The Rate of eCommerce Acceleration, Why It Matters and What Next

COVID-19 accomplished what it would have taken brands and retailers years to achieve

"Numerator's advanced analytics combine rigorous experimentation on novel methodologies, using over 5 years of robust transaction-level data, with the agility to apply models in near real-time. Being able to thoroughly understand historical consumer behavioral changes and then apply these insights to a rapidly changing consumer landscape is essential to planning during this crisis."

James Fontaine | *Numerator Labs*

Executive Summary:

In just 10 weeks, COVID-19 has drastically changed the eCommerce landscape, vastly accelerating usage. This study leverages 4+ years of longitudinal data across Numerator's omnipanel to quantify the extent of acceleration in households using online to purchase 14 CPG categories. The analysis powers Numerator's eCommerce Acceleration Index which measures the acceleration in households using online to purchase each category — and shows acceleration up to 18x versus multi-year pre-pandemic baselines. Note: Acceleration rate is one of several factors brands need to consider to understand this dynamic and plan accordingly.

Numerator eCommerce Acceleration Index
Table reads as: The rate of HH's using online to purchase Hand Sanitizer during COVID (March 1 - May 15) was 18x the pre-COVID multi-year baseline.

CATEGORY	INDEX
Hand Sanitizer	1807
Ice Cream & Novelties	899
Bath Tissue	830
Liquid Hand Soap	816
Canned Foods	736
Frozen Foods	721
Soda & Sports & Energy Drinks	575
Cookies & Crackers	544
Toothpaste	532
Pain Relievers	476
Makeup	459
Laundry Detergent	359
Shampoo & Conditioner	205
Deodorants & Antiperspirants	186

This white paper details the advanced analytics used to establish control groups, evaluate conversion of new buyers to online shopping, and determine the acceleration of online shopping among existing buyers. Implications for brands are documented as related to recommended shifts in online marketing to anticipate consumer behavior moving forward.

A full suite of metrics (basket size, trips, etc.), brand level detail and other custom studies are available via Numerator Labs to provide additional insights.

INTRODUCTION

In times of change, brands and retailers seek to understand not just what has happened but what is likely to happen next. In the case of COVID-19 and the subsequent economic downturn, one of the key dynamics is the acceleration in conversion to online buying. To understand the significance of this to brands and retailers requires careful analysis of switching behavior between retail channels over time and at the category level.

In undertaking an analysis of this scope, one is advised to:

1. **Evaluate omnichannel purchasing data tied to specific panelists.** Said another way, the data must track panelist behavior across all retail channels. Many companies seek to compensate for the absence of true omnichannel behavior by stitching data sets together. This fails to capture the switching behaviors fundamental to understanding longitudinal shifts in e-commerce behaviors. While it can be factor-adjusted to replicate an approximation, it lacks insight into the very behaviors one seeks to understand. (This applies to other applications as well.)

2. **Review longitudinal data over time.** The critical issue is understanding behavioral change over time. Analysis of data at scale done over time is needed to provide brands the confidence in anticipated change that can be expected at the category level.

KEY FOCUS AREAS

For this study, we focused on three key questions:

1. **How has purchasing behavior been changing when households started buying a category online?**
2. **Has the historical pattern of online adoption increased (accelerated) since the COVID-19 outbreak?**
3. **What are the future implications of any changes observed since COVID-19?**

To conduct the analyses required to address these questions requires a significant amount of scalable Omnichannel data, so these analyses leverage the Numerator Omnipanel which secures fast moving consumer goods purchasing data from a panel of over 450,000 panelists.

Specifically, a minimum of two years of consistent reporting for both Brick & Mortar and eComm/Online purchases are required for each panelist included in many of these analyses so that a 12-month Pre vs 12-month Post period can be established surrounding the first Online purchase for a category. That is, a unique, time-aligned Pre vs Post period is needed for each panelist based on when they first converted to online purchasing for a given category. Additionally, data must be demographically and geographically balanced to provide the right view of Total U.S. behavior.

Hence this complex time-aligned approach to assessing behavioral changes cannot be replicated by stitching multiple data sources together, but must source from the same households tracked over time and across all channels. The Numerator Omnipanel is in a unique position to provide these insights.

> **For pre/post analyses, at least 2 years of reporting is required for each panelist across both their Brick & Mortar and Online purchases -- with demographic and geographic alignment to U.S. population.**

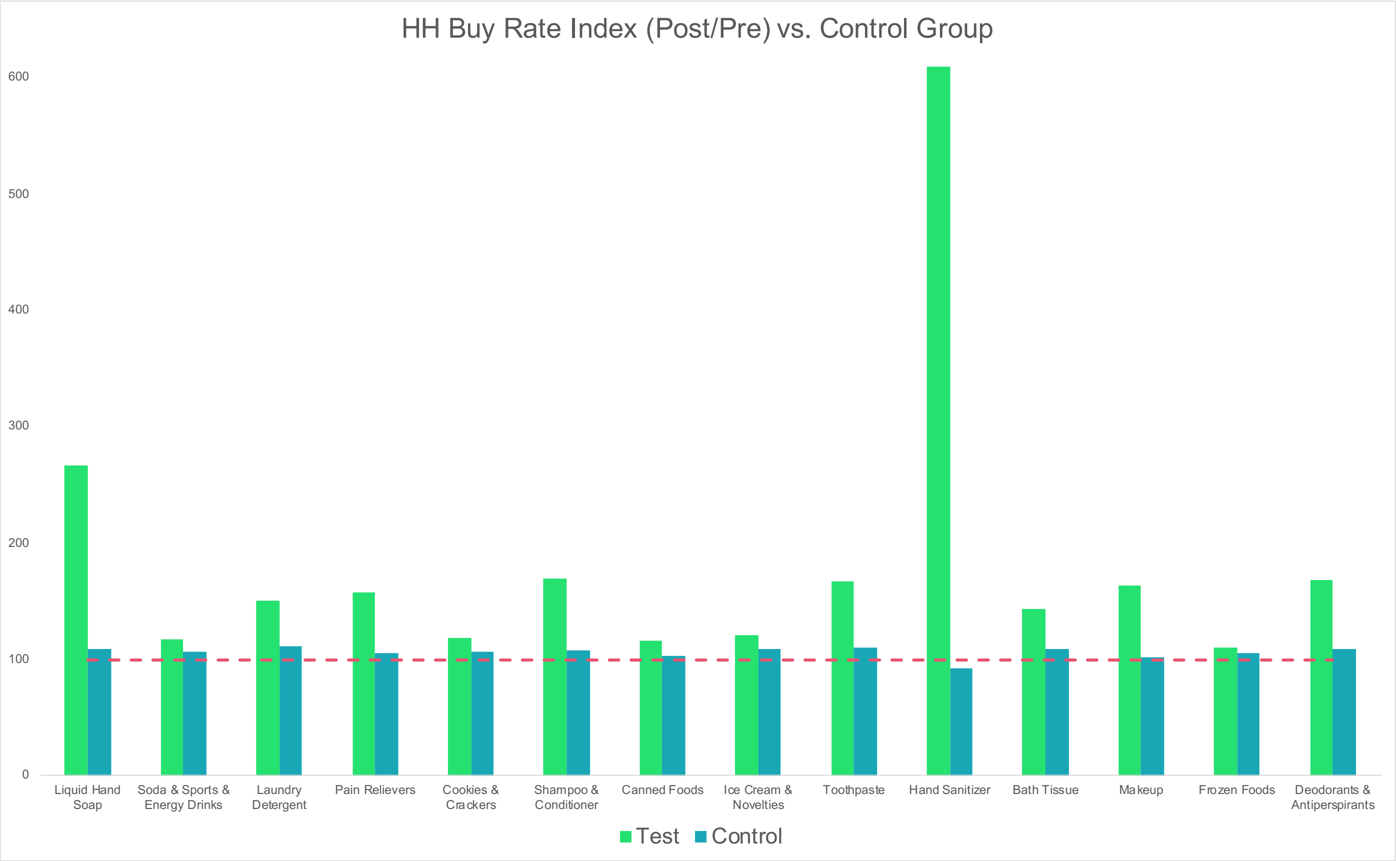
IMPLICATIONS | OBSERVATIONS

1. Behavioral Changes When Consumers Convert to Online Purchasing

Baseline Purchasing Behavior Changes: The shifts that take place in consumer buying once online purchasing is initiated are sweeping across the 14 reviewed categories (and are available for more in-depth exploration with the Numerator Consulting team). Across all analyzed categories, Buy Rate (average amount households spent on a category) increased substantially from the Pre Period to the Post Period. For example Liquid Hand Soap spend increased from about $13.29 per household in the Pre Period to about $35.38 per household in the Post Period (an index of 266).

To ensure that the changes being observed were valid (for example, that they were not just driven by other marketplace changes that were impacting a category), Control groups were created for each category to examine their Pre vs Post behavior. As shown in Figure 1 below, the increase in Buy Rates seen for the Test group (First-Time Online Converters) were substantially higher than the Control group. Though the Control group did post Buy Rate increases for some of the categories, the level of increase was not as strong as the levels seen for the Test group.

FIGURE 1:
Post vs Pre Period Buy Rate Index for Test (First-Time Online Buyers) vs Control



Brand Note: Category spend increases after the conversion to online buying.

Examining Pre vs Post total spend by Channel (In-Store/Brick & Mortar vs Online) showed another compelling advantage for categories when they attracted New Online buyers. Figure 2 below provides a visual on how overall spending levels increased for the First-Time Online buyers after they started buying the category online. For all categories analyzed, spend for that category grew in the Post Period. In fact, in most cases, In-Store (Brick & Mortar) sales held (or slightly dipped) while most incremental spend came from Online purchases.

FIGURE 2:
Pre vs Post Period Spend by Channel Among First-Time Online Category Buyers

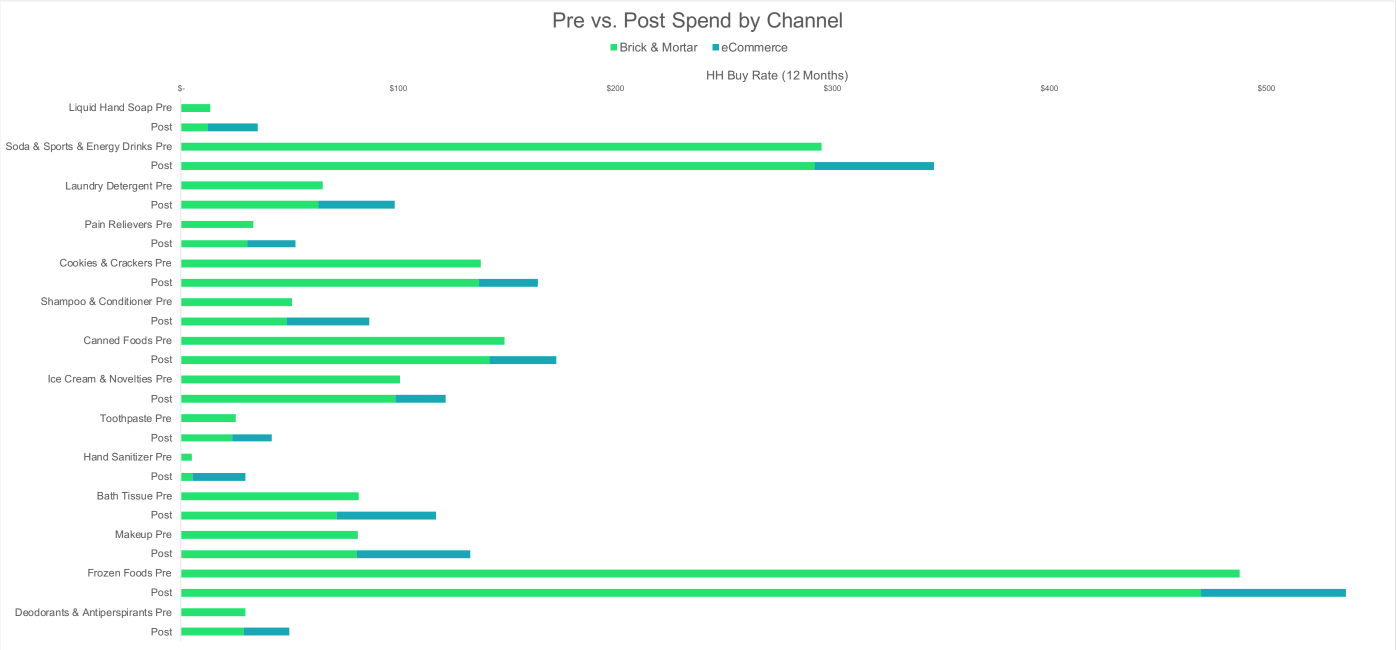
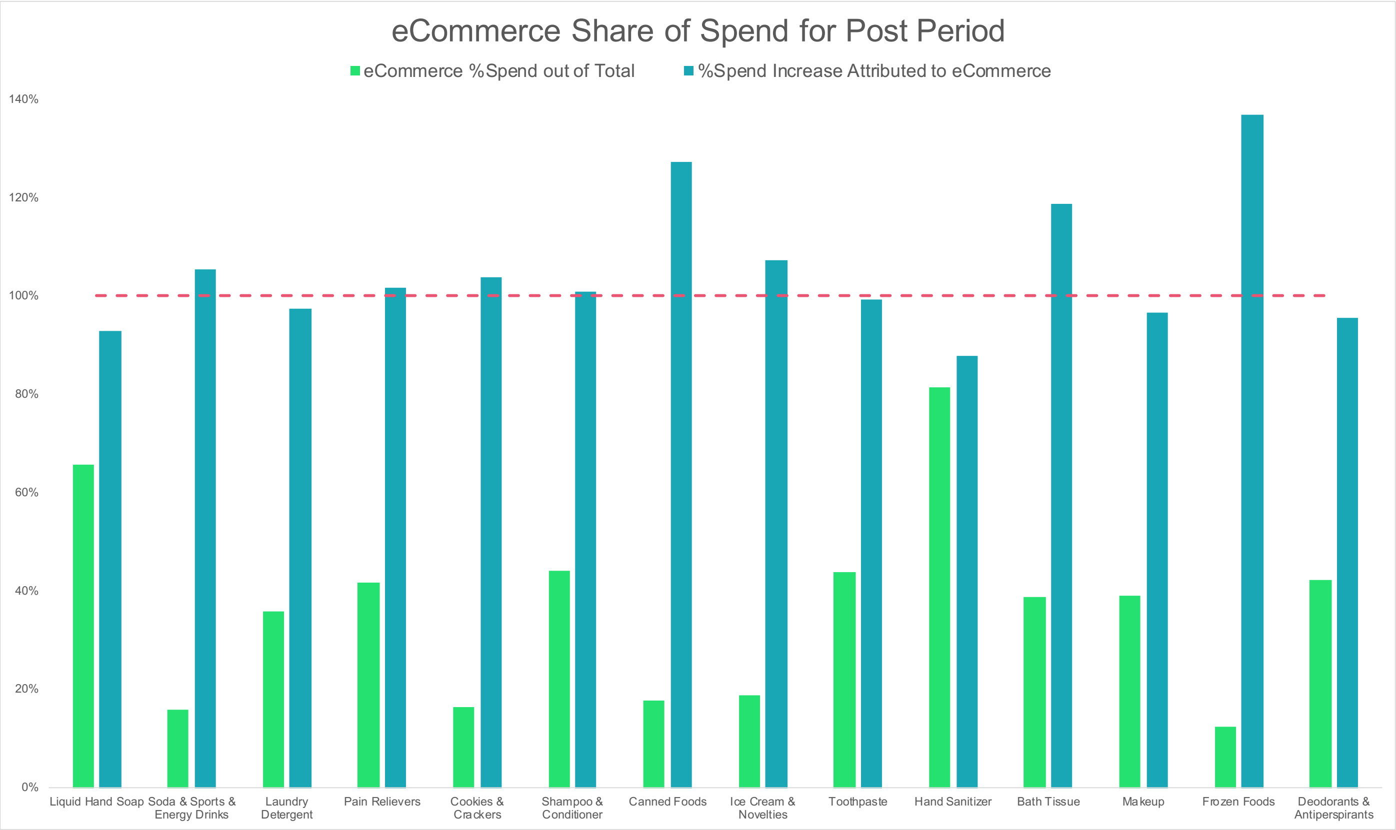


Figure 3 (below) shows another way to look at the incrementality observed for the Online purchasing of First-Time Category Converters. Here, the light green bar represents the share of Online spend for the Post Period. (For example, 66% of Liquid Hand Soap spend during the Post Period among First-Time buyers was spent Online.) And the teal bar represents the percent of the increased spend in the post period (vs. pre period) for these households that was attributed to Online spending as opposed to In-Store (in the case of Liquid Hand Soap, 93% of the incremental spend resulted from Online spend, while only 7% of the incremental spend was attributed to In-Store/Brick & Mortar spend.)

Across all categories, Online spend for the First-Time Converters was the main (and in many cases only) contributor to category growth. In some cases, Online spend even supplanted existing In-Store spend - when the teal bar exceeds the 100% line (red dotted line), this indicates that Online cannibalized some In-Store/ Brick & Mortar sales, as In-Store sales dropped.

FIGURE 3:
Post Period % Online Spend and % Spend Increase Attributed to Online Purchasing



Key areas brands need to understand about online buying:

Once HH Converts to Online

Category spend increases

HHs buy more often

Spend / unit goes up

2. Baseline Conversion vs COVID Acceleration of Conversion Rates

Baseline Conversion: This analysis isolates those consumers shifting to online to identify the percentage of households converting to online as it relates to specific categories. Note that the category level analysis leads to more meaningful and actionable insights for marketers, hence this approach.

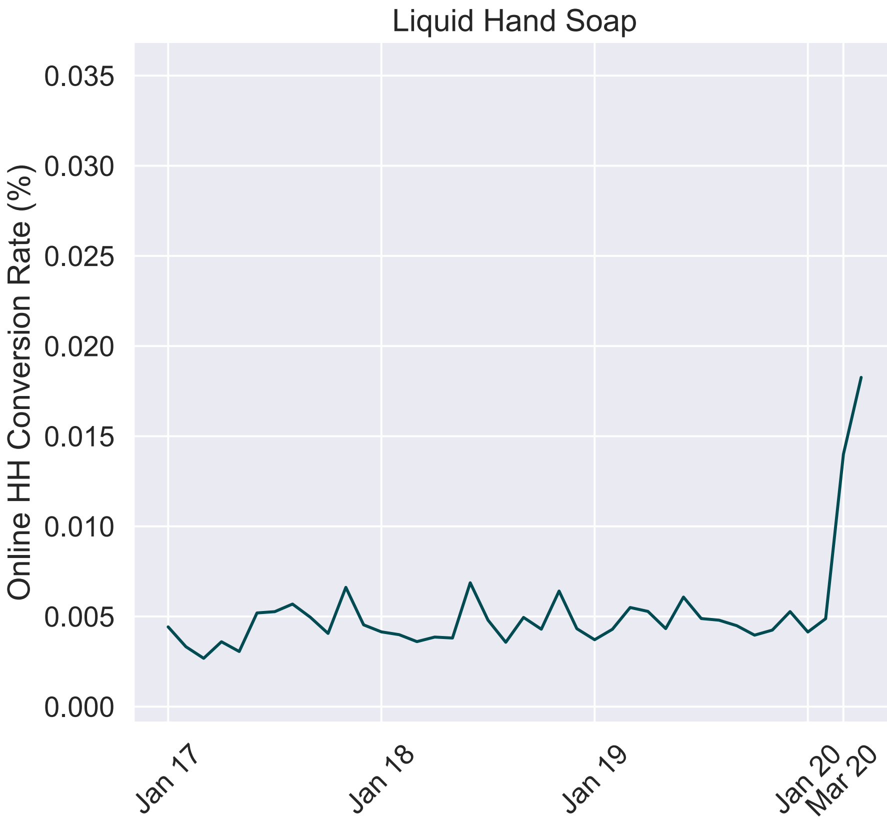
We are able to see that the percentage of new households converting to online has been relatively stable for most categories over the past three years. In this case, to be considered "New", the household had not purchased the category online for a period of 12 months preceding the online purchase.

COVID Conversion Rates (first two months of COVID): Our first observation was that household conversion to online spiked noticeably in March 2020. Growth rates across the 14 categories analyzed all showed growth vs the historical norm, some rates even up to 7x higher depending upon the category.

Figure 4 provides a view of this online conversion for the Liquid Hand Soap category for the historic 3-year period through the first two months of COVID. (Views for the other analyzed categories may be found in the Appendix and most show a similar pattern of conversion.)

Pre COVID-19, the % of HHs converting to online has been relatively stable over three years. This changed during COVID.

FIGURE 4:
Liquid Hand Soap % Households Converting to Online Purchasing



To test this initial monthly observation, we executed our final analysis on a daily basis for the COVID period spanning March 1st through May 15th. This was done in part to determine if the lift had been driven by a 2-3 week "panic" behavior in the early time of COVID. The reality is that the impact of this shift remains elevated at a sustained rate for most categories as detailed in section 3.

3. Future Implications

Overall Impact to Categories: The final piece of the study brings all Online buyers (New and Existing) together to assess the overall impact the New Online category buyers are having on the category. For this analysis, a metric of "Online Household Share" was used. This measure examines the extent to which a given category is attracting Online households within the last 12 months using the following calculation:

$$\frac{\text{\# of Online Active HH's who bought the category Online}}{\text{\# of Online Active HH's who bought the category Anywhere (eComm or B\&M)}}$$

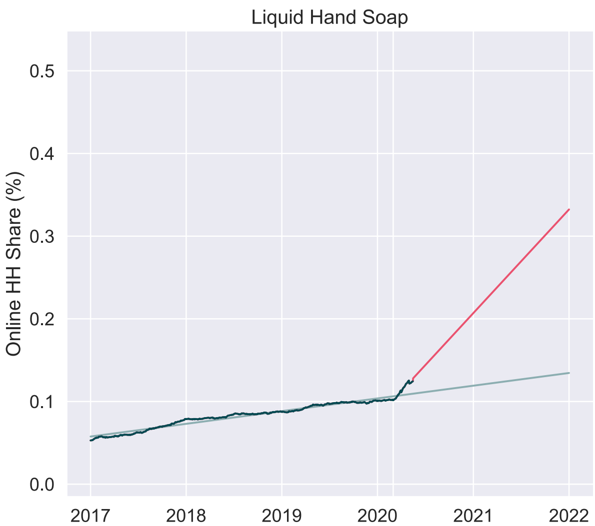
For example, if 9,000 Households bought Liquid Hand Soap Online and 90,000 Households bought this category anywhere (whether it was Online or in a Brick & Mortar channel), then Liquid Hand Soap had a 10% Online Household share.

Data was then examined on a 12-month rolling period basis at a daily interval, using the Online Household Share metric. To evaluate the trends for Online purchasing, this 12-month rolling period approach was used for data starting January 1, 2017 through the COVID period ending May 15, 2020. The observed trend is shown in Figure 5 as the dark teal line.

Two different extrapolations of the growth trend were then created. The first (shown as the light teal line in Figure 5) was based on a linear prediction of where Online Household Share would have ended up if the historical growth rate continued. This extrapolation was based on the growth rate established from 2017 through February 2020 (the historical trend line that fits the trend line to pre March 2020 data).

The second extrapolation (shown as the red line in Figure 5) was based on a linear prediction of Online Household Share using the data during the COVID Period, and depicts what would happen if the growth rate stays at its current new rate (extrapolated from March 1, 2020 - May 15, 2020). That is, the new growth rate does not have a slow down effect built into it.

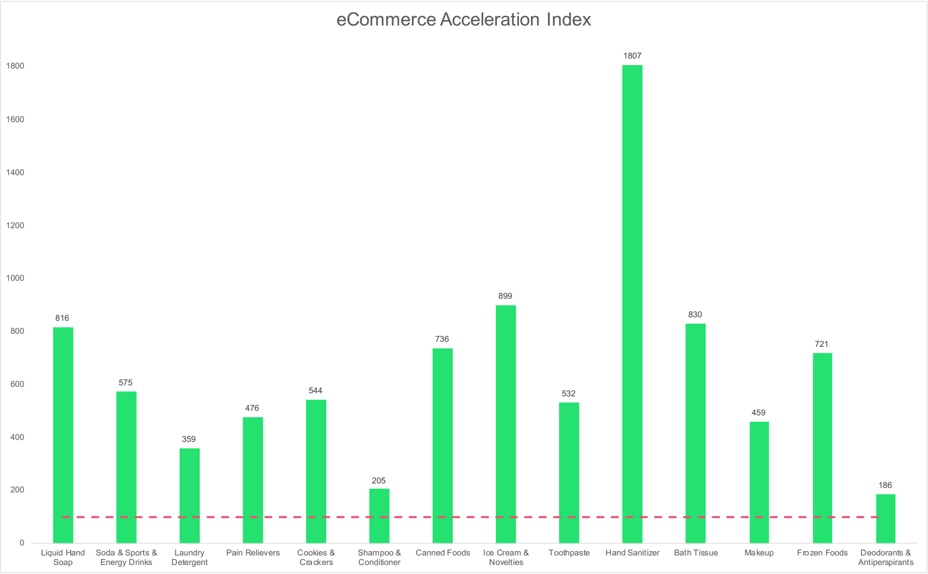
FIGURE 5:
Liquid Hand Soap % Households Converting to Online Purchasing



Using these two extrapolations, calculations can be made on the extent to which a category has converted/attracted Online buyers at a faster rate than what previously would have been predicted (presented as Numerator's eCommerce Acceleration Index in Figure 6). For example, based on the trajectory of the accelerated conversion rate for Liquid Hand Soap since COVID, this category could see a growth rate 8 times higher than what was likely (based on the multi-year Pre-COVID baseline growth rate). Said another way, this means that, for every month the COVID growth rate continues, Liquid Hand Soap's conversion of Online buyers moves forward by an additional 7 months vs what would have been expected prior to COVID. Thus, 2+ months into COVID, this category is already more than a year ahead of the game.

The growth is fueled by the impact of First-Time Online buyers as well as existing Online buyers continuing to purchase in the Online channel. As different categories started with different levels of conversion growth rates (based on Pre-COVID), the magnitude of the acceleration varied across categories, but all 14 categories examined showed substantial increases in rates. For example, extrapolating out to the end of 2021 for the Liquid Hand Soap category would indicate this category may see the percent of households buying Online increase from ~12% (on May 15, 2020) up to ~33%, whereas the Online HH Share for Ice Cream & Novelties could increase from ~6% up to ~19% over the next two years (charts for all 14 categories analyzed are included in the Appendix).

FIGURE 6 :
eCommerce Acceleration Index (COVID vs Historical)



SUMMARY & ACTIONS

COVID-19 has had a significant impact on the rate at which households are converting to online buying. This accelerated rate varies by category, but has moved the migration forward by months if not years ahead of where it would have been Pre-COVID.

By examining behavioral changes when households start to adopt online purchasing for a category, we know that other important things happen for that category. Households buy more often, their category spend increases, and their spend per unit increases. Hence, knowing about this accelerated growth rate provides marketers with essential information on what these changes could mean to categories and brands. And, it makes it clearer than ever that having an Omnichannel view of consumers that provides insights based on the same consumer across channels, categories, and brands over time is a critical component for success in a Post-COVID world.

COVID-19 has moved the migration to online buying ahead by more than a year for many categories.

To take full advantage of this growth opportunity, it is important for marketers to take several factors into account when developing the right strategies for competing in the digital/e-Commerce space, such as:

RECOMMENDATION	RATIONALE
Bolster your content	When consumers are shopping online, they cannot pick up the box and turn it around to see the ingredients and content unless you provide pictures, labels, etc. to help educate them and to make it easier, especially for new buyers, to make their purchase decisions. Help educate your buyers.
The internet levels the playing field, so know your online competitive set	Competitors online are different from those in-store. Small brands have an equal seat at the table, so new/smaller brands will be present in the online channel that compete against established Big Box brands and they can prevail. Consumers may shop in different retailers online because their primary retailer doesn't offer or can't meet delivery requirements or timing. Since these consumers are now shopping in a different retailer, they may be more open to trying or accepting different brands than what they typically see on the shelf or that are in their typical consideration set. (We have seen this in Brick & Mortar retailers as well, but this may be more pronounced in the online channel.) Even consumers searching for your brand directly may see a competitor's brand placed on top of the search based on that brand's spend for placement (and their desire to "one-up" you). This leads to brands not getting their fair share of search responses.
Plan on being more nimble	Competitors' strategies and reactions can change daily. A risk of not staying on top of online strategies is that you may grow sales but lose share. It is more important than ever to have fast, complete and detailed information at your fingertips.
Knowledge is power, especially when it comes to pricing	Make sure you know your competitors' prices online, and be prepared for them to change quickly. Though you need to be competitively priced, that doesn't always mean you need to be the lowest price option to be successful. Especially given supply chain challenges and in a time when out-of-stocks are occurring more frequently, sometimes it doesn't matter who has the lowest price but who has it at all.
Understanding placement strategy and key words are critical	More opportunities exist to improve placement of products online vs. in store. Brands can pay for sponsored listing spaces that appear when consumers shop in adjacent or related categories (e.g, toilet paper brands may advertise in searches not just for toilet paper but for toilets, laxatives, etc.) Know what else is going into the online cart with your category to look for other placement ideas and efficiencies. Capitalize on using keywords that are more important to your key demographics. For example, older households may be doing more searches on "anti-bacterial" or younger households may be interested in "sustainable packaging", so if your brand has that characteristic, make it part of the keyword strategy you use for paying for placement.

The challenges of the COVID-19 outbreak are many but opportunities are being revealed at an accelerating rate, especially in the online/e-commerce environment. Successful marketers will be armed with the best Omnichannel information and partners who understand, track, and provide the right insights on how consumers habits and purchasing behavior are changing.

Note that these custom analyses are done by the Numerator Labs team and are not replicable inside the Insights platform. However, a full suite of metrics as well as Brand level and other custom studies are available to provide additional insights. Please contact your Numerator representative for more information regarding custom studies with the Numerator Labs team or for how to leverage in-platform analyses to further understand the impact of COVID-19.

APPENDIX

Additional details on methodology:
These analyses leveraged the Numerator Omnipanel which secures fast moving consumer goods purchasing data from a panel of over 450,000 participants. From this robust group of panelists, we identified demographically and geographically balanced sets of households who were consistent reporters for both Brick & Mortar and Online channels over a minimum period of one year (or more, depending on the analysis). Note that consistent reporting was not dependent upon reporting for any specific category, it was to ensure panelists included in the study were active reporters for all channels during the study time period.

Categories for this study included 14 categories that were expected to be impacted by the COVID-19 breakout:

1. **Liquid Hand Soap**
2. **Soda & Sports & Energy Drinks**
3. **Laundry Detergent**
4. **Pain Relievers**
5. **Cookies & Crackers**
6. **Shampoo & Conditioner**
7. **Canned Foods**
8. **Ice Cream & Novelties**
9. **Toothpaste**
10. **Hand sanitizer**
11. **Bath tissue**
12. **Makeup**
13. **Frozen foods**
14. **Deodorants & Antipersperants**

Details on the methodology specific to each analysis used for this white paper are included in the sections below. Key points:

- Omnichannel data over 4+ years (starting January 2016 through the COVID period) was required to establish baselines, historic growth rates and behavioral changes used for the various analyses
- Two-year panelist-specific analysis periods were created (to accommodate a one-year pre-period vs a one year post-period from the "trigger" (first online purchase date)
- Control groups were established to ensure behavioral changes were significant and driven by online conversion vs other marketplace phenomenon
- Daily reads of rolling twelve-month periods were examined for each day of the COVID time period analyzed

METHODOLOGY:
Behavioral Changes When Consumers Convert to Online Purchasing (Section 1)

Approach
The 14 categories were analyzed using a time-aligned pre/post approach. This allows for an aggregation of panelist-level data across a wide time frame (in this case approximately 4 years) in order to compare category purchasing behavior before and after a specified trigger point which can occur at a different time for each panelist. The trigger point for the analysis was the first date an individual panelist purchased a given category online.

Time Periods

The entire analysis used a time frame of 01/01/2016 - 02/29/2020 (the analysis does not contain data from the "COVID-19" time period, which began 03/01/2020). The pre-period for each panelist was defined as the 12 month period prior to the trigger point whereas the post-period was defined as the 12 month period after the pre period (including the trigger point as the first day of the post period). Thus, the possible trigger point window used was 01/01/2017 - 02/28/2019 so that each eligible panelist could be analyzed for a complete 12 months pre/post within the overall analysis time frame. This also ensured that only panelists with at least 12 months of prior non-online purchasing history for the category would be eligible for analysis.

Panelist Eligibility

To qualify for the analysis, a panelist must have been part of Numerator's Brick & Mortar Static Panel for the entire 24 month period surrounding their trigger point (combined pre/post period). This static panel is demographically weighted and balanced as well as requiring consecutive monthly in-store receipt upload in each month (i.e. each panelist included must have uploaded at least one Brick & Mortar receipt (for any product) in each of the 24 months of their entire analysis period).

Additionally, each panelist was also required to exhibit a measure of consistent online purchasing to be included in the analysis. All panelists used in the analysis must have submitted at least one eCommerce receipt (for any product) consecutively for every 3 months of their entire analysis period (meaning that all panelists demonstrated online activity for each of the 8 different 3-month splits within the overall 24 month period).

Control Groups

In order to test whether or not the move to online was responsible for any potential changes in purchasing behavior (as opposed to some other undefined factor), control groups were created for each of the 14 analysis categories using panelists who did not exhibit any online purchasing behavior for the given category during the entire analysis period. These control group panelists were matched to the test group panelists 1:1 on demographic attributes (age, income, ethnicity, household size) as well as pre-period purchase frequency and pre-period buy rate for the category. In order to be eligible, the control group panelist must have also been part of Numerator's Brick & Mortar Static Panel for the same 24 month period as the test group panelist that the panelist was matched to. Note: a valid match could not be found for all test panelists due to time-alignment restrictions. Thus, the control groups have smaller base sizes than the test groups.

Base Sizes

CATEGORY	TEST	CONTROL
Hand Sanitizer	2,753	1,914
Ice Cream & Novelties	3,095	2,948
Bath Tissue	3,945	3,461
Liquid Hand Soap	2,386	1,965
Canned Foods	4,452	3,999
Frozen Foods	6,421	5,745
Soda & Sports & Energy Drinks	3,704	3,498
Cookies & Crackers	1,534	1,414
Toothpaste	3,844	3,364
Pain Relievers	916	435
Makeup	3,771	3,257
Laundry Detergent	8,218	7,030
Shampoo & Conditioner	3,263	3,008
Deodorants & Antiperspirants	4,067	3,411

Significance Testing

A paired two-sample t-test was performed on each group's buy rate (test and control), post vs pre in order to determine if the measured difference in buy rate was statistically significant. Furthermore, this difference was converted into an effect size (using Cohen's d) to understand if these differences were meaningful (+/- 0.2 is used as a threshold). Additionally, an unpaired two-sample t-test was performed for each category on this effect size, test vs control, in order to determine if a statistically significant difference was observed between the pre/post differences in buy rate for the test group compared to the control group.

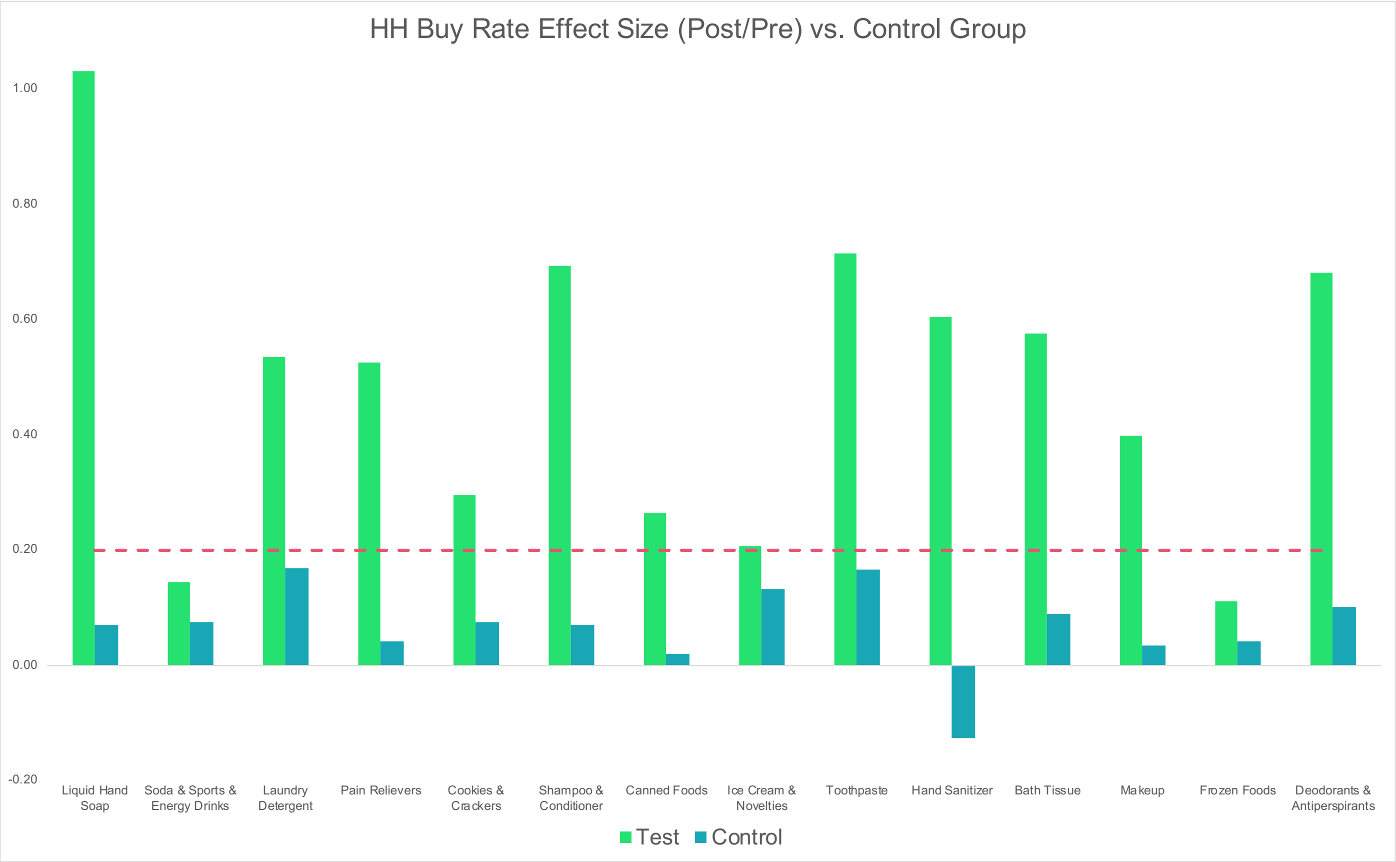
All 14 test group buy rate differences post vs pre were deemed to be statistically significant at an alpha level of $\alpha = 0.05$. 12/14 test group categories achieved a meaningful effect size (>= |0.2|).

TEST GROUP	BUY RATE DIFF	EFFECT SIZE	P VALUE - BUY RATE DIFF
Liquid Hand Soap	$ 22.09	1.03	< 0.001
Soda & Sports & Energy Drinks	$ 52.10	0.15	< 0.001
Laundry Detergent	$ 33.30	0.53	< 0.001
Pain Relievers	$ 19.15	0.53	< 0.001
Cookies & Crackers	$ 25.98	0.29	< 0.001
Shampoo & Conditioner	$ 35.72	0.69	< 0.001
Canned Foods	$ 24.02	0.27	< 0.001
Ice Cream & Novelties	$ 20.80	0.21	< 0.001
Toothpaste	$ 16.73	0.72	< 0.001
Hand Sanitizer	$ 24.73	0.60	< 0.001
Bath Tissue	$ 35.76	0.57	< 0.001
Makeup	$ 51.79	0.40	< 0.001
Frozen Foods	$ 48.72	0.11	< 0.001
Deodorants & Antiperspirants	$ 20.37	0.68	< 0.001

12/14 control group buy rate differences post vs pre were deemed to be statistically significant at an alpha level of α = 0.05. However, none of the control group categories achieved a meaningful effect size (>= |0.2|).

CONTROL GROUP	BUY RATE DIFF	EFFECT SIZE	P VALUE - BUY RATE DIFF
Liquid Hand Soap	$ 1.29	0.07	0.003
Soda & Sports & Energy Drinks	$ 16.61	0.08	< 0.001
Laundry Detergent	$ 6.47	0.17	< 0.001
Pain Relievers	$ 1.73	0.04	0.018
Cookies & Crackers	$ 7.37	0.08	< 0.001
Shampoo & Conditioner	$ 3.34	0.07	< 0.001
Canned Foods	$ 4.73	0.02	0.002
Ice Cream & Novelties	$ 7.77	0.13	< 0.001
Toothpaste	$ 2.32	0.17	< 0.001
Hand Sanitizer	$ -0.51	-0.13	0.254
Bath Tissue	$ 6.56	0.09	< 0.001
Makeup	$ 1.78	0.04	0.078
Frozen Foods	$ 22.77	0.04	< 0.001
Deodorants & Antiperspirants	$ 2.58	0.10	< 0.001

FIGURE 7:
Buy Rate Effect Size, Test vs. Control



All categories except for Ice Cream & Novelties showed a statistically significant effect size difference vs the control group at an alpha level of α = 0.05.

CATEGORY	EFFECT SIZE DIFF, TEST vs CONTROL	P VALUE - BUY RATE DIFF
Liquid Hand Soap	0.96	< 0.001
Soda & Sports & Energy Drinks	0.07	< 0.001
Laundry Detergent	0.37	< 0.001
Pain Relievers	0.48	< 0.001
Cookies & Crackers	0.22	< 0.001
Shampoo & Conditioner	0.62	< 0.001
Canned Foods	0.24	< 0.001
Ice Cream & Novelties	0.07	0.122
Toothpaste	0.55	< 0.001
Hand Sanitizer	0.73	< 0.001
Bath Tissue	0.49	< 0.001
Makeup	0.36	< 0.001
Frozen Foods	0.07	0.010
Deodorants & Antiperspirants	0.58	< 0.001

In general, these tests tell us that for the most part, buy rate changes in the test group from the pre-period to the post-period were statistically significant and of a substantial size. Whereas although there was statistical significance for most categories on this metric in the control group as well, none of the control group's buy rate differences were substantial. Furthermore, when comparing these buy rate differences (in terms of effect size) from the test group to the control group, we find that all but one group demonstrated a statistically significant difference, test vs. control. In other words, we can be confident that the households that moved online for these categories (outside of Ice Cream & Novelties) did indeed exhibit significantly increased purchasing behavior compared to those who continued to only buy In-Store.

METHODOLOGY:

Baseline Conversion vs COVID Acceleration of Conversion Rates (Section 2)

Approach

In order to determine the conversion rate to online purchasing for a given category, the following calculation was used:

$$\text{Online HH Conversion Rate} = \frac{\text{\# of Online Active category buyers who bought the category Online for the first time this month}}{\text{\# of Online Active category buyers who had not bought the category Online prior to this month}}$$

This gives us the % of new HHs converting to online in a given month out of the possible online eligible HHs for the category (those who have not already converted to online purchasing for the category for the full year prior to their trigger purchase but had made a category purchase in a Brick & Mortar channel).

Time Periods

The entire analysis used a time frame of 01/01/2016 - 04/30/2020. The data was calculated at monthly intervals, requiring a 12 month pre-period for panelist purchase history checks (whether or not there was a previous online category purchase). Thus the window for the monthly interval calculation begins on 01/01/2017.

Panelist Eligibility

To qualify for the analysis, a panelist must have been part of Numerator's Brick & Mortar Static Panel for at least 12 months as of the calculation month. This static panel is demographically weighted and balanced as well as requiring consecutive monthly in-store receipt upload in each month (i.e. each panelist included must have uploaded at least one Brick & Mortar receipt (for any product) in each of the 12 months of their analysis period).

Additionally, each panelist was also required to exhibit a measure of consistent online purchasing to be included in the analysis. All panelists used in the analysis must have submitted at least one eCommerce receipt (for any product) consecutively for every 3 months of their analysis period (meaning that all panelists demonstrated online activity for each of the 4 different 3-month splits within the overall 12 month period).

Finally, eligible panelists must have had at least one Brick & Mortar (non-online) purchase for the given analysis category in the 12 month pre-period. This ensures that we are not measuring those panelists who are buying a category for the first time anywhere but rather only those who are converting to online purchasing of a category that they had already been buying in-store.

This portion of the analysis focuses on those who are converting to online purchasing of a category that they had already been buying in-store.

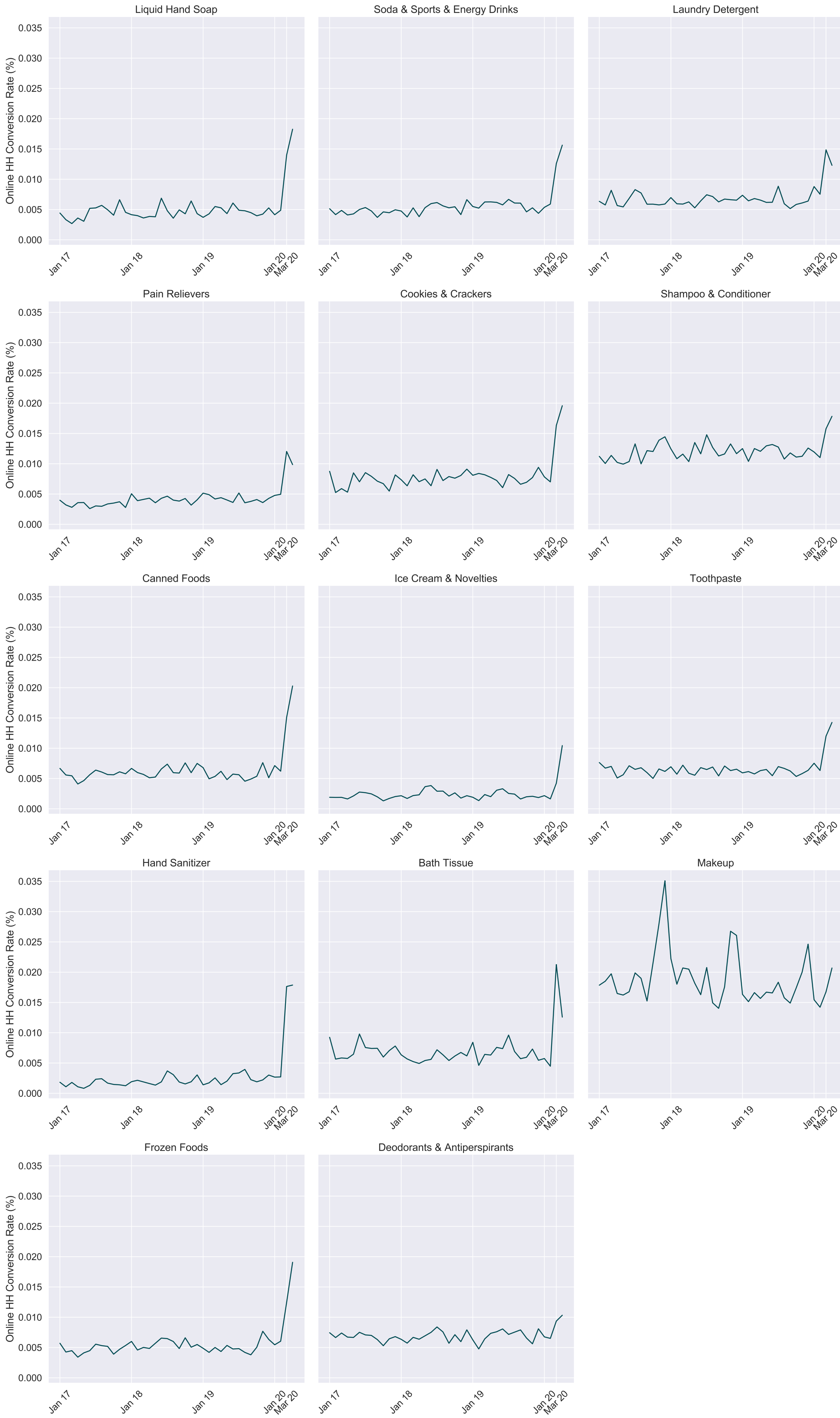
Base Sizes

Note: base sizes are presented in a range for this analysis as the size varied for each monthly interval the data was calculated on (generally these sizes grew over time). Each base size represents eligible panelists for a 12 month rolling period.

CATEGORY	BASE SIZE MINIMUM	BASE SIZE MAXIMUM
Liquid Hand Soap	18,350	27,133
Soda & Sports & Energy Drinks	26,142	39,206
Laundry Detergent	23,404	34,871
Pain Relievers	22,105	32,952
Cookies & Crackers	25,469	38,071
Shampoo & Conditioner	21,235	30,797
Canned Foods	26,107	39,078
Ice Cream & Novelties	26,410	40,859
Toothpaste	23,673	35,089
Hand Sanitizer	10,334	15,453
Bath Tissue	23,660	35,900
Makeup	16,654	24,145
Frozen Foods	26,590	39,956
Deodorants & Antiperspirants	22,861	33,780

Figure 8 (next page) showcases the percentage of households converting to online. The reader will quickly notice the significant spike in conversions taking place during the COVID-19 time period.

FIGURE 8:
% Households Converting to Online Purchasing (All Categories)



METHODOLOGY:

Future Implications (Section 3)

Approach

Online Household Share was calculated for each of the 14 categories (using the calculation explained in section 3) at daily intervals for the entire analysis period. This data was then split into two datasets, one for the time period before COVID-19 (labeled "Historical") and the other for during COVID-19 (labeled "COVID"). A regression analysis was performed on both datasets allowing for future predictions of Online HH Share in order to understand the potential impact of COVID-19 to online adoption by category.

Time Periods

The entire analysis used a time frame of 01/01/2016 - 05/15/2020. The data was calculated at daily intervals with a rolling 12 month pre-period for panelist purchase history checks. Thus the window for the daily interval calculation begins on 01/01/2017. The COVID time frame begins on 03/01/2020.

Panelist Eligibility

To qualify for the analysis, a panelist must have been part of Numerator's Brick & Mortar Static Panel for at least 12 months as of the calculation date. This static panel is demographically weighted and balanced as well as requiring consecutive monthly in-store receipt upload in each month (i.e. each panelist included must have uploaded at least one Brick & Mortar receipt (for any product) in each of the 12 months of their analysis period).

Additionally, each panelist was also required to exhibit a measure of consistent online purchasing to be included in the analysis. All panelists used in the analysis must have submitted at least one eCommerce receipt (for any product) consecutively for every 3 months of their analysis period (meaning that all panelists demonstrated online activity for each of the 4 different 3-month splits within the overall 12 month period).

Brick & Mortar purchasing for the category was not a requirement for this analysis as the goal was to look at the complete picture of online purchasing HHs for a category. In other words, panelists who only buy the category online, and never in-store, are included in this analysis.

Base Sizes

Note: base sizes are presented in a range for this analysis as the size varied for each daily interval the data was calculated on (generally these sizes grew over time). Each base size represents eligible panelists for a 12 month rolling period.

CATEGORY	BASE SIZE MINIMUM	BASE SIZE MAXIMUM
Liquid Hand Soap	19,364	32,409
Soda & Sports & Energy Drinks	27,081	43,697
Laundry Detergent	25,289	41,152
Pain Relievers	22,839	37,897
Cookies & Crackers	27,236	44,127
Shampoo & Conditioner	25,026	40,569
Canned Foods	27,268	44,095
Ice Cream & Novelties	26,688	43,317
Toothpaste	25,096	41,117
Hand Sanitizer	10,740	18,333
Bath Tissue	26,234	42,354
Makeup	23,824	38,070
Frozen Foods	27,406	44,372
Deodorants & Antiperspirants	24,660	40,302

Regression Analysis

First-degree univariate linear regressions were performed on each of the 14 analysis categories during the Historical and COVID periods. For Laundry Detergent, Bath Tissue, and Deodorants & Antiperspirants (and to a lesser degree, Shampoo & Conditioner) a quadratic model would result in higher fidelity fit; this is thought to be attributed to a property of these categories. Ultimately, the quadratic model was not used in the final analysis in order to keep predictions conservative and to maintain a methodology that could be widely applied to many categories without adjustment. R^2 values for the first-degree trend lines are shown in the table below.

CATEGORY	R^2 HISTORICAL	R^2 COVID
Liquid Hand Soap	0.964	0.947
Soda & Sports & Energy Drinks	0.991	0.988
Laundry Detergent	0.974	0.764
Pain Relievers	0.994	0.945
Cookies & Crackers	0.990	0.969
Shampoo & Conditioner	0.980	0.863
Canned Foods	0.964	0.964
Ice Cream & Novelties	0.920	0.967
Toothpaste	0.974	0.968
Hand Sanitizer	0.983	0.950
Bath Tissue	0.840	0.797
Makeup	0.935	0.975
Frozen Foods	0.940	0.987
Deodorants & Antiperspirants	0.964	0.769

The first degree regression trend lines were used to predict out what we would have expected Online HH Share to look like as of 02/29/2020 (Historical) vs what we could potentially expect to see if the current COVID trends continue (as of 05/15/2020). The eCommerce Acceleration Index was calculated for each category by dividing the COVID trend line coefficient (growth rate) by the Historical trend line coefficient.

FIGURE 9:
Online Household Share (All Categories)

Dark teal = **Observed** Light teal = **Historical** Red = **COVID**