Adoption Patterns over Time: A Replication

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Abstract

Based on new data, we replicate Mahajan, Muller, and Srivastava's (1990) paper on adopter categories, and Goldenberg, Libai, and Muller's (2002) paper on saddles; and offer explanations and extensions. We use a new dataset to replicate the results, namely the U.S. Consumer Technology Association's Sales & Forecasts, which provides longitudinal data on numerous consumer electronic products. Goldenberg, Libai, and Muller utilized the same source for 1999, while we use the updated 2021 report for the adopter category as well as the saddle replication, thus employing the same data source for both studies. We find that in the adoption of consumer electronics, there are fewer saddles, and these saddles are shorter and shallower in 2021 than they were in 1999. Regarding adopter categories, we break the data down by decades, and show that, while the early adopter categories just barely decelerated over the six decades of our analysis, the average growth of the new dataset is much faster, with the peak occurring considerably sooner than that of the earlier data.

Keywords: acceleration; adopter categories; Bass model; innovation; new products; peak time; saddles

1. Introduction

Based on new data, we replicate Mahajan, Muller, and Srivastava (1990) (hereinafter: "MMS") on adopter categories, and Goldenberg, Libai, and Muller (2002) ("GLM") on saddles; and offer explanations and extensions. Adopter categories, namely Innovators, Early Adopters, Early and Late Majority, and Laggards, are the traditional segments for new products, used for targeting new customers, and for developing and retaining current ones (Sood and Kumar 2017; Rogers 2003). This segmentation has been updated for technology innovations to a dual market structure – Early and Main Markets – that are in some cases separated by a temporal slump in sales, or a saddle. The main difference between these two segments is based on the benefits that consumers gain from the product; see also Golder and Tellis (2004), Hauser, Tellis and Griffin (2006), Van den Bulte and Joshi (2007), Chandrasekaran and Tellis (2011), and Chu et al. (2017). While previous studies have chronicled the relative sizes of the categories, as well as the prevalence of saddles, on datasets that were available at the time, we use a new dataset to replicate the results and discuss the differences.

We observe that not only has the average depth of saddles decreased, their average duration has considerably shrunk from almost four years to slightly more than two years. Moreover, their occurrence dropped considerably from 50% to less than 30%. Thus, in the adoption of consumer electronics, there are fewer saddles, and these saddles are shorter and shallower in 2021 than they were in 1999.

Regarding adopter categories, we break the data down by decades, as doing so yields a more accurate picture of the results, and shows that while the early adopter categories just barely decelerated over the six decades of our analysis, the average growth of the new dataset is faster, with peak occurring considerably sooner than that of the earlier data.

2. Data

We use *U.S. Consumer Technology Sales & Forecasts*, a biannual report published by the Consumer Technology Association (CTA, formerly CEA) that provides longitudinal data on numerous consumer electronic products. While GLM utilized this source for 1999, we use the updated 2021 report for both the adopter category and the saddle replication, thus using the same data for both studies. As did GLM, we used products with at least 8 datapoints, and removed products that were mere groupings of other product categories (e.g., Wireless Phone Accessories); did not have unit sales data (i.e., had dollar sales or penetration rates); were a subset of a product (e.g., wireless around-the-ear headphones versus "wireless headphones"), or for which the data was provided late in the life cycle of the product, such that the time series was already showing a rapid decline . GLM used products with at least 8 datapoints, and had data up to 1998, thus these products began selling in the USA prior to 1991. We thus use this year (1991) as the cutoff point for our products, hence including all products with at least 8 datapoints that began selling in the USA in or after 1992, thereby ensuring that no product appears in both datasets. We denote these datasets as the 1999 and 2021 datasets respectively, while for the adopter categories, we break the data down by decades as doing so yields a more accurate picture of the results.

The GLM (1999) dataset contained 32 products, while the new dataset (2021) contains 48 products. We also included in the data six products that had 7 data points, which we refer to as the Extended dataset: While we do not consider these products in the saddle analysis, as they are too short a series to examine, and we wish to precisely replicate GLM that had a minimum of 8 points, we do consider these products when we explored the change in the diffusion coefficients in Section 4. The full list of products and their attributes is in Appendix A.

3. The Decline in Prevalence of Saddles

Early and Main Market adopter segments develop differently over time: If the Early Market diffuses earlier and faster than the Main Market, and there is a partial break in social contagion between the two segments, a saddle, that is a temporary decline in the sales of the product, ensues. This saddle will wither over time, as the adoption of the Main Market speeds up. Note that this is a more general definition than the one found in GLM as it does not require the two segments to be related to their appreciation and knowledge of high technology. Any two segments that consistently differ in their speed of adoption might create a saddle.

To identify saddles in the 2021 dataset, we use the exact same specification of GLM, of a saddle that has either a minimum duration of one year with minimum depth of 10%, or else a minimum duration of 2 years with no minimum depth[1]. Table 1a lists the summary statistics of both datasets, Table 1b lists the saddles found in the new data, and Figure 1 depicts two saddles from the new data (GLM presented examples of saddles from their own data).

What we observe from the tables is that while the average depth of saddles has somewhat decreased, their average duration has considerably shrunk from almost four years to slightly over two years. Moreover, the occurrence of saddles dropped considerably from 50% to less than 30%. We can conclude that in the adoption of consumer electronics, over the course of 20 years, there are fewer saddles, and those saddles are shorter and shallower.

Table 1a: Prevalence of saddles, by dataset

Datasets	**Number of new products**	**Products with saddle**	**% with saddle**	**Ave. depth (%)**	**Ave. duration (years)**
New (2021)	48	14	29%	22%	2.4
GLM (1999)	32	16	50%	25%	3.9

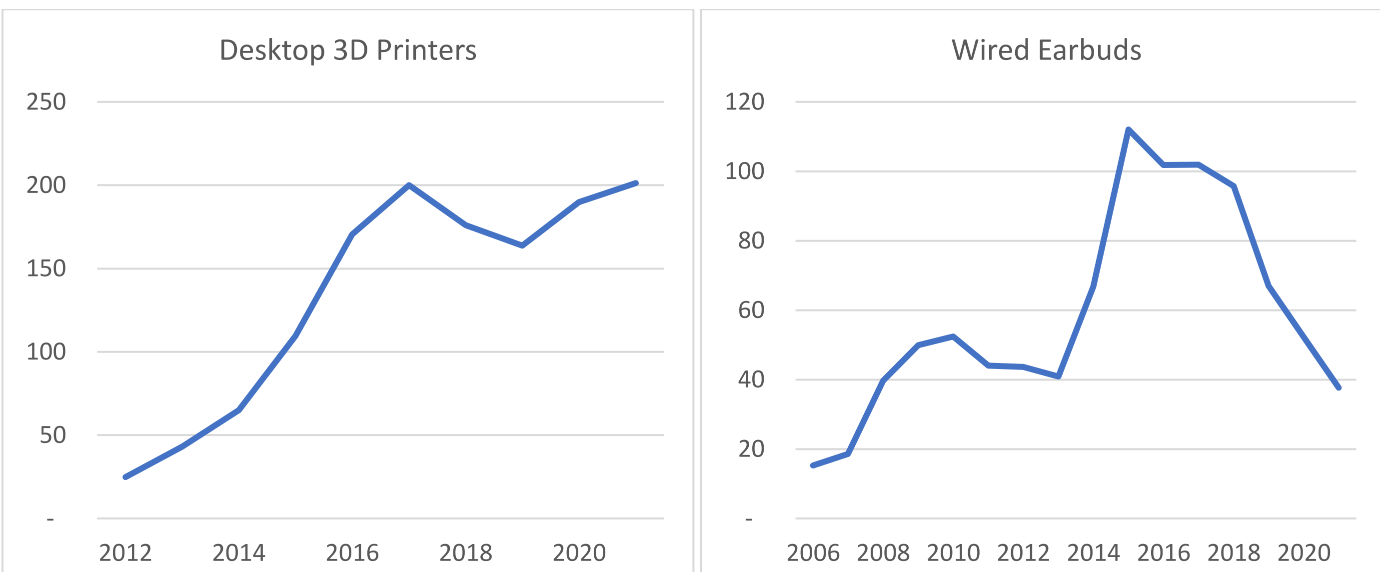
[1] This is the "relaxed" version of the definition in GLM Table 1, though the wording in the text is somewhat imprecise. The exact definition is the one given here: A minimum duration of one year with depth of at least 10%; or else a minimum duration of 2 years.

Table 1b: Saddle Properties of the 2021 dataset

Saddle start year	Innovation with saddle	Relative depth (%)	Duration (years)
1997	Home theater-in-a-box*	20%	2
2003	Standard DVD players	15%	2
2007	Wireless headphones*	27%	5
2008	OLED TV*	89%	4
2009	Cable set-top boxes	8%	2
2009	Laptop/Notebook PCs	10%	3
2010	Home robots	8%	2
2010	Wired earbuds*	22%	3
2012	Digital Video Recorders (DVRs)	18%	2
2012	Wired headphones	21%	1
2015	Smartwatches	15%	1
2017	Desktop 3D printers	18%	3
2017	Digital TV sets and displays	11%	2
2017	Smart TVs	21%	1

* With GLM's strict definition of at least 2 years and 20% depth, the new dataset has 4 saddles vs 11 of GLM.

Figure 1: Saddle in Desktop 3D Printers and Wired Earbuds (new data)*



* Desktop 3D Printers and Wired Earbuds are in thousands and millions of units respectively. 2021 figures are estimates.

There are three main reasons why we find fewer saddles in the newer dataset: First, GLM showed that the main reason for the saddle is a (partial) break in communication between the early and main markets (see Chandrasekaran and Tellis 2011 for an in-depth review of the phenomenon). However, in more recent times, the flood of information with respect to new products and their attributes that newer markets exhibit, renders the lack of information transmission between early and late market less impactful. Many of these new products, such as smartphones and streaming media players, are in themselves agents of such communication, bringing accessible innovation to multitudes of consumers.

Second, firms are taking the possibility of a saddle into account and are working to mitigate its effect (Goldenberg et al. 2006), and thus what we see is a resultant market structure that follows these actions, namely with a lower likelihood of a saddle. Research has proposed that "seeding" the market with free samples can help mitigate the saddle effect (Lehmann and Esteban-Bravo 2006), and it has become far easier for companies to run free sampling and seeding campaigns, as they can release those in digital form (Li, Jain, and Kannan 2019).

Third, the advent of the internet and subsequently social media has made information sharing faster and accessible from virtually any location. We observe two concurrent effects here, as the internet enabled faster diffusion of any message, providing an infrastructure for digital advertising and social media platforms, thereby enabling the internal and external coefficients to increase over time, as can be seen in Table 2a. Social media platforms, on the other hand, enabled consumers to communicate better, pushing the internal coefficient to higher levels over time. Considering new innovation, from virtual influencers to augmented reality, we can safely predict that social media will only increase in importance, and in turn increase our ability to communicate and influence others over time (Appel et al. 2020).

One important thing to note is that increase in social communication as a process preceded the advent of social media, or even the internet. Looking at the scatter plots of the internal coefficient in Figure W1 of Web Appendix A, it seems that the internal coefficient began accelerating in the 1960s, long before the advent of social media or the internet (and similarly for the external coefficient). From the plots, it seems that the variance of the coefficients increased with the introduction of the internet and social media.

4. The Acceleration of Adoption Curves

Next, we estimated the diffusion coefficients for the products in both datasets using the NLS method (Srinivasan and Mason 1986). One benefit of this method is that it enables us to use the actual launch year (i.e., the year the product was first introduced to the market) rather than the data start year (i.e., the year data on the product was first available in the CEA dataset) in our estimations. We used historical analysis (Golder and Tellis 1993) to identify the launch year for the products in both datasets. This method provided a more accurate analysis, and more stable estimations yielding higher R^2 values.

Adopter categories is the traditional segmentation method for new products, defined by the inflection points and the peak time of the Bass diffusion model (Rogers 2003, MMS 1990). As shown in Appendix A, the individual Bass model regressions work well on the data, yielding an average R-Square of 86%. While these data are summarized in Table 2a, Table 2b shows the developing nature of the adopter categories over the decades of our data.

Table 2a: Per-period average diffusion parameters and peak times

Period	# of products	External coefficient (p)	Internal coefficient (q)	Peak time	p/q
Pre 1970	12	0.001	0.18	51	0.005
1970-1979	12	0.002	0.27	27	0.008
1980-1989	18	0.007	0.31	22	0.022
1990-1999	20	0.013	0.48	14	0.027
2000-2009	15	0.019	0.44	13	0.043
Post 2010	9	0.024	0.48	10	0.049

Table 2b: Adopter categories by decades

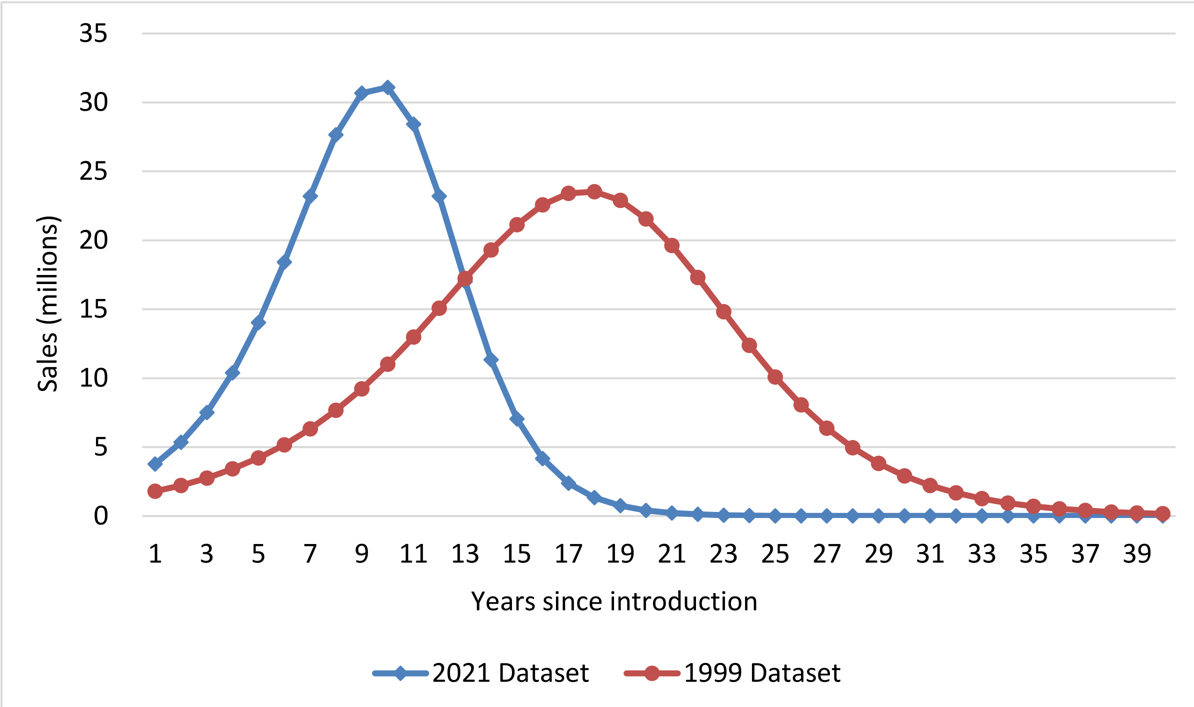
Period	# of products	Innovators + Early Adopters	Early Majority	Late Majority	Laggards
Pre 1970	12	20.7%	29.0%	29.0%	21.2%
1970-1979	12	20.5%	29.1%	29.1%	21.3%
1980-1989	18	19.4%	29.5%	29.5%	21.6%
1990-1999	20	19.0%	29.6%	29.6%	21.7%
2000-2009	15	17.8%	30.1%	30.1%	22.0%
Post 2010	9	17.3%	30.3%	30.3%	22.2%

It appears from the categories that products are being adopted later in the product life cycle, as the number of Innovators and Early Adopters has slowly dropped decade by decade. This drop is absorbed almost equally by the other three categories, slightly increasing the latter's sizes over time (using the equations of the product categories in MMS, it is straightforward to prove that this is entirely explained by the increase in the ratio of p/q as shown in Table 2a). Interestingly, adopter categories only give a partial picture of the product life cycle, as the more remarkable nature of the data's change over time lies in the recent left-skewness of the data. To demonstrate, observe Figure 2 that shows the new product diffusion curves, averaged over the two main datasets (1999 and 2021).

Though as we showed, the adopter categories seem to shift slowly to later adoption over time, the adoption curves themselves changed. The new adoption curve is faster, with peak occurring much sooner than that of the earlier data. In fact, the time it takes to be considered a Laggard now, would label the same consumer as Early Market (if not earlier) in earlier times.

While the figure demonstrates the left-skewness effect for the two datasets, Table 2a shows that this is a consistent phenomenon: Time to peak has gotten considerably shorter over the last decades, and the diffusion coefficients are getting larger, both monotonically over time.

Figure 2: Average new product diffusion by dataset*



* The market potential of the 2021 dataset is actually smaller than that of the 1999 dataset (269m vs 363m, on average). The 2021 sales curve reaches this smaller potential much faster.

5. Managerial implications

In this paper we find that in the adoption of consumer electronics, there are fewer saddles, and these saddles have become shorter and shallower in 2021. We also show that, while most adopter categories barely changed over the six decades of our analysis, the average growth in the new dataset is faster, with peak occurring sooner than that of the earlier data. Yet this is not limited to electronic goods, as other recent innovations have also demonstrated an accelerated growth pace. A notable example is the explosion of the various “sharing economy” platforms such as Uber, Airbnb, or Postmates, allowing people to share their cars, home, or free time with others for a fee (Zervas, Proserpio, and Byers 2017; Muller 2020). These platforms have grown at a pace never before seen in other products. For example, the first-ever Uber ride was requested on July 5, 2010, and it took Uber just over five years to reach their billionth ride (Mclean 2015). For comparison, even McDonald's needed more than eight years to sell a billion burgers (Wilson 2013), a product cheaper and more accessible than an Uber ride.

Likewise, in the 2021 data, we observe products that in a few short years have become commonplace, such as home robots, tablet PCs, and Bluetooth speakers. Interestingly, more complex technological advances, such as smartwatches and smart TVs, still exhibit a saddle. Perhaps the complexity of these products deters the early market from adopting earlier.

The left-skewness of the newer data is a market structure that follows decisions of firms that market new innovations, where marketing managers are not limited to traditional digital marketing methods such as advertising on social media platforms and websites. These marketers have introduced new and disruptive marketing methods that have been termed "growth hacking": The term describes a collection of disruptive growth strategies that relies on any mechanism, including hacking, that will spur growth via usage of social media and increased social contagion. Arguably the best example of this strategy is the "integration" of Craigslist into Airbnb in its early days, where a potential user who clicked on an Airbnb listing in Craigslist would be transferred to Airbnb's website, thus enabling the latter to tap into the massive user base of the former (see growthhackers.com/growth-studies). The result of such strategies, both traditional and disruptive, is left skewness of the diffusion curves, as demonstrated in the paper.

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Appendix A: Diffusion parameters and peak time of innovations, by data start year*

Product	Data Start Year	Launch Year	Dataset	*p*	*q*	*N* (million)	*T**	R^2
Monochrome TV	1946	1939	GLM (1999)	0.0077	0.09	275	27	67%
Home Radios	1950	1920	GLM (1999)	0.0004	0.10	1,392	57	76%
Color TV	1954	1954	GLM (1999)	0.0014	0.11	783	41	97%
VCR Decks	1974	1972	GLM (1999)	0.0031	0.17	359	25	87%
Aftermarket PC Monitors	1980	1960	GLM (1999)	0.0002	0.11	336	57	92%
Compact Audio Systems	1980	1960	GLM (1999)	0.0003	0.11	732	58	80%
Cordless Phones	1980	1977	GLM (1999)	0.0008	0.16	2,183	35	98%
PC Printers	1980	1970	GLM (1999)	0.0001	0.19	770	41	93%
Personal Computers	1980	1974	GLM (1999)	0.0006	0.15	944	40	93%
Rack Audio Systems	1980	1958	GLM (1999)	0.0001	0.30	24	31	64%
Blank Videocassettes	1982	1976	GLM (1999)	0.0066	0.19	8	19	87%
Corded Phones	1982	1930	GLM (1999)	0.0001	0.09	1,257	73	63%
Personal Word Processors	1982	1982	GLM (1999)	0.0334	0.20	48	9	81%
Telephone Answering Devices	1982	1960	GLM (1999)	0.0001	0.24	308	36	96%
LCD Monochrome TV	1983	1982	GLM (1999)	0.0278	0.19	10	10	58%
Portable Tape Players	1983	1975	GLM (1999)	0.0053	0.24	285	18	90%
Total CD Players	1983	1982	GLM (1999)	0.0030	0.35	427	16	98%
Cellular Phones	1984	1983	GLM (1999)	0.0018	0.48	111	15	99%
Color TV with Stereo	1984	1984	GLM (1999)	0.0097	0.17	319	18	95%
Modems / Fax Modems	1984	1962	GLM (1999)	0.0000	0.48	80	37	100%
Blank Audio Cassettes	1985	1964	GLM (1999)	0.0014	0.18	10	29	87%
Camcorders	1985	1973	GLM (1999)	0.0023	0.21	68	24	92%
Laserdisc Player	1985	1978	GLM (1999)	0.0010	0.53	2	15	90%
LCD Color TV	1985	1984	GLM (1999)	0.0161	0.26	5	12	94%
Projection TV	1985	1978	GLM (1999)	0.0009	0.16	76	36	95%
Videocassette Players	1985	1977	GLM (1999)	0.0046	0.30	6	16	76%
DBS Satellite	1986	1975	GLM (1999)	0.0000	0.67	17	22	92%
VCR Decks with Stereo	1986	1982	GLM (1999)	0.0009	0.23	484	27	98%
Blank Floppy Diskettes	1987	1981	GLM (1999)	0.0121	0.23	10	14	96%
Fax Machines	1987	1980	GLM (1999)	0.0032	0.32	37	17	92%
Portable CD Equipment	1987	1984	GLM (1999)	0.0040	0.41	211	14	96%
TV/VCR Combinations	1990	1986	GLM (1999)	0.0085	0.34	32	13	91%
Aftermarket Remote Controls	1991	1985	New (2021)	0.0043	0.25	494	19	95%
Digital Cameras	1996	1990	New (2021)	0.0008	0.40	373	19	95%
Home Theater-in-a-Box	1996	1994	New (2021)	0.0110	0.31	48	12	94%
Caller ID Devices	1996	1991	New (2021)	0.0281	0.42	48	8	95%
Family Radio Devices	1997	1996	New (2021)	0.0316	0.23	162	9	57%
Set-Top Internet Devices	1997	1996	New (2021)	0.0831	0.61	7	4	96%
Standard DVD Players	1997	1997	New (2021)	0.0223	0.27	283	10	90%
Digital TV Sets and Displays	1998	1998	New (2021)	0.0068	0.19	869	19	91%
Digital Projection TV	1999	1998	New (2021)	0.0233	0.66	19	7	97%
Plasma Flat Panel TV	1999	1997	New (2021)	0.0032	0.51	33	13	95%
Portable Media Players	1999	1998	New (2021)	0.0076	0.46	384	11	89%
Digital Direct-View TV	2000	1998	New (2021)	0.0027	1.16	12	8	78%
Personal Digital Assistants	2000	1993	New (2021)	0.0260	0.33	68	9	99%

Product	**Data Start Year**	**Launch Year**	**Dataset**	***p***	***q***	***N*** (million)	***T****	**R^2**
Portable Navigation Devices	2000	1989	New (2021)	0.0001	0.47	118	21	75%
Front Projection	2002	1973	New (2021)	0.0003	0.20	23	36	87%
Cable Set-Top Boxes	2003	1950	New (2021)	0.0000	0.15	412	64	82%
Digital Video Recorders	2003	1999	New (2021)	0.0082	0.34	209	13	75%
Laptop/Notebook PCs	2003	1983	New (2021)	0.0003	0.16	1,802	42	96%
Smartphones	2003	1995	New (2021)	0.0008	0.31	2,371	22	96%
VoIP Adapters	2003	2003	New (2021)	0.0490	0.53	58	6	92%
IPTV	2004	2004	New (2021)	0.0220	0.28	56	10	82%
Streaming Media Players	2004	2002	New (2021)	0.0026	0.31	279	18	98%
Digital-to-Analog Converters	2005	2005	New (2021)	0.0857	1.47	57	4	74%
Blu-ray Players	2006	2006	New (2021)	0.0395	0.38	92	7	90%
Digital Photo Frames	2006	1999	New (2021)	0.0051	0.53	67	11	90%
E-readers	2006	2004	New (2021)	0.0196	0.37	104	9	39%
Full HDTV (1080p)	2006	2005	New (2021)	0.0198	0.37	252	9	91%
Wired Earbuds	2006	1984	New (2021)	0.0000	0.37	1,039	32	76%
Wired Headphones	2006	1910	New (2021)	0.0000	0.19	499	103	72%
Wireless Headphones	2006	1999	New (2021)	0.0000	0.62	74	21	98%
OLED TV	2008	2008	New (2021)	0.0011	0.62	23	14	98%
Soundbars	2008	1998	New (2021)	0.0003	0.39	105	22	97%
Health and Fitness Technology	2009	1981	New (2021)	0.0000	0.38	310	38	85%
Portable Wireless Speakers	2009	1999	New (2021)	0.0000	0.69	388	21	98%
Smart TVs	2009	2008	New (2021)	0.0094	0.34	434	12	94%
Tablet PCs	2009	2002	New (2021)	0.0055	0.37	713	14	61%
Home Robots	2010	1982	New (2021)	0.0000	0.52	35	39	98%
4K Ultra HDTVs	2012	2012	New (2021)	0.0109	0.58	222	9	97%
Action Camcorders	2012	2004	New (2021)	0.0052	0.36	28	14	78%
Desktop 3D Printers	2012	2001	New (2021)	0.0008	0.41	2	18	86%
Smartwatches	2012	1999	New (2021)	0.0001	0.55	171	21	95%
Connected Thermostats	2013	2008	New (2021)	0.0150	0.30	27	11	38%
Drones	2013	2010	New (2021)	0.0100	0.52	29	10	91%
Fitness Activity Trackers	2013	1981	New (2021)	0.0000	0.33	246	37	37%
IP/Wi-Fi Cameras	2013	1999	New (2021)	0.0000	0.65	73	21	97%
Rear View Cameras	2013	2002	New (2021)	0.0015	0.31	16	20	98%
Smart Smoke Detectors	2014	2013	New (2021)	0.0634	0.03	21	1	11%
Wireless Earbuds	2014	2014	New (2021)	0.0071	1.22	313	7	99%
360° Cameras	2015	2011	Extended	0.0071	0.70	2	9	97%
Connected Health Devices	2015	2010	Extended	0.0007	0.49	423	17	99%
Connected Switches	2015	2012	Extended	0.0290	0.26	44	9	74%
Dash Cameras	2015	2009	Extended	0.0047	0.16	28	24	80%
Pet Tech	2015	2011	Extended	0.0043	0.22	322	20	100%
Smart Speakers	2015	2014	Extended	0.0798	0.32	216	5	77%

* Data Start Year is the year in which the product first appeared in the CTA dataset. It forms the basis for the division of datasets to GLM and the New dataset. The Extended dataset contains six products with seven datapoints only, and thus these products are not included in the saddle analyses.

Web Appendix A: Examining the association between internet, social media, and the internal coefficient

Figure W1: Scatter plot of the internal coefficient (q) over time with an overlay of internet and social media penetration