast increased the number of TV viewers by 1.94 million ($p < .01$), that World Cup games increased the number by 8.25 million ($p < .01$), and that special broadcasts featuring the US election increased the number by 2.08 million ($p < .01$). All three IVs thus seem to be suitable exogenous shocks — albeit of different magnitude and nature— that allow the identification of more causal effects.

A comparison between the descriptive estimates of Model 1 and the instrumented estimates of Models 2-4 reveals that concentrating on exogenous variance clearly reveals a significant effect of the number of TV viewers on sales. When we estimated OLS (Model 1 in Table 2), we found that the number of TV viewers positively correlates, albeit insignificantly, with sales ($p > .2$). However, due to a number of potentially omitted variables, this result is likely to be biased. We ran the pendant for the Durbin-Wu-Hausman test that is robust to various violations of conditional homoscedasticity. Based on this test, we can reject the null hypothesis that the endogenous regressor can actually be treated as exogenous ($p < .01$) in the OLS model. We therefore cannot rely on OLS estimates and need to apply IV regressions.

When estimating IV regressions (Models 2-4), the outcome changes: the number of TV viewers appears to have a negative effect on online sales ($p < .05$ for all IV models). The estimates of

Model 2 indicate, for example, that an increase of 1 million TV viewers decreased sales by 1.48 in a particular observation period (two hours) on Platform.com, which is a decrease of about 2.27% for the focal platform. Figure 3 illustrates that the total number of TV viewers varies substantially, which can have an important impact on online sales.

The estimates for Model 5 (i.e., an alternative OLS model with a proxy variable) point in the same direction: when we control for the likelihood of being at home and its interaction with the number of TV viewers, we can observe a negative effect of TV viewership on sales ($p < .1$), and, further, a significant negative interaction effect "*Daylight in Min X TV Viewers*" ($p < .01$). The interaction effect indicates that if people watch TV on days with longer periods of daylight, they focus on the TV more exclusively than on an average day of the year. For example, although people may not watch much TV in the summertime, some events (e.g., soccer World Cup, Euro games, or Olympic Games) seem to be distracting, ultimately lowering sales on Platform.com. At first sight, it might be surprising that we observed a positive sign in Model 1 (i.e., the OLS specification) and negative signs in the other specifications. If, however, an omitted variable exists and, for instance, being at home positively influences the likelihood of our dependent variable (participation in online auctions is more likely when viewers are at home) and our explanatory variable of interest (watching TV is more likely when viewers are at home), we should not be surprised about this observation. Levitt (1997) presented another prominent example of a switching sign; his analysis showed that the number of sworn officers is positively related to the violent crime rate in his OLS model (because a high crime rate also leads to more sworn officers). However, by employing different IVs, he showed that the causal effect of sworn officers on crimes is negative.

With respect to the day and time dummies, we also recognize that the IV results show substantially more face validity (fewer sales in the early morning hours [e.g., between 8:00 am and 10:00 am] than at night [between 10:00 pm and 11:59 pm], $p < .01$) when compared to the OLS results. Therefore, we focus on the results yielded by the IV regression and conclude that TV and online auction sales may be more of a substitute than a complement because a good (i.e., popular, attention-grabbing) TV program might hurt online auction sales. Seemingly, both types of media are likely to compete for consumer attention and the average consumer cannot or is not willing to handle both at the same time.

The results in Table 2 also demonstrate that the weather has a significant effect on online auction sales. With respect to rain, auction sales increase ($p < .01$), whereas higher temperatures cause a decrease in sales ($p < .01$). This suggests that if the temperature is high, consumers seem to be more likely to spend their time outside and are hence less prone to buy products in online auctions. This effect goes beyond the seasonal effects for which we controlled. We also found that eBay's advertising expenditures have a negative influence on sales ($p < .01$). For every 1.1 Million EUR spent by eBay, Platform.com loses one unit sale. Because Platform.com is a startup and does not have financial resources for advertising, an increase in competitive advertising expenditure results in a real loss for Platform.com. With respect to budget, we found that market anomalies do not occur exclusively only in financial markets but also in other electronic markets such as online auction platforms.

Sales increase by 1 with every 2.9 million EUR reported in bank accounts. The effect seems small, but is significant ($p < .01$) and is thus another illustrative example of an offline-online spillover. Finally, with respect to time and seasonality effects, sales are high between the hours of 6:00 PM to midnight and low during the hours between midnight and 10:00 AM; sales peak on Sundays when considering the impact of TV; public holidays decrease online sales ($p < .1$); and sales are extraordinarily high during the peak Christmas season.

	(1)		(2)		(3)		(4)		(5)	
	OLS Descriptive Estimates		Disaster IV, 2nd Stage		World Cup IV, 2nd Stage		US Election IV, 2nd Stage		OLS with Daylight Proxy	
Number of TV Viewers in M.	0.016	(0.015)	-1.477**	(0.645)	-0.272**	(0.119)	-3.650***	(0.977)	-0.029*	(0.016)
eBay Advertising in kEUR	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Bank Balance in MEUR	0.330***	(0.073)	0.290***	(0.093)	0.323***	(0.074)	0.232***	(0.077)	0.326***	(0.072)
Temperature in deg. C	-0.116***	(0.013)	-0.411***	(0.129)	-0.173***	(0.027)	-0.842***	(0.194)	-0.123***	(0.013)
Precipitation (e.g., rain) in mm	0.031**	(0.013)	0.127***	(0.044)	0.049***	(0.015)	0.266***	(0.064)	0.037***	(0.013)
Public Holiday (0/1)	-4.161***	(0.282)	-1.947*	(1.071)	-3.734***	(0.341)	1.275	(1.474)	-4.013***	(0.285)
Time	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Monday (0/1)	1.756***	(0.220)	-4.074	(2.536)	0.631	(0.515)	-12.562***	(3.820)	1.435***	(0.218)
Tuesday (0/1)	0.963***	(0.202)	-5.024*	(2.599)	-0.192	(0.515)	-13.739***	(3.922)	0.638***	(0.202)
Wednesday (0/1)	0.911***	(0.201)	-5.460**	(2.759)	-0.319	(0.547)	-14.735***	(4.167)	0.559***	(0.202)
Thursday (0/1)	0.493**	(0.193)	-5.903**	(2.777)	-0.741	(0.546)	-15.216***	(4.191)	0.140	(0.193)
Friday (0/1)	-0.034	(0.185)	-5.691**	(2.458)	-1.126**	(0.487)	-13.926***	(3.707)	-0.352*	(0.187)
Saturday (0/1)	-1.045***	(0.178)	-5.492***	(1.942)	-1.903***	(0.398)	-11.966***	(2.917)	-1.312***	(0.180)
Sunday (0/1)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
00:00-01:59 (0/1)	-3.340***	(0.466)	-44.415**	(17.763)	-11.267***	(3.281)	-104.213***	(26.882)	-5.744***	(0.511)
02:00-03:59 (0/1)	-3.830***	(0.576)	-56.372**	(22.720)	-13.970***	(4.197)	-132.865***	(34.384)	-6.895***	(0.633)
04:00-05:59 (0/1)	-4.728***	(0.599)	-59.376**	(23.631)	-15.274***	(4.365)	-138.936***	(35.763)	-7.915***	(0.658)
06:00-07:59 (0/1)	-4.110***	(0.580)	-57.448**	(23.065)	-14.403***	(4.259)	-135.100***	(34.906)	-7.179***	(0.638)
08:00-09:59 (0/1)	-0.149	(0.536)	-48.421**	(20.875)	-9.465**	(3.857)	-118.698***	(31.591)	-2.924***	(0.590)
10:00-11:59 (0/1)	3.842***	(0.509)	-39.560**	(18.770)	-4.534	(3.475)	-102.746***	(28.401)	1.336**	(0.560)
12:00-13:59 (0/1)	4.113***	(0.416)	-28.789**	(14.224)	-2.236	(2.640)	-76.689***	(21.531)	2.164***	(0.452)
14:00-15:59 (0/1)	4.321***	(0.359)	-21.093*	(10.987)	-0.584	(2.047)	-58.093***	(16.631)	2.795***	(0.384)
16:00-17:59 (0/1)	4.205***	(0.327)	-14.444*	(8.067)	0.606	(1.506)	-41.594***	(12.203)	3.022***	(0.343)
18:00-19:59 (0/1)	3.472***	(0.249)	8.047***	(2.019)	4.355***	(0.453)	14.709***	(3.008)	3.616***	(0.251)
20:00-21:59 (0/1)	3.334***	(0.396)	34.535**	(13.513)	9.355***	(2.516)	79.960***	(20.429)	5.100***	(0.454)
22:00-23:59 (0/1)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
January (0/1)	-5.180***	(0.395)	-3.315***	(0.917)	-4.820***	(0.422)	-0.601	(1.280)	-5.115***	(0.392)
February (0/1)	-5.629***	(0.390)	-4.065***	(0.798)	-5.327***	(0.410)	-1.789	(1.092)	-5.575***	(0.387)
March (0/1)	-5.317***	(0.398)	-4.922***	(0.477)	-5.241***	(0.402)	-4.346***	(0.475)	-4.502***	(0.301)
April (0/1)	-5.069***	(0.390)	-5.921***	(0.581)	-5.234***	(0.399)	-7.160***	(0.682)	-3.448***	(0.228)
May (0/1)	-5.079***	(0.406)	-6.096***	(0.648)	-5.276***	(0.418)	-7.576***	(0.781)	-3.094***	(0.231)
June (0/1)	-3.506***	(0.425)	-3.472***	(0.504)	-3.500***	(0.429)	-3.423***	(0.427)	-1.315***	(0.224)
July (0/1)	-2.121***	(0.453)	-2.551***	(0.560)	-2.204***	(0.458)	-3.176***	(0.532)	0.000	(.)
August (0/1)	-3.054***	(0.423)	-3.716***	(0.572)	-3.182***	(0.431)	-4.680***	(0.605)	-1.198***	(0.214)
September (0/1)	-2.866***	(0.433)	-3.533***	(0.572)	-2.995***	(0.439)	-4.505***	(0.614)	-1.830***	(0.270)
October (0/1)	-3.728***	(0.404)	-3.600***	(0.459)	-3.703***	(0.406)	-3.413***	(0.413)	-2.976***	(0.292)
November (0/1)	-0.337	(0.439)	0.274	(0.548)	-0.219	(0.443)	1.162*	(0.608)	-0.317	(0.435)
December (0/1)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
Daylight in Min									-0.112	(0.144)
Daylight in Min X TV Viewers									-0.031***	(0.003)
Constant	-3.511***	(1.077)	65.039**	(29.676)	9.718*	(5.530)	164.839***	(44.850)	-0.485	(1.127)
F-Value	363.322		275.746		361.398		363.463		358.719	
R^2	0.534		0.300		0.525		0.534		0.537	
RMSE	6.866		8.416		6.930		6.872		6.847	
N	17,023		17,023		17,023		17,023		17,023	

Robust Standard Errors in parentheses, $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Table 2: Estimation Results for all Models

Discussion of Potential Confounding Effects Regarding the IV

The use of IVs typically raises questions with regard to potential confounding effects that may bias the estimation results. Therefore, we evaluate and discuss potential problems in our modeling. All three IV models offer some advantages but come with potential limitations that we evaluate in the following.

(1) Disasters as Instrumental Variable. A major advantage of the disasters IV is that disasters are truly exogenous and unpredictable and can thus serve as shocks to the system. However, we identified several concerns that may arise using this IV.

Mood Impact of Disaster Special Broadcasts. One concern is that disaster-related news may have an impact on viewers' mood, which may, in turn, influence purchase behavior (Perse, 1990). This is an interesting idea and indeed a potentially confounding effect. Perse (1990) found that sad or distressed shoppers may show an increase in purchases of snack foods, music CDs, and flashy clothes, but much less change in their purchases of light bulbs, toilet paper, or oven cleaners. It is, however, unclear whether news on the television can really change behaviors above and beyond the potential attention tradeoff for which we argue. We approached this concern from two sides: First, assuming that mood states such as sadness are invoked by the consumption of special TV broadcasts on disasters, we would expect to also find an impact during the aftermath of the special broadcasts, as moods cannot be expected to alter immediately after the end of a broadcast. Second, the disasters listed in Table 1 may differ with respect to the potential sadness they invoke; while the train collision and the school shooting led to a large number of deaths, the extreme weather situations were unpleasant but may not have caused the same widespread misery as disasters 3 and 4.

Emotions and moods can be distinguished with respect to their duration. While genuine emotions last only between 0.5 and 4 seconds (Ekman, 1984), moods are longer-term states of mind. Psychology and medicine have shown that daily life events can impact subjects' mood (Clark and Watson, 1988; Stone and Neale, 1984), and it is also well-established in the marketing literature that emotions and mood states can impact purchase behavior (Perse, 1990). Hormone levels typically take some time to return to baseline levels after an exogenous invocation. For example, after termination of stress exposure, cortisol levels need about 1-2 hours to return to the norm (Kirschbaum and Hellhammer, 1989). Assuming that special broadcasts on disasters lead to negative feelings, which ultimately impact sales above and beyond the pure attention loss effect, we would expect to also observe this effect after the end of the broadcasts.

We can easily test this with our dataset and used the two hours after special broad casts as IV. The Kleibergen-Paap rk LM statistic is nearly zero and highly insignificant ($p > .8$), and the Kleibergen-Paap rk Wald F statistic is also nearly zero, indicating that this IV is not at all suitable. The coefficient of the variable "*Number of TV Viewers in M*" is highly insignificant ($p > .85$). If we integrate this dummy in the OLS regression illustrated in Equation (1) as the control variable, we also find an insignificant impact ($p > .1$) of potential effects of emotion on sales. These results indicate that the attention effect is stronger than potential emotion effects. However, we cannot truly check whether disasters impact behavior beyond the distraction effect for the duration of special broadcasts as there might be, for example, a non-linear relationship between mood state and purchase behavior. Thus, we cannot fully rule out that emotions impact sales beyond the distraction effect.

However, a comparison of unpleasant natural disasters with unequivocally tragic disasters might yield new insights as there are reasons to believe that the four disasters had a different impact on sales. The weather-related disasters (disasters 1 and 2) are unlikely to have had a mood effect as strong as that of the disasters resulting in high numbers of deaths (disasters 3 and 4). Moreover, bad weather might increase sales (though this should be captured by our weather controls). However, the different kinds of disasters allow for an interesting analysis. When exclusively using the weather-related situations as the IV and comparing the results to an analysis using only the tragic disasters as the IV, the impact of an interesting TV program on sales remains negative in all cases. While the aggregation of all four disasters in our main model leads to a coefficient for the variable "*Number of TV Viewers in M*" of -1.48 ($p < .05$), the weather disasters IV yields a coefficient of -1.05 ($p < .05$), and the model with truly tragic disasters as IV yields a coefficient of -2.36, which is admittedly insignificant (p = .11). However, all IVs point to the same negative effect of TV viewership on online auction sales.

Stock up on Necessities. Upon finding out about an impending natural disaster, people are likely to go to physical grocery stores to stock up on necessities to ensure that they have enough food and supplies for when the flood, snowstorm, or other phenomenon hits their location. Time taken to do physical shopping takes away time for making online purchases, giving rise to a disaster-related impact on the dependent variable, which undermines the exclusion restriction condition[8]. To check the validity of this argument, we conducted an analysis at the ZIP-code level for the locally restricted natural disaster, the flood in Bavaria. We compared the likelihood of orders coming from Bavaria (ZIP code beginning with "8") to the likelihood of orders coming from the rest of Germany for four different periods. We examined this likelihood during the period of the natural disaster (August 20 to August 23, 2005) and compared it with three different control periods (July before the disaster, September after the disaster, and the same period one year later in 2006) and tested whether the fraction of sales coming from Bavaria was different during the

8 We thank one anonymous reviewer for this comment.

natural disaster. We did not observe such a difference in behavior, as the fraction of orders from the affected area was not statistically significantly different from the control periods ($p > .2$ for all group comparisons). We can thus conclude that the natural disaster itself — which was quite moderate from a global perspective but rather extraordinary for Germany — did not cause the stocking-up behavior described above and is thus unlikely to substantially bias the model. Another potential way to address this issue would be to analyze disasters in foreign countries. However, only Hurricane Katrina in August 2005 gave rise to a special broadcast in Germany, and it failed to attract a substantial number of TV viewers[9]; therefore, this does not constitute an exogenous shock as it fails to meet the first-level requirements of the IV regression.

(2) World Cup Games as Instrumental Variable. The World Cup IV is not exclusively related to potential negative mood states like the disaster IV; social events such as this attract people's attention regardless of their current location. However, this IV might suffer from other potential confounding effects.

Mood Effect. As discussed with the disasters IV, soccer games can also evoke emotions and have mood effects that cannot be fully ruled out. However, this IV allows us to test whether there are differences with respect to positive and negative mood states[10]. The German team won five matches in a row, then lost the semi-final, and, finally, won the third-place play-off. This allowed us to use the positive and the negative outcomes each as a single IV. The positive outcome IV again revealed a negative impact of the number of TV viewers on sales (coefficient = -.31, $p < .05$) while the negative outcome IV produced a negative – though insignificant

9 Last accessed 10-01-2014 http://www.pressetext.com/news/20050901037

10 We thank one anonymous reviewer and the AE for this idea.

(coefficient = -.17, $p > .05$) – impact of the number of TV viewers on sales. The small number of lost games may also explain these insignificant effects. However, we did not observe a difference between potential positive mood states (World Cup games won) and potential negative mood states (disasters) with respect to the influence of TV on auction sales.

Sellers' Anticipation of Timing. A further concern is that a seller is able to predict the timing of games well in advance, possibly adapting the timing of their sales postings accordingly. Consequently, a seller may want to avoid listing during games precisely because of the predictability of buyers' demand. This is a valid argument and would certainly hold true on auction platforms like eBay. The focal platform, however, applies a continuous double-auction type of pricing mechanism, where sellers offer a large number of products over a long period. The average offer duration is 292.5 days, and it is unlikely that sellers look forward over such a long period of time. However, 20.5% of all offers run for seven days or less, and this could put the perfect orthogonality of the IV at risk.

Segmentation Effect. Additionally, there is a concern that gender segmentation might occur during the World Cup, with men following the matches while women shop online. This pattern can be observed during weekly sporting events and might cause problems for our estimation approach. However, we do not expect this to be a problem in the case of the 2006 World Cup, due to the fact that soccer EUROs (European Championships) and World Cups are known to attract the attention of men and women equally. For example, for EURO 2008, slightly more female fans (>14 years) watched the final than male fans (>14 years) in absolute figures: 12.72 million female fans (75.5% of this group) and 11.66 million male fans (83.3% of this group) watched the match[11].

Effects on Sales beyond the Distraction Effect. There may be further effects on sales beyond the distraction effect. First, it can be argued that the World Cup itself has led to a higher number of soccer jersey sales, thereby having a direct impact on sales. There is, however, no category for jerseys on Platform.com, which mitigates this concern, but there is a subcategory ‘sports>soccer’ that consists mainly of soccer balls; according to management, it is insignificant in terms of sales.

Second, the World Cup is a very social event and this may influence sales beyond the pure effect that we use as orthogonal variance. To assess the impact of such a potential omitted effect, we conducted a small simulation and found that if there is no direct effect of the IV on sales above and beyond the effect of attention given to TV, we are able to perfectly recover the true values of the data generating process, which indicates that the identification strategy works perfectly. If, however, there is a positive effect of the World Cup itself on sales beyond the effect of increased attention paid to the event (e.g., higher sales of soccer balls), the coefficient of TV viewers will be positively biased. If the IV itself has a negative impact on sales (e.g., fewer sales because people prepare fan fests), the coefficient of TV viewership will be negatively biased. For this reason, we checked whether the period during the World Cup (June 9 to July 9, 2006) had a significant impact on overall sales while controlling for the effect of TV viewership and all other covariates listed in Table 2. We found no effect of the World Cup period above and beyond the impact of TV viewership on sales (coefficient = -.1098, $p > .6$). Therefore, we concluded that we can also neglect the last two concerns.

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11 Last accessed 10-01-2014 http://www.welt.de/fernsehen/article2162577/Gute-Quoten-fuer-das-EM-Finale.htm

(3) US Election as Instrumental Variable. This IV offers the advantage that the election of a foreign head of state is of interest but is unlikely to evoke strong emotions and mood states in the same way that the previous IVs did. It is thus more comparable to everyday news and broadcasts. However, this IV has the disadvantage (like the World Cup IV) that sellers could anticipate the timing, which would constitute a behavior change beyond the exogenous shock that we use for causal inference. We discussed this point in the previous section.

Robustness Checks

To rule out the possibility that our results are driven by high-priced products, we repeated the estimations (using disasters as IV) excluding all periods with product prices > 300 EUR and product prices > 200 EUR from the analysis and arrived at substantially the same results: the number of TV viewers has a negative impact on sales in units (coefficient = -2.22 / coefficient = -2.25, $p < .05$ / $p < .05$), and all other important requirements for the validity of the IV are fulfilled. We also tested models where we controlled for the number of opened sellers' offers and the results did not change considerably.

We also used the two disaster types as IVs and the estimated effect of TV viewership on sales was then -1.07 ($p < .01$). We also recoded the World Cup IV and used "1" for all German matches, other matches in the same group, and matches with potential opponents for the next round in the knockout stage. The results still held and were even slightly better with respect to the significance level. In this case, the estimated effect of TV viewership on sales is -.25 and highly significant ($p < .01$). The estimated coefficient is, however, very close to the estimate for Model 3 (coefficient = -.27).

We also jointly included all IVs in one model in the first stage (see Model 6 in the Appendix for detailed results). All three IVs were found to be highly significant during the first stage (p <.01), with the impact of TV viewership on sales at -.367 ($p < .05$). Moreover, we estimated a model that uses disaggregated information on all events (i.e., different dummies for the four disasters or two dummies for the soccer matches with respect to their outcomes), and the effect of TV viewership was always negative and significant ($p < .05$). The Kleibergen-Paap rk Wald F statistic is very high at a value of 133.22, indicating that there is no weak IV problem. Using all IVs in one model allows us to test whether the instruments are not satisfying the orthogonality conditions required for their employment. The Hansen J statistic (over-identification test) for the model with all IVs indicates valid IVs as the over-identification restriction is satisfied (the null hypothesis cannot be rejected at the 10% level, $p > .15$).

As a last robustness test, we also checked the orthogonality of our IVs by the following procedure: We used one event as the IV and analyzed the direct influence of the two remaining events above and beyond the influence from TV programs and included them as simple covariates. For example, using the disasters as the IV and the World Cup and the US elections as covariates reveals that the influence of TV on auction sales is negative (coefficient = -1.47, $p < .05$) while the World Cup ($p > .1$) and the US presidential elections ($p > .1$) have no direct influence on auction sales above and beyond that captured by the number of TV viewers. The robustness of the results makes us confident that we can trust our results.

Generalizability

For a better understanding of the generalizability of our results, we replicated the study for another platform and in another context. We were able to collect a second extensive data set for the US context for the year 2013. We collected online purchase and click data from the Internet measurement firm Comscore. Comscore follows 100,000 US-based Internet users every year and reports their demographics, time-stamped clicks on websites, and online purchase transactions.

Using the Comscore data, we focused on the clicks on eBay because the number of actual sales on eBay in the sample was low. We restricted our data to the New York region to eliminate issues with viewers watching shows across different time zones in the US and thereby eliminated further problems of aggregated data on a national level. We complemented these data with data from a TV audience measurement company, using one-hour intervals as the unit of observation. We introduced time controls and controls for weather and public holidays in the New York area. A simple OLS regression with clicks on eBay as a dependent variable shows a positive correlation between TV viewership and activity on eBay. As outlined before, this is not the causal effect. To identify the causal effect, we estimated another IV regression. Again, we used a disaster as the IV (advantages and disadvantages are comprehensively discussed in previous sections). The Boston Marathon bombings were a series of attacks and incidents that took place on April 15, 2013, with two bombs exploding during the Boston Marathon at 2:49 pm EDT, killing three people and injuring many more.

For the first stage of IV regression, we found that on average, this incident and the induced program changes increased the number of TV viewers by 161,946 per hour for the subsequent 24 hours ($p < .01$) in the New York area. All relevant test statistics confirm that this incident qualifies as a significant and substantial shock on the number of TV viewers ($p < .05$). The second stage of the IV regression revealed that an increase in the number of TV viewers was accompanied by a significant decrease in activity on eBay, measured by the number of clicks on eBay coming from the New York area sample. Based on these estimates, we can infer that an increase of 100.000 people watching TV is associated with an activity decrease of 7.77% at the same time on eBay ($p < .1$). Though this effect is only weakly significant, we believe that it is another indicator for the attention competition of TV viewing and online auction participation in a different cultural context and on another auction platform. We further find that higher temperatures (an increase of 1ºF leads to -0.7 clicks, $p < .01$) decrease and rainy weather (1 mm of precipitation leads to +14.3 clicks, $p < .1$) increases levels of activity on eBay, which corroborates our previous findings with respect to the covariates.

Final Remarks

Good instruments are notoriously hard to find, and perfect orthogonality is impossible in real-world settings. Even textbook examples for IVs such as the hiring of firemen as an instrument for hiring of policemen to identify the causal effect of police on crime (Levitt, 2002) can potentially suffer from endogeneity (e.g., one could easily argue that in districts with higher crime rates we could expect more fires and thus more intensive hiring of firemen). However, we believe that our selection of IVs offers creative and valid orthogonal variation. Table 3 presents the different approaches and lists the potential confounding effect for each approach. Our analysis in the section entitled “Discussion of Potential Confounding Effects Regarding the IV” shows that many of these issues are likely to constitute a possibility rather than a concrete problem. Moreover, even if we cannot fully rule out every potential confounding effect, the selection of the IVs is complementary; at any one time, at least one IV is unaffected by a given potential confound. Therefore, it is difficult to imagine that all approaches produce the same result by chance. Taken together, the triangulation supports our confidence in our findings and allows us to argue that distraction caused by TV is likely to induce a drop in sales on auction platforms.

	Potential Confounding Effect					Evaluation
	Direct Effect on Sales	**Negative Mood**	**Positive Mood**	**Antici-pation**	**Reverse Causality**	
Disasters IV	Yes	Yes	No	No	No	Offers the advantage of a truly exogenous shock but may cause negative feelings
World Cup IV	Unlikely	Yes	Yes	Yes	No	Emotional (positive and negative) event that attracted a lot of attention
US Election IV	No	Unlikely	Unlikely	Yes	No	Informative news about election outcomes in foreign country without high involvement of spectators
Proxy Variable	-	-	-	-	Yes	Proxies latent probability to be at home, but estimates may still be biased due to omitted variables or reverse causality

Table 3: Evaluation of Different Modeling Approaches

The three IVs presented in this paper are based on extraordinary events. Because an exogenous shock on TV viewing is required for the first stage of IV regression, such events seem promising. However, the choice of these events raises the concern that while captivating TV shows have a negative effect on sales, such IVs might be ineffective at showing that watching boring shows (reality TV shows, for instance) has a negative effect on sales. We agree that this is a valid concern but refer to the proxy variable regression, which also yields a negative coefficient for the influence of TV viewership on auction sales.

The main purpose of this paper is to show that cross-media effects exist and to reveal the direction of these effects. Our work presents a first assessment on the relationship between TV viewing and online auction sales; we plan to extend this work to other domains in future research.

DEFERRED SALES OR LOST SALES

Our analysis prompts questions as to whether sales are lost because of TV consumption or simply deferred to a later period. TV programs may distract consumers from online shopping, but it is conceivable that consumers simply delay their online shopping to the end of a particular TV show or even to the next day or later, rather than forgoing it entirely. The uncertainty around deferral makes the analysis more complex.

We chose the following approach to address this question: assuming that sales are deferred, we would expect to observe autocorrelation in the error terms. To negate this effect and see the direct impact of the dependent variables (i.e., loss of sales), we thus applied the automatic lag selection in covariance matrix estimation by Newey and West (1994). The Newey and West (1994) procedure yielded 63 periods as the optimal bandwidth for autocorrelation correction. A bandwidth of 63 periods means that there is an approximate five-day autocorrelation effect (i.e., an event on Saturday such as rain or sunshine) can still have a sales impact on Wednesday of the following week. Consequently, we then estimated the IV model using disasters as the IV with statistics robust to heteroskedasticity and long-term autocorrelation (bw=63 periods) and arrived at the estimates listed in Table 4.

We can observe that two of the previously significant effects become insignificant. First, the bank balance no longer significantly impacts online sales. One possible explanation for this result is that consumers are postponing shopping according to their available budget; if they have a low account balance at the end of the month, sales go down, but sales then rebound once consumers receive their salaries.

The same can be observed with respect to public holidays. Taking all the autocorrelation effects into account, these do not seem to impact sales. Perhaps consumers make use of their public holidays and postpone ordering their products to other periods. Prospective buyers simply seem to defer their auction participation to the following days.

However, Table 4 illustrates that TV consumption, competition, and weather all directly impact sales, suggesting that this is an indicator of lost sales caused by these competing factors. This is still a preliminary analysis, however, and future research should look at this question in more detail.

Variable /Model Fit Statistics	**2nd Stage Estim. (RSE), dependent variable: Online Sales**
Number of TV Viewers	-1.477** (.599)
eBay Advertising in kEUR	-.001*(.000)
Bank Balance in EUR	2.90e-07 (.000)
Temperature in deg. C	-.411*** (.129)
Precipitation (e.g., rain) in mm	.127** (.054)
Public Holiday (0/1)	-1.947 (1.424)
Time	.001*** (.000)
Constant	65.039** (28.016)
Weekday Dummies	yes
Time of the Day Dummies	yes
Months Dummies	yes
F-Value	34.03
Prob > F	0
R sq. adj	29.95%
RMSE	8.416

Note: *$p < .1$, ** $p < .05$, *** $p < .01$, two-tailed significance levels Estim.: Estimates, RSE: Robust Standard Errors, RMSE: Root Mean Square Error.

Table 4: Estimation Results with Optimal Autocorrelation Correction

GENERAL DISCUSSION

Online auctions sites like eBay constitute a multimillion-dollar business. Therefore, it is important to attract as many potential buyers at the same point in time to maximize the outcome and properly time the auctions. We examine whether other media channels, namely the consumption of TV, are a substitute for the use of Internet auctions and result in reduced online sales. Using data from a German auction platform, we found that there is a significant cross-media effect from TV viewing to auction sales that may be caused by a scarcity in consumer attention to online auctions. The effect is negative, indicating that TV and the Internet are substitutes for each other rather than complements, at least in the domain of online auctions. Consequently, popular shows or blockbusters may demand the attention of consumers, distracting from online auctions.

Research Contribution

We are the first to provide evidence of a *negative cross-media effect of TV viewing on online auction sales*. We show that exogenous factors in offline channels can impact demand in online channels, indicating that prospective buyers are distracted by TV consumption and that consumer attention should be treated as a scarce resource. Our analyses further confirm findings in previous literature on inattention to relevant exogenous factors; online auction sellers who fail to consider factors such as weather, bank balance, and TV consumption will arrive at biased sales predictions and, ultimately, suboptimal auction timing.

Our study shows that the impact of exogenous factors themselves may result in a deferral of sales: online auction buyers may postpone shopping when faced with a low bank balance or sunny weather. However, our results also suggest that sellers' inattention towards TV viewing, temperature, competition, and holidays leads to complete sales losses because of the time-sensitive nature of auction closing times.

Managerial Implications

Our study shows that there are several exogenous effects that may impact online auction demand. Considering these effects, sellers can set auction timing to maximize the outcome accordingly. Of course, natural disasters cannot be predicted and hence online sellers cannot plan for such an event in advance. However, since all of our IVs point in the same direction, we can conclude that the relationship between TV viewing and auction sales is negative. We suggest coinciding the timing of auction closures with bad weather forecasts or times when TV viewership is low. Many sellers will suffer from inattention to these effects, whereas sellers with sophisticated demand prediction models that incorporate exogenous effects can exploit this information to their advantage. Accurate demand prediction is also helpful for inventory management and for the correct timing of marketing promotions.

To assess the economic relevance of our finding, we provide the following example: If we assume a linear relation between TV viewership and sales and believe that identification delivers reliable results, we can calculate the elasticity between the distraction effect and online auction sales, which we call the Distraction-Sales-Elasticity: an increase of the number of TV viewers by 1% comes with a decrease of auction sales of about 0.93%. The effect, however, is limited as the mean number of TV viewers does not show unlimited variation. For prime time (8pm to 10pm) the number of TV viewers does not normally (confidence interval=95%) decrease by more than 21% or increase by more than 15%, which would thus result in sales changes between +19.5% (on an evening with very low-quality TV programs) and -14% (on an evening with very high0quality TV programs). The event with the largest impact on TV viewership that we observed in our dataset would result in a sales decrease of about 18% on Platform.com.

We believe that the distraction effect is not only statistically significant but also of economic relevance and that it might be worth using this information to better time auctions.

Overall, we also found the following exogenous factors to have a negative impact on demand: periods of good weather, high TV consumption, low dispensable budget, competitor advertising, spending, and public holidays. Many of these factors may lead not only to phases of lower demand but also real losses in sales, whereas public holidays or budget restrictions seem to lead only to defered sales. These effects can have a direct impact on online auction success and it might be beneficial, therefore, for online auction sellers or intermediaries such as eBay to insure themselves against such exogenous events. Online retailers could hedge against such risks by investing in weather derivatives, for example, as agricultural industry participants do (Campbell and Diebold, 2005).

For prospective buyers interested in cheap prices, our research suggests that they should focus on auctions that close during unanticipated 'inattention gaps'. There may be less competition for auctions during a blockbuster's diffusion or events such as the Super Bowl.

Limitations and Directions for Further Research

Our work has several limitations that are relevant to further research. First, it is important to find instruments that are perfectly orthogonal to the system being examined. Although we believe that our suggested IVs work as intended, the coefficients might be slightly biased. The magnitude of coefficients does not matter for the theoretical contribution of this paper, but perfect orthogonality would be necessary for a working demand prediction model in business practice. Field experiments might be helpful in such cases.

Second, one could make an argument that TV viewership patterns from one set of users in one part of Germany is being correlated with the online auction behavior of users from another part of Germany. For instance, residents in rural areas may stay at home to watch TV after work since there is not much outdoor entertainment in which they can engage in their towns while urban-dwellers may spend their after-work hours at a restaurant or pub in the city, which limits their online auction usage levels. Under this plausible scenario, the TV viewership of the rural population would spuriously produce a negative correlation with the online activities of city dwellers, giving rise to the observed regression results. To control for this effect, we would like to add location fixed-effects to our model specifications. While we could, in principle, use our sales data at the ZIP-code level, we do not have TV viewership data at this level and need to frankly discuss this as limitation. However, the country of our study, Germany, considers rural areas to be as important as urban areas, and all efforts are made to develop them equally. Unlike in some countries, where rural areas are known for being backward when compared to urban areas, Germany avoids this with its policy of providing egalitarian living conditions. Rural areas receive nearly equivalent attention as urban areas (Wikipedia 2015). However, we cannot fully rule out this potential problem as there could be other location effects for which we cannot control.

Third, we studied the exogenous effects on sales of a single, particular platform and used major events as exogenous shocks. This may have led to the overestimation of the effect of TV on online auction outcomes as these events attract a very high level of attention. However, we believe that the use of proxy regression and the US election as an IV mitigate this concern. Nevertheless, research would benefit from analyses of additional platforms (e.g., from other countries) and from using different approaches (e.g., a field experiment).

Fourth, it would be very interesting to study the effect of particular shows on sales to determine patterns that would allow better prediction and understanding of cross-media effects. The inclusion of the interplay between TV and social media might be useful for this purpose.

Fifth, as mentioned before, a large majority of auctions on Platform.com have a rather long duration. Our results are applicable to shorter-term auctions.

Finally, as we examine the effect on a macro level, an individual level analysis would yield new insights. We believe that the intersection between offline and online media channels provides promising avenues for future research and that despite its limitations, this study provides a valuable first step in this direction.

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APPENDIX

	(1)		(2)		(3)		(4)		(5)	
	OLS Descriptive		Disaster IV, 2nd Stage		World Cup IV, 2nd		US Election IV, 2nd Stage		OLS with Daylight	
Number of TV Viewers in	-2.834	(2.367)	-269.064**	(112.268)	-28.590**	(13.667)	-457.302**	(119.488)	-8.571**	(2.422)
eBay Advertising in kEUR	-0.110**	(0.015)	-0.080**	(0.024)	-0.107**	(0.016)	-0.059**	(0.020)	-0.108**	(0.016)
Bank Balance in MEUR	37.913**	(11.349)	30.760**	(15.254)	37.221**	(11.395)	25.702**	(11.720)	37.373**	(11.326)
Temperature in deg. C	-17.478**	(2.046)	-70.186**	(22.416)	-22.577**	(3.288)	-107.454**	(23.803)	-18.331**	(2.055)
Precipitation (e.g., rain) in	6.246**	(1.920)	23.344**	(7.668)	7.901**	(2.092)	35.432**	(7.919)	7.055**	(1.918)
Public Holiday (0/1)	-537.864**	(39.302)	-143.065	(184.232)	-499.669**	(44.853)	136.077	(181.205)	-519.017**	(39.674)
Time	0.146**	(0.002)	0.133**	(0.006)	0.145**	(0.002)	0.125**	(0.006)	0.145**	(0.002)
Monday (0/1)	299.274**	(32.823)	-740.553*	(441.148)	198.677**	(63.652)	-1475.762**	(467.549)	258.459**	(32.532)
Tuesday (0/1)	194.034**	(29.134)	-873.619*	(451.909)	90.745	(61.150)	-1628.501**	(479.845)	152.666**	(29.150)
Wednesday (0/1)	209.143**	(30.731)	-927.097*	(479.748)	99.218	(65.925)	-1730.474**	(508.598)	164.463**	(30.730)
Thursday (0/1)	124.573**	(28.155)	-1016.264**	(483.012)	14.204	(65.403)	-1822.891**	(512.493)	79.622**	(28.341)
Friday (0/1)	52.719*	(27.053)	-956.149**	(427.376)	-44.883	(58.364)	-1669.469**	(453.485)	12.308	(27.303)
Saturday (0/1)	-108.281**	(24.330)	-901.372**	(337.466)	-185.008**	(47.425)	-1462.126**	(356.974)	-142.252**	(24.554)
Sunday (0/1)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
00:00-01:59 (0/1)	-483.870**	(71.612)	-7809.400**	(3089.834	-1192.571**	(377.005)	-12988.909**	(3288.180	-789.448**	(78.200)
02:00-03:59 (0/1)	-555.157**	(88.842)	-9925.898**	(3952.030	-1461.720**	(482.027)	-16551.470**	(4205.628	-944.876**	(97.155)
04:00-05:59 (0/1)	-723.309**	(91.905)	- [illegible]	(4110.442	-1666.212**	(501.087)	-17360.847**	(4374.700	-1128.594**	(100.261)
06:00-07:59 (0/1)	-655.753**	(89.910)	- [illegible]	(4012.009	-1576.050**	(488.849)	-16894.397**	(4269.884	-1046.038**	(98.245)
08:00-09:59 (0/1)	-146.821*	(83.781)	-8755.970**	(3630.977	-979.705**	(443.053)	-14843.060**	(3864.065	-499.629**	(91.652)
10:00-11:59 (0/1)	353.917**	(77.576)	-7386.645**	(3264.889	-394.936	(400.172)	-12859.600**	(3473.689	35.348	(84.803)
12:00-13:59 (0/1)	433.886**	(64.386)	-5434.095**	(2474.026	-133.806	(304.681)	-9583.045**	(2633.367	186.002**	(69.420)
14:00-15:59 (0/1)	499.323**	(55.519)	-4033.247**	(1911.550	60.824	(238.070)	-7237.995**	(2034.004	305.290**	(58.681)
16:00-17:59 (0/1)	511.211**	(51.953)	-2814.772**	(1403.102	189.442	(174.870)	-5166.405**	(1492.023	360.732**	(53.969)
18:00-19:59 (0/1)	429.243**	(38.297)	1245.322**	(350.801)	508.194**	(58.005)	1822.330**	(369.224)	447.628**	(38.553)
20:00-21:59 (0/1)	452.931**	(58.509)	6017.647**	(2349.497	991.284**	(289.998)	9952.173**	(2499.413	677.554**	(65.909)
22:00-23:59 (0/1)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
January (0/1)	-645.508**	(54.903)	-312.968**	(154.620)	-613.337**	(57.708)	-77.846	(158.637)	-637.321**	(54.659)
February (0/1)	-618.105**	(55.930)	-339.215**	(133.979)	-591.124**	(57.964)	-142.026	(136.622)	-611.226**	(55.694)
March (0/1)	-603.821**	(57.362)	-533.285**	(74.104)	-596.997**	(57.735)	-483.413**	(65.567)	-521.323**	(44.677)
April (0/1)	-590.686**	(55.893)	-742.534**	(93.551)	-605.377**	(56.628)	-849.898**	(88.362)	-432.030**	(32.160)
May (0/1)	-585.917**	(58.610)	-767.236**	(105.569)	-603.458**	(59.573)	-895.438**	(100.309)	-394.188**	(33.048)
June (0/1)	-326.010**	(62.878)	-319.969**	(78.860)	-325.426**	(63.106)	-315.697**	(63.023)	-113.408**	(32.786)
July (0/1)	-203.703**	(65.366)	-280.345**	(87.474)	-211.118**	(65.675)	-334.534**	(73.426)	0.000	(.)
August (0/1)	-275.108**	(61.794)	-393.135**	(91.280)	-286.526**	(62.401)	-476.586**	(80.947)	-96.078**	(31.270)
September (0/1)	-181.775**	(64.187)	-300.822**	(91.229)	-193.292**	(64.629)	-384.994**	(82.978)	-81.779**	(41.227)
October (0/1)	-347.585**	(58.358)	-324.717**	(69.941)	-345.373**	(58.508)	-308.549**	(59.401)	-273.141**	(42.758)
November (0/1)	189.164**	(67.143)	298.021**	(88.277)	199.695**	(67.461)	374.989**	(86.902)	191.611**	(66.822)
December (0/1)	(omitted)		(omitted)		(omitted)		(omitted)		(omitted)	
Daylight in Min									6.846	(21.532)
Daylight in Min X TV									-3.897**	(0.419)
Constant	-332.052**	(162.497)	11893.828**	(5161.005	850.728	(639.283)	20538.123**	(5484.294	52.694	(167.620)
F-Value	219.123		155.169		219.408		219.281		214.553	
R^2	0.416		0.028		0.412		0.416		0.419	
RMSE	1065.824		1374.625		1069.128		1066.893		1064.270	
N	17,023		17,023		17,023		17,023		17,023	

Robust Standard Errors in parentheses, $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Table 5: Estimation Results for all Models with Sales in EUR as Dependent Variable

DV: TV Viewership	(1) Disaster 1st		(2) World Cup IV, 1st		(3) US Election IV, 1st	
Disaster IV	1.940***	(0.610)				
World Cup Broadcast IV			8.257***	(2.926)		
US Presidential Election IV					2.081***	(0.652)
eBay Advertising in kEUR	0.000**	(0.000)	0.000**	(0.000)	0.000**	(0.000)
Bank Balance in Mio. EUR	-0.026	(0.036)	-0.032	(0.036)	-0.028	(0.036)
Temperature in deg. C	-0.198***	(0.007)	-0.199***	(0.007)	-0.198***	(0.007)
Precipitation (e.g., rain) in	0.064***	(0.007)	0.065***	(0.007)	0.064***	(0.007)
Public Holiday (0/1)	1.482***	(0.248)	1.480***	(0.248)	1.482***	(0.248)
Time	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Monday (0/1)	-3.906***	(0.111)	-3.902***	(0.112)	-3.906***	(0.111)
Tuesday (0/1)	-4.012***	(0.109)	-4.027***	(0.108)	-4.010***	(0.108)
Wednesday (0/1)	-4.273***	(0.109)	-4.272***	(0.109)	-4.271***	(0.109)
Thursday (0/1)	-4.286***	(0.108)	-4.282***	(0.108)	-4.285***	(0.108)
Friday (0/1)	-3.791***	(0.109)	-3.796***	(0.109)	-3.789***	(0.109)
Saturday (0/1)	-2.979***	(0.126)	-2.989***	(0.125)	-2.979***	(0.126)
Sunday (0/1)	(omitted)		(omitted)		(omitted)	
00:00-01:59 (0/1)	-27.514***	(0.130)	-27.504***	(0.128)	-27.516***	(0.130)
02:00-03:59 (0/1)	-35.196***	(0.113)	-35.180***	(0.111)	-35.199***	(0.113)
04:00-05:59 (0/1)	-36.607***	(0.114)	-36.591***	(0.112)	-36.610***	(0.114)
06:00-07:59 (0/1)	-35.730***	(0.118)	-35.718***	(0.117)	-35.733***	(0.118)
08:00-09:59 (0/1)	-32.336***	(0.108)	-32.324***	(0.107)	-32.338***	(0.108)
10:00-11:59 (0/1)	-29.073***	(0.119)	-29.062***	(0.118)	-29.075***	(0.119)
12:00-13:59 (0/1)	-22.042***	(0.117)	-22.022***	(0.115)	-22.041***	(0.117)
14:00-15:59 (0/1)	-17.026***	(0.121)	-17.006***	(0.119)	-17.025***	(0.121)
16:00-17:59 (0/1)	-12.493***	(0.132)	-12.491***	(0.129)	-12.493***	(0.132)
18:00-19:59 (0/1)	3.064***	(0.166)	3.059***	(0.165)	3.065***	(0.166)
20:00-21:59 (0/1)	20.899***	(0.165)	20.890***	(0.164)	20.900***	(0.165)
22:00-23:59 (0/1)	(omitted)		(omitted)		(omitted)	
January (0/1)	1.251***	(0.156)	1.239***	(0.156)	1.248***	(0.156)
February (0/1)	1.048***	(0.133)	1.040***	(0.133)	1.047***	(0.133)
March (0/1)	0.257**	(0.129)	0.256**	(0.130)	0.264**	(0.129)
April (0/1)	-0.569***	(0.136)	-0.563***	(0.136)	-0.569***	(0.136)
May (0/1)	-0.681***	(0.155)	-0.667***	(0.155)	-0.679***	(0.155)
June (0/1)	0.023	(0.176)	-0.044	(0.175)	0.024	(0.176)
July (0/1)	-0.286	(0.181)	-0.293	(0.180)	-0.287	(0.181)
August (0/1)	-0.445***	(0.164)	-0.429***	(0.164)	-0.442***	(0.164)
September (0/1)	-0.449***	(0.156)	-0.440***	(0.156)	-0.447***	(0.156)
October (0/1)	0.086	(0.139)	0.087	(0.139)	0.085	(0.139)
November (0/1)	0.407***	(0.126)	0.405***	(0.126)	0.402***	(0.126)
December (0/1)	(omitted)		(omitted)		(omitted)	
Constant	45.914***	(0.440)	45.963***	(0.440)	45.933***	(0.440)
F-Value	12386.839		12372.213		12365.442	
R^2	0.967		0.967		0.967	
RMSE	3.264		3.254		3.264	

Robust Standard Errors in parentheses, * $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: First Stage Results for IV Models with TV Viewership as Dependent Variable

	First Stage DV: TV		Second Stage DV: Sales	
Number of TV Viewers in			-0.367**	(0.147)
Disaster IV	1.955***	(0.612)		
World Cup Broadcast IV	8.260***	(2.926)		
US Presidential Election IV	2.094***	(0.652)		
eBay Advertising in kEUR	0.000**	(0.000)	-0.001***	(0.000)
Bank Balance in Mio. EUR	-0.032	(0.036)	0.320***	(0.074)
Temperature in deg. C	-0.199***	(0.007)	-0.192***	(0.032)
Precipitation (e.g., rain) in	0.066***	(0.007)	0.055***	(0.016)
Public Holiday (0/1)	1.479***	(0.248)	-3.592***	(0.370)
Time	-0.000***	(0.000)	0.001***	(0.000)
Monday (0/1)	-3.902***	(0.112)	0.258	(0.616)
Tuesday (0/1)	-4.029***	(0.108)	-0.575	(0.622)
Wednesday (0/1)	-4.280***	(0.109)	-0.726	(0.659)
Thursday (0/1)	-4.283***	(0.108)	-1.150*	(0.660)
Friday (0/1)	-3.798***	(0.109)	-1.487**	(0.588)
Saturday (0/1)	-2.989***	(0.125)	-2.188***	(0.476)
Sunday (0/1)	(omitted)		(omitted)	
00:00-01:59 (0/1)	-27.503***	(0.128)	-13.895***	(4.048)
02:00-03:59 (0/1)	-35.180***	(0.111)	-17.331***	(5.180)
04:00-05:59 (0/1)	-36.591***	(0.112)	-18.770***	(5.388)
06:00-07:59 (0/1)	-35.719***	(0.117)	-17.816***	(5.257)
08:00-09:59 (0/1)	-32.323***	(0.107)	-12.553***	(4.759)
10:00-11:59 (0/1)	-29.061***	(0.118)	-7.311*	(4.285)
12:00-13:59 (0/1)	-22.023***	(0.115)	-4.341	(3.250)
14:00-15:59 (0/1)	-17.007***	(0.119)	-2.210	(2.516)
16:00-17:59 (0/1)	-12.491***	(0.129)	-0.587	(1.851)
18:00-19:59 (0/1)	3.058***	(0.165)	4.647***	(0.529)
20:00-21:59 (0/1)	20.886***	(0.164)	11.351***	(3.101)
22:00-23:59 (0/1)	(omitted)		(omitted)	
January (0/1)	1.240***	(0.156)	-4.701***	(0.436)
February (0/1)	1.040***	(0.133)	-5.227***	(0.421)
March (0/1)	0.247*	(0.130)	-5.216***	(0.404)
April (0/1)	-0.560***	(0.136)	-5.288***	(0.404)
May (0/1)	-0.665***	(0.155)	-5.341***	(0.424)
June (0/1)	-0.042	(0.175)	-3.498***	(0.432)
July (0/1)	-0.291	(0.180)	-2.231***	(0.460)
August (0/1)	-0.430***	(0.164)	-3.224***	(0.435)
September (0/1)	-0.442***	(0.156)	-3.037***	(0.443)
October (0/1)	0.087	(0.139)	-3.695***	(0.408)
November (0/1)	0.397***	(0.126)	-0.180	(0.446)
December (0/1)	(omitted)		(omitted)	
Constant	45.965***	(0.440)	14.103**	(6.808)
F-Value	11730.834		358.586	
R²	0.967		0.518	
RMSE	3.254		6.979	
N	17,023		17,023	

Robust Standard Errors in parentheses, $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Table 7: All IVs Jointly in One Model (Model 6)