MORNING CONSULT

ANALYST REPORT

New Methodology for Benchmarking U.S. Consumer Spending Data

Introducing our enhanced process for estimating U.S. consumer spending levels

JUNE 2022

TABLE OF CONTENTS

SUMMARY

When Morning Consult first reported on its survey of U.S. Consumer Spending in mid-2021, estimates of nominal spending were constructed by taking a weighted average of multiple-choice responses to pre-set spending ranges. In addition to being relatively simple to calculate, this method reduced the volatility of spending aggregates by smoothing out the impact of individual outliers on the survey results — a feature that initially was viewed as a benefit.

Over time, however, it became clear that estimated spending levels for certain categories of goods and services calculated with this methodology were diverging from government data that tracks similar concepts. Elevated inflation likely exacerbated these discrepancies, as the pre-set spending ranges remained unchanged despite relatively large shifts in nominal prices.

We have therefore decided to revise our methodology. The changes described in this document generate nominal spending levels that more closely align with official government statistics on consumer spending and more accurately capture changes over time. Rather than using responses to multiple-choice questions, our new methodology instead relies upon open-ended numerical response data that we have been collecting alongside responses to the pre-set spending ranges.

This new method allows reported nominal spending levels to more freely drift over time, eliminating the downward bias that arises from using static spending ranges for goods and services during periods of sustained inflation. Another benefit of this process is that it can be applied to international spending data as coverage expands to other countries, many of which are also experiencing rapid inflation.

However, working with the numerical response data comes with its own set of challenges, including outliers and other erratic data points. In order to identify a robust statistic to use as our estimated spending level, we evaluated several factors affecting the distribution of responses, their volatility over time and their correlation with relevant benchmarks from official government statistics.

For each spending category, we tested statistics including modes, medians, simple means and trimmed means with various cutoff points. Overall, trimmed means provided the most promising results: less volatile than the simple mean, but still capturing sufficient variation to align well with government benchmarks. The steps taken to analyze, validate and benchmark our consumer spending data are summarized in the following slides, with additional detail included in the appendix section.

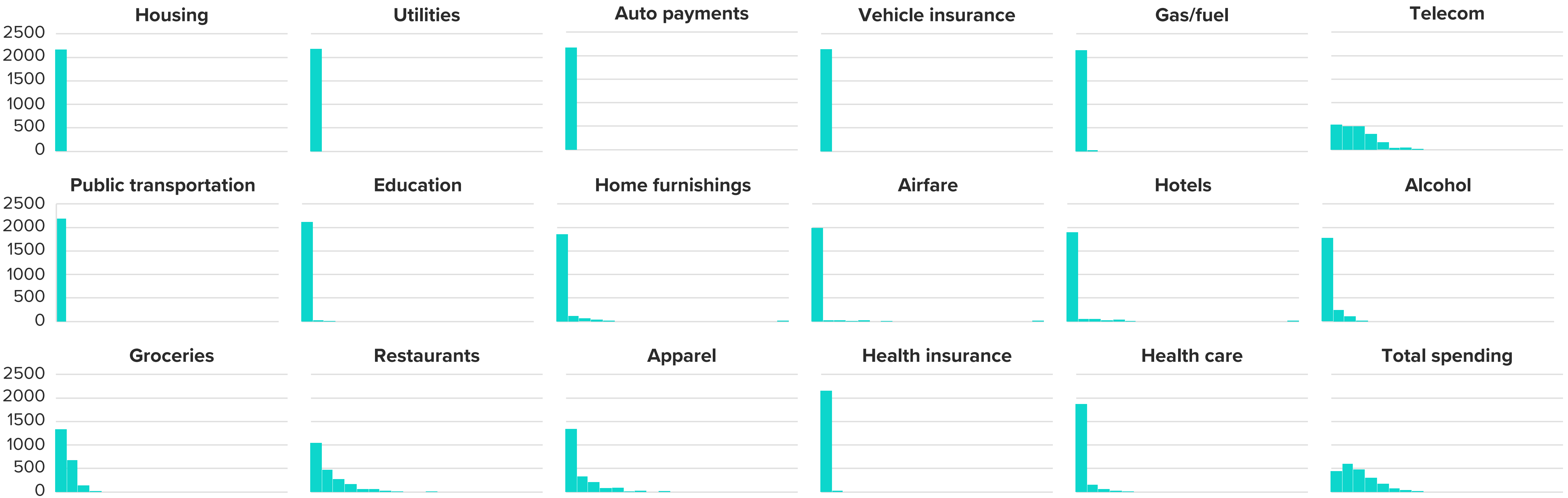
Here is a summary of advantages of the new methodology, using open-end numerical responses in place of the old methodology, which used weighted averages of pre-set spending ranges.

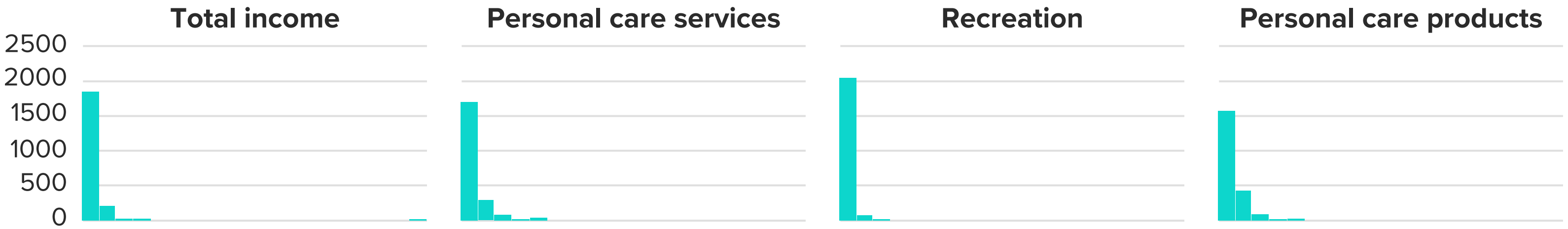
- **Robust to inflation:**
  This eliminates downward bias associated with pre-set spending ranges.
- **More closely aligned with benchmarks:**
  The new methodology yields spending estimates that are more closely aligned with government data or other standard benchmarks tracking similar concepts.
- **Internationally applicable:**
  As coverage expands to more countries, many of which sometimes experience high inflation rates, it will be even more critical to implement a nimble methodology that adjusts naturally to shifts in price and spending levels.
- **Lays the groundwork for seasonal adjustment in the future:**
  The new method is better equipped to capture seasonal fluctuations in spending, enabling future calculation of adjustment factors to better differentiate underlying trends from seasonal factors.

SECTION 2

DISTRIBUTION ANALYSIS

Distributions of May 2022 numerical response data

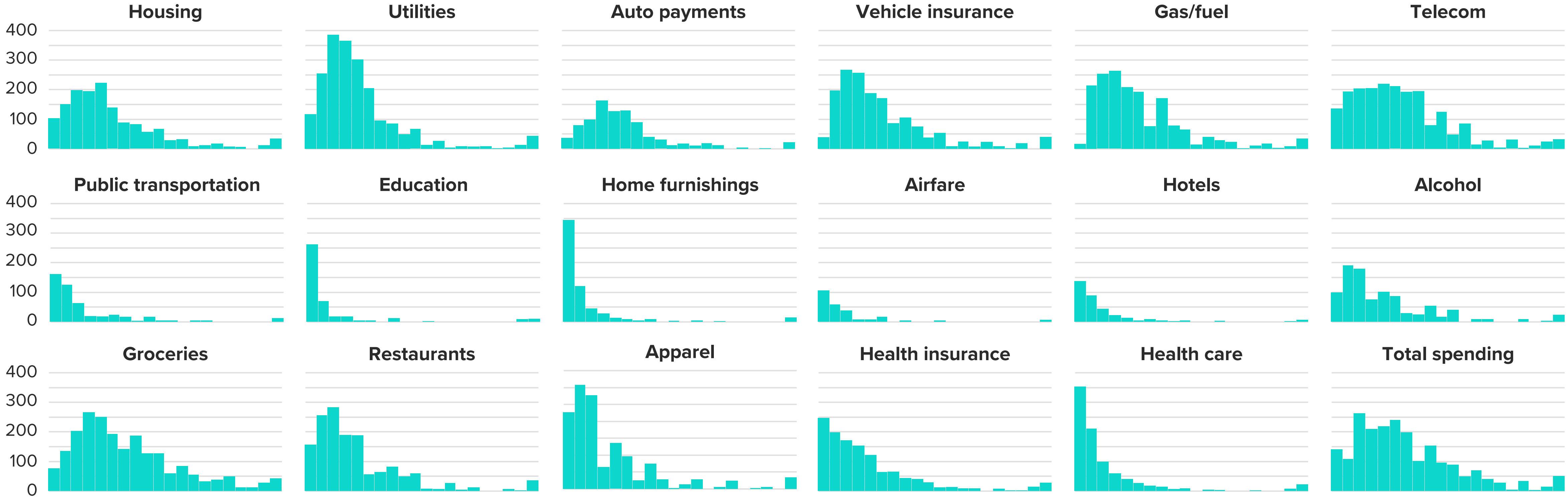




The numerical response data for each category revealed a large concentration of small denomination responses (mostly zeroes), and massive large denomination outliers that biased the simple average as an estimate of the central tendency for spending.

May 2022 data excluding zeroes (top bucket = 97.5th percentile +)

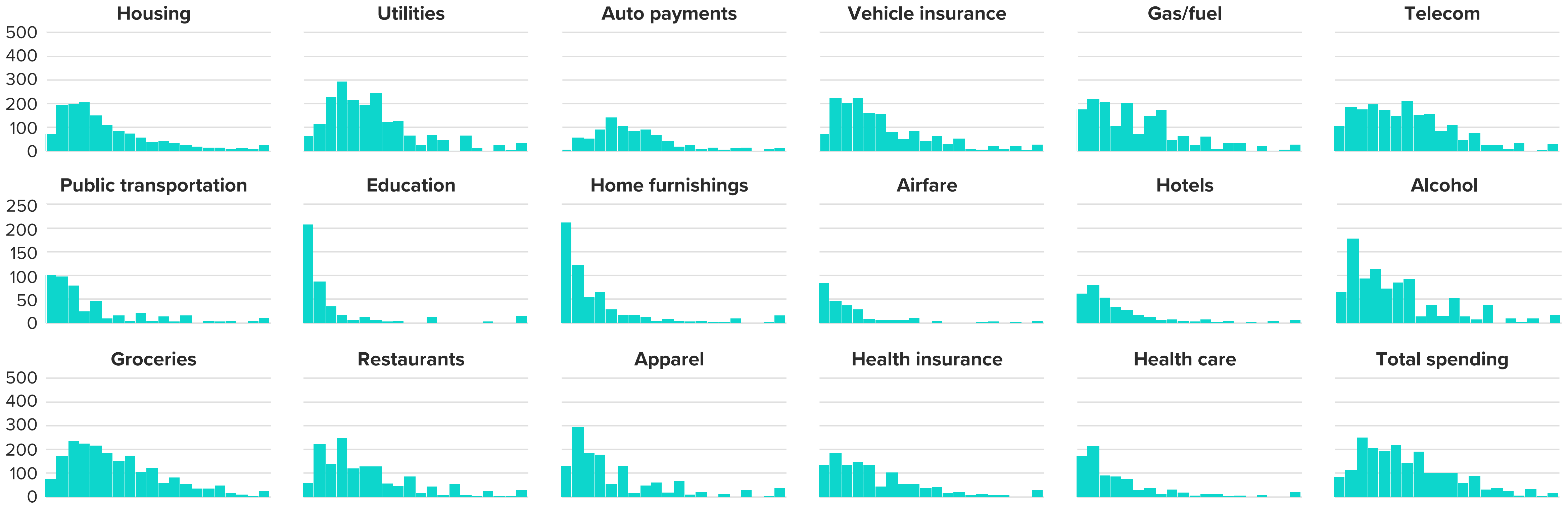
Note difference in scales across rows

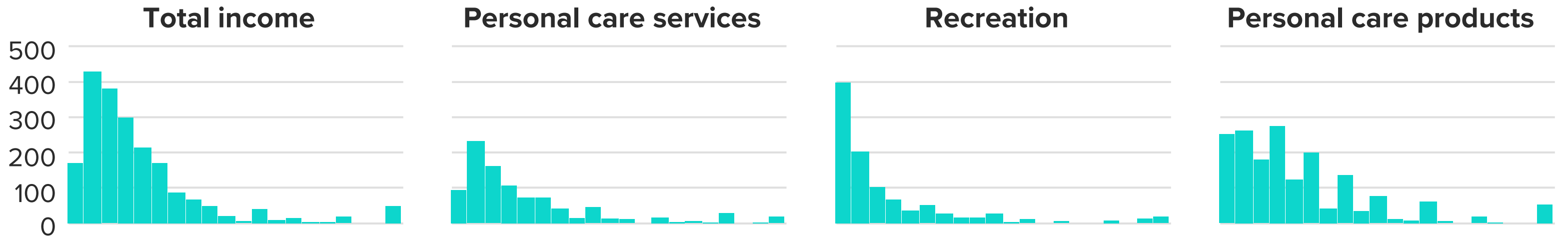


Eliminating the zero responses from the simple average helped reduce the skewness of the response distributions at the lower end — however, many large outliers remained (grouped in the far-right bucket, capturing the top 2.5% of responses).

May 2022 data excluding zeroes, with 2.5% trimmed at each end

Note difference in scales across rows

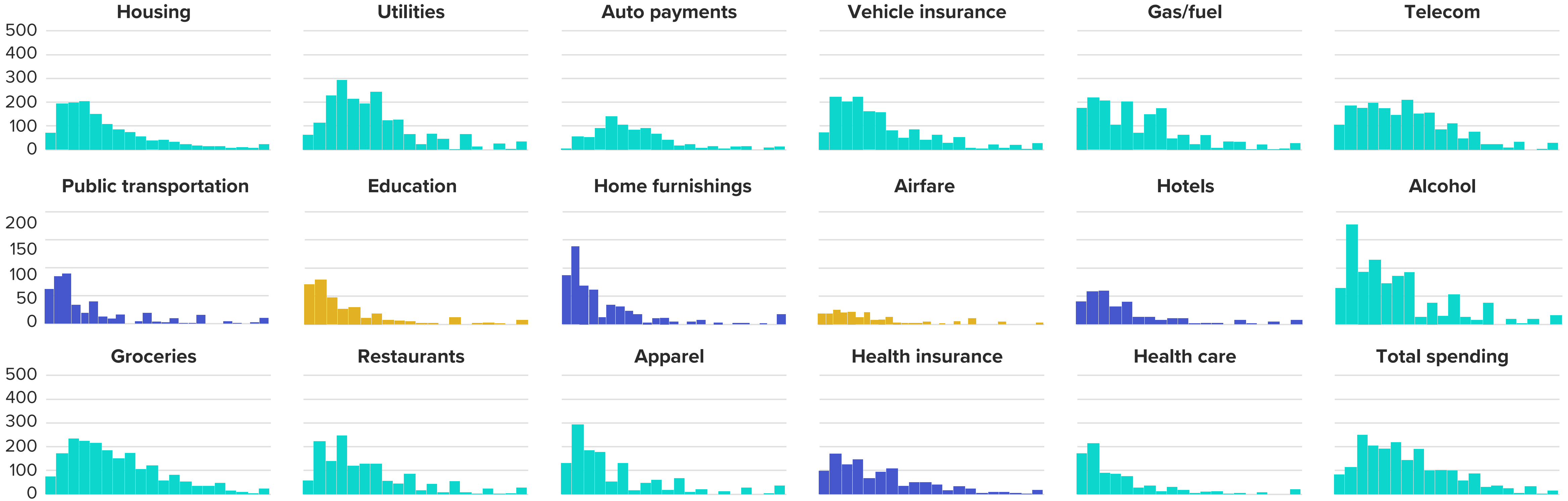




Trimming the top and bottom 2.5% of responses further reduced skewness for most categories, though some (such as education, home furnishings and airfare) still had a substantial skew, as measured by the difference between the simple mean and mode.

May 2022 data excluding zeroes, with 2.5%, 5% or 10% trimmed at each end

Note difference in scales across rows



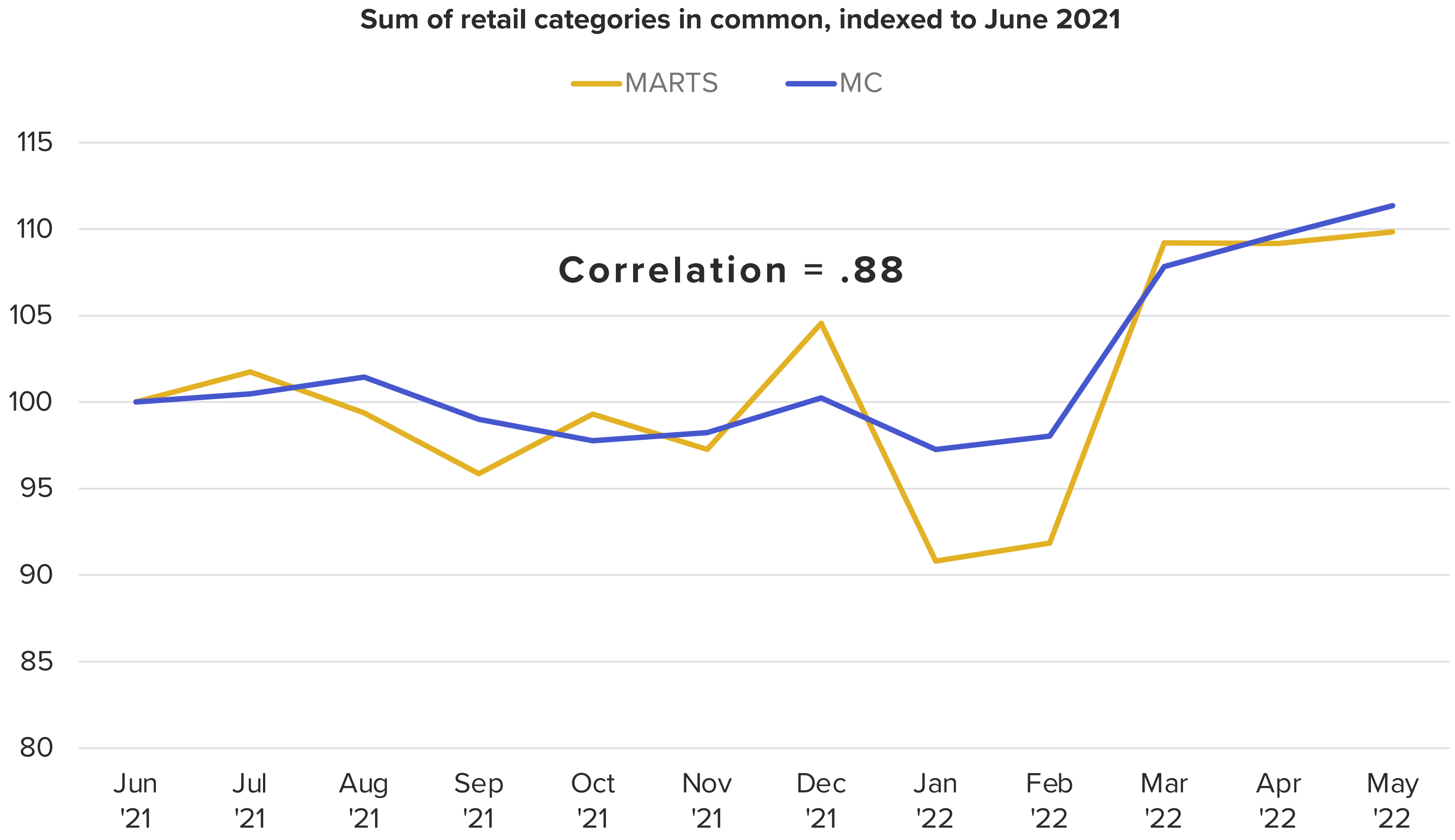
For categories with mode-mean differentials greater than 40%, we applied a trim of 5% to each end. If 5% wasn't sufficient to visibly reduced the skewness of the distribution, we applied a 10% trim.

Note: 20 bins are shown unless more were needed to show that the mode is not lowest bucket

SECTION 2

BENCHMARKING

Retail categories common to our survey and the MARTS are highly correlated



Retail categories = grocery, gas, restaurants, autos, apparel, home furnishings, alcohol

To validate our new methodology, we compare our results against the Census Bureau's Advance Monthly Retail Trade Survey. Morning Consult's topline spending data differs from the Census Bureau's monthly retail sales data as it includes many nonretail categories, such as housing and other services. For this reason, we compare only the categories that both surveys share, enabling an apples-to-apples view of spending coverage between Morning Consult's data and retail sales. For the subset of categories tracked by both surveys (indexed to 100 in June 2021), we find a very strong correlation (.88) over the 12 months of available history.

Correlations comparison: benchmark vs. old and new methodologies

Categories with strong benchmarks

Category	Old methodology	New methodology	Difference	Benchmark
Total spending	0.72	0.82 ✓	+ 0.10	PCE
Housing	0.55	0.70 ✓	+ 0.15	PCE
Sum of retail categories	0.27	0.86 ✓	+0.61	MARTS
Gas	0.86	0.91 ✓	+ 0.05	MARTS
Furniture	-0.10	0.62 ✓	+ 0.72	MARTS
Apparel	0.58	0.58 ✓	+ 0.01	MARTS
Grocery	0.17	0.61 ✓	+ 0.44	MARTS
Restaurant	0.19	0.81 ✓	+ 0.62	MARTS
Alcohol	0.44	0.54 ✓	+ 0.10	MARTS
Auto payments	0.28	0.35 ✓	+ 0.07	MARTS
Airfare	0.25	0.56 ✓	+ 0.31	TSA throughput * CPI
Hotels	0.42	0.81 ✓	+ 0.39	STR daily rates * occupancy
Utilities	0.80 ✓	0.78	-0.01	Quarterly Services Survey

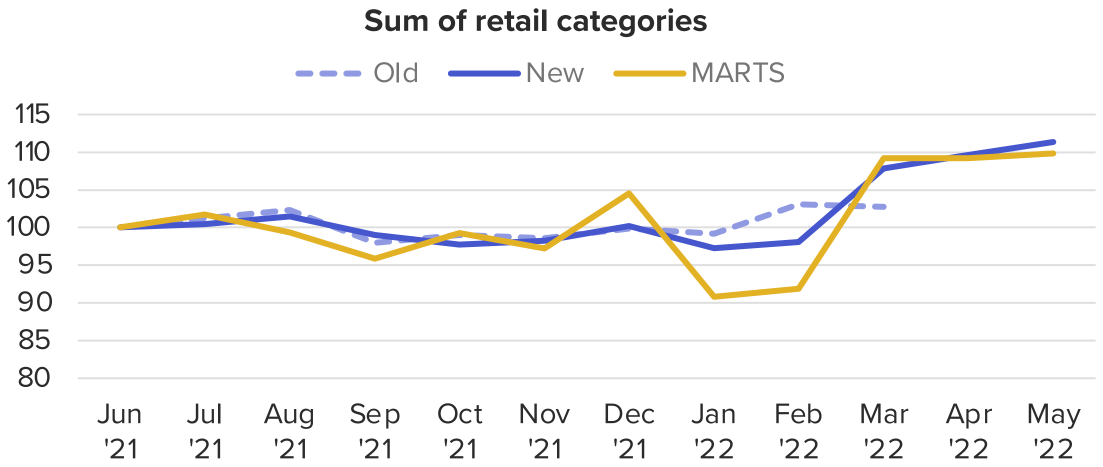
KEY

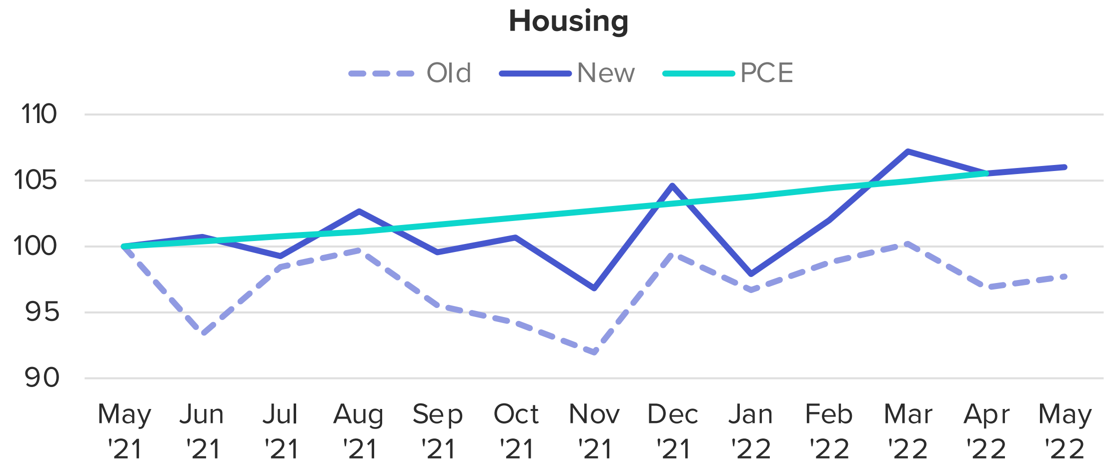
Negative	**<0**
Weak	**0-0.49**
Moderate	**0.50-0.47**
Strong	**0.75+**
Better fit	✓

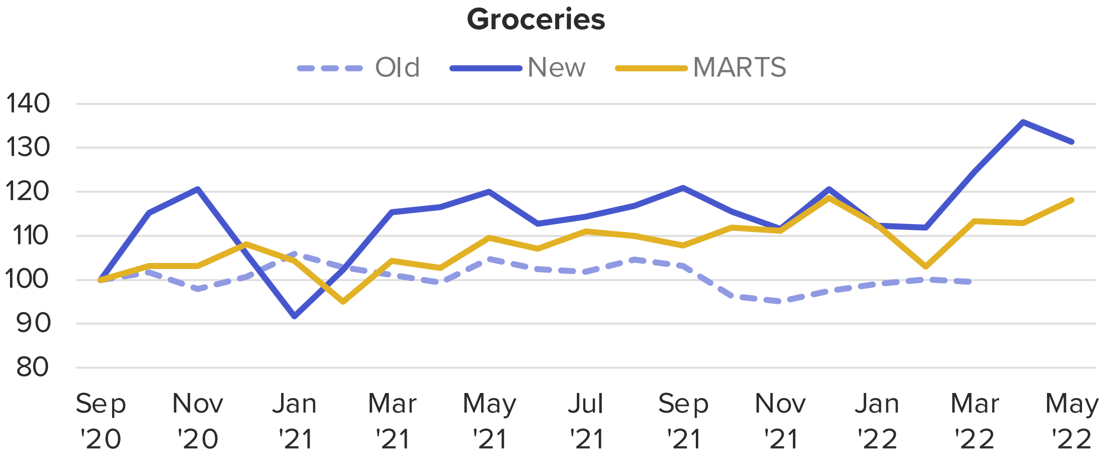
Every category with a clearly defined benchmark, from government data or other commonly used industry metrics, shows a similar or improved correlation with its relevant benchmark using the new vs. the old methodology for constructing nominal spending levels from the U.S. Consumer Spending survey.

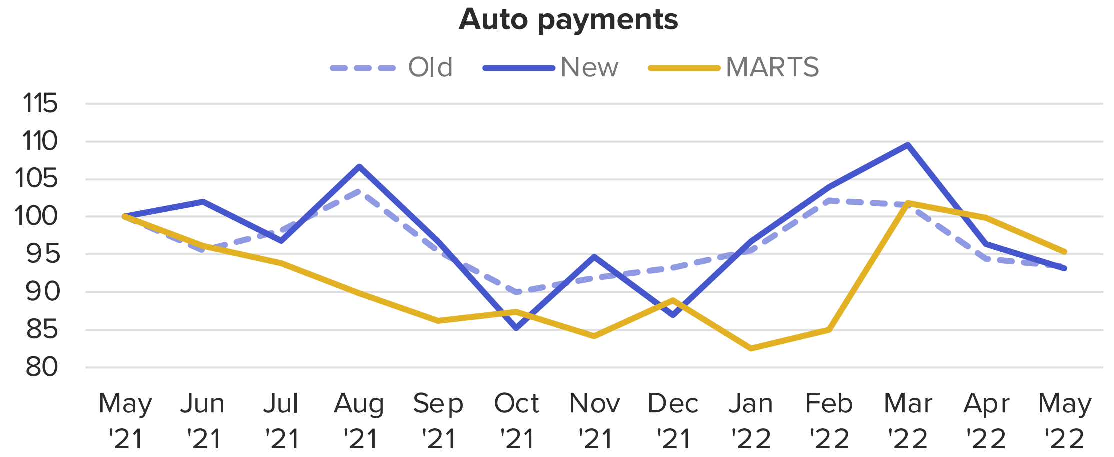
Old and new methodology vs. benchmark

Note difference in scales across charts





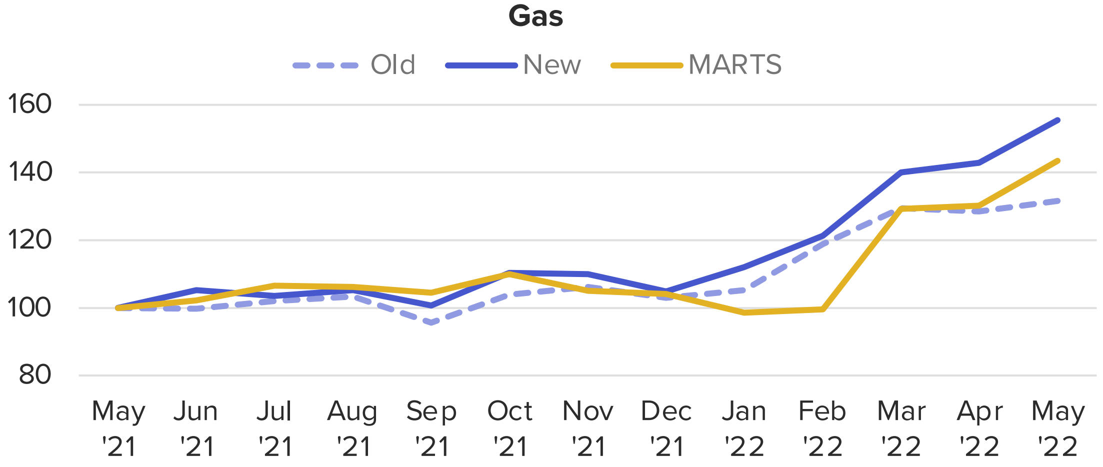


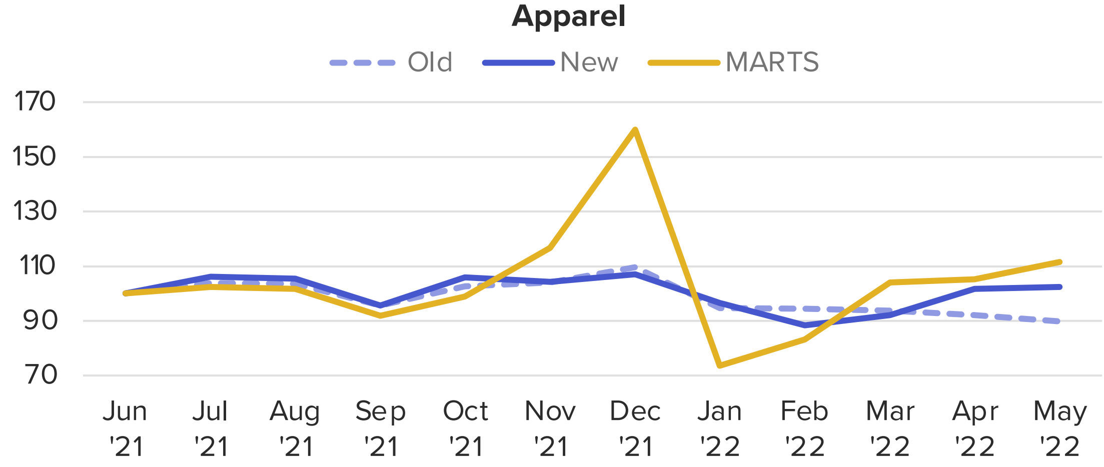


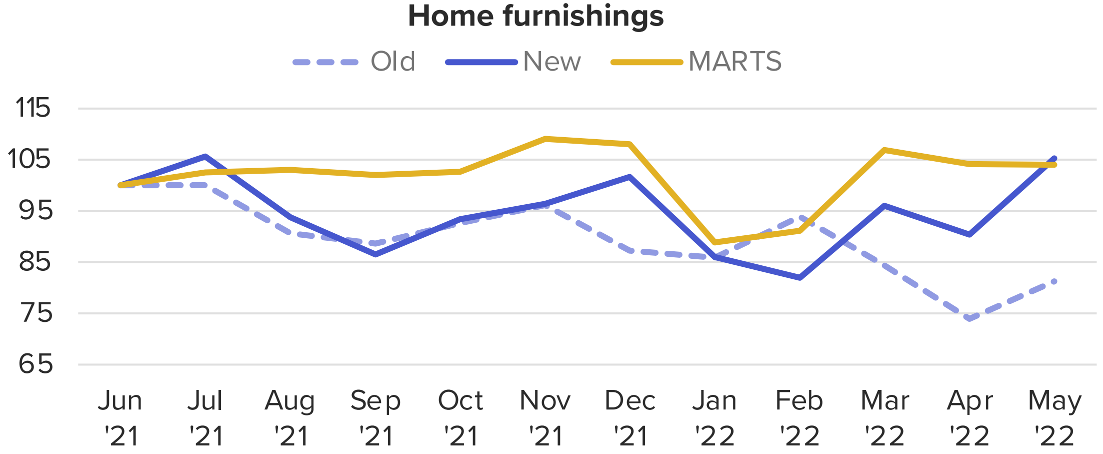
*Includes grocery, gas, restaurant, auto payments, apparel, home furnishings, restaurants, alcohol

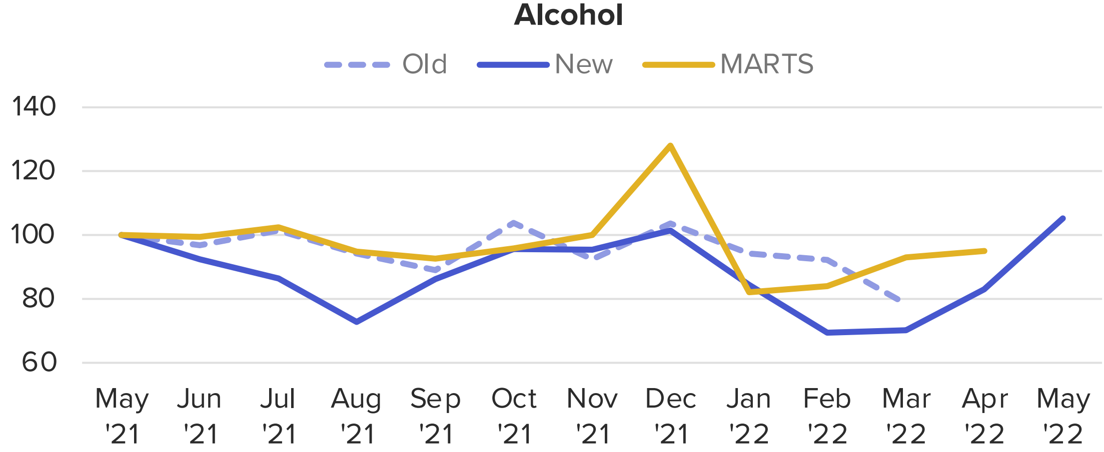
Old and new methodology vs. benchmark

Note difference in scales across charts



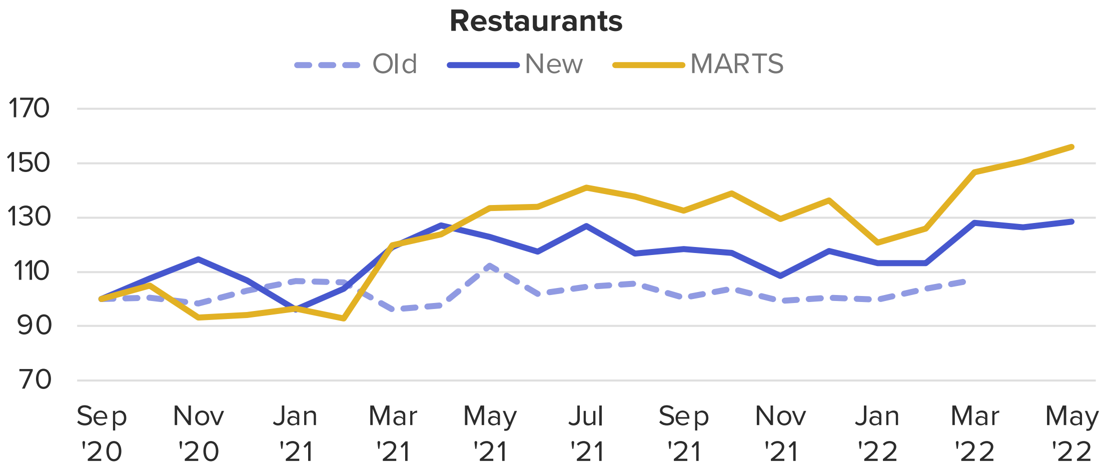


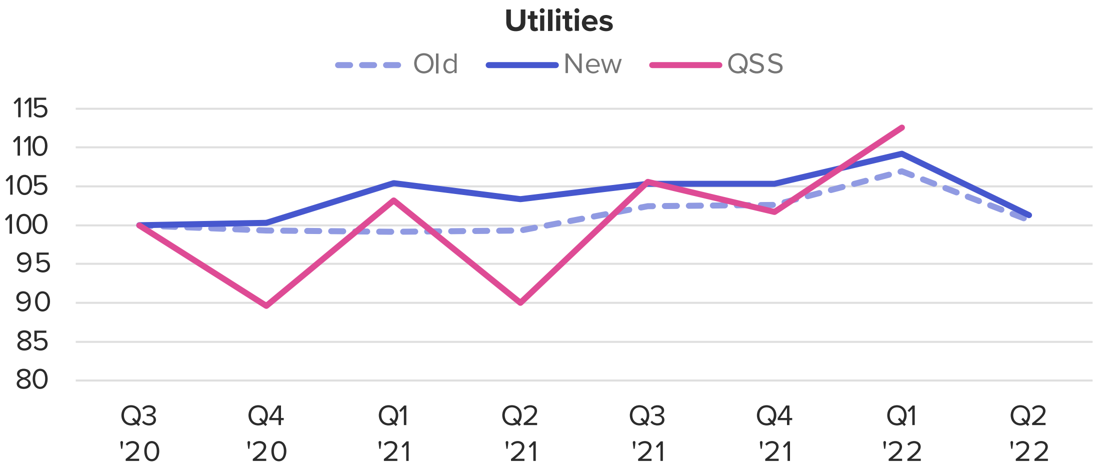


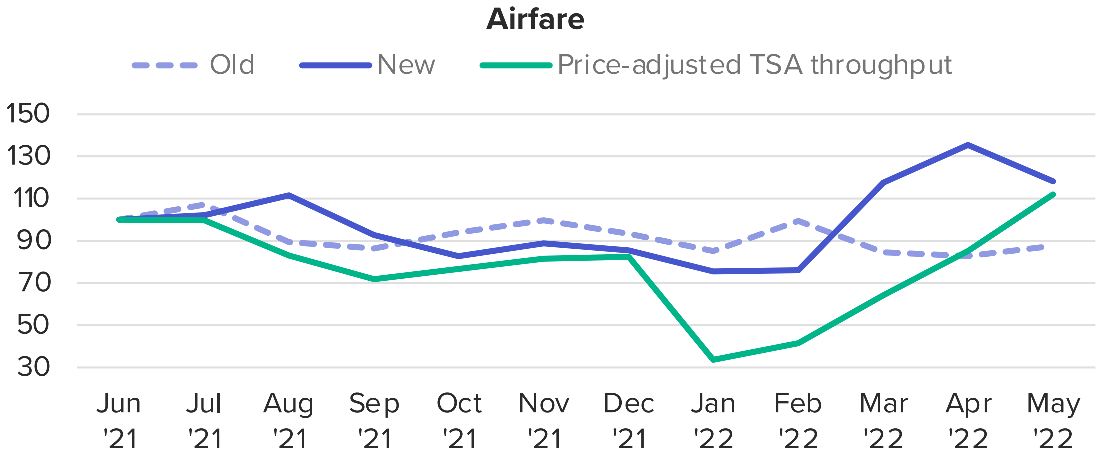


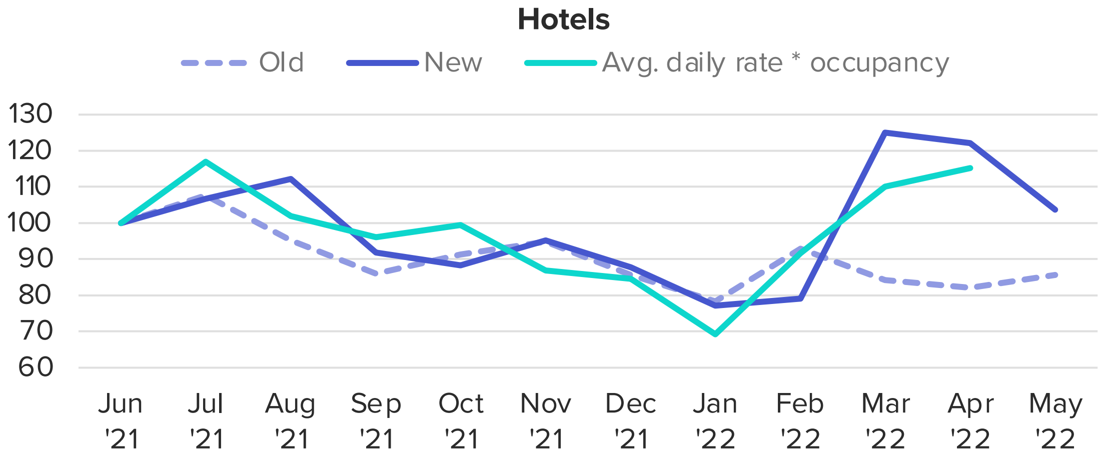
Old and new methodology vs. benchmark

Note difference in scales across charts









Correlations comparison: Benchmark vs. old and new methodologies

Categories without strong benchmarks

Category	Old methodology	New methodology	Difference	Benchmark	Primary discrepancy driver
Vehicle insurance	-0.05	0.12 ✓	+0.17	PCE	Unknown
Health care	-0.74	-0.45 ✓	+0.29	PCE	Category mismatch
Telecom	0.33	0.39 ✓	+0.06	PCE	Category mismatch
Personal care services	0.34	0.34	--	PCE	Unknown
Personal care products	0.38	0.38	--	PCE	Unknown
Health insurance	-0.62	-0.31 ✓	+0.31	PCE	Category mismatch
Education	-0.74	0.20 ✓	+0.94	PCE	Category mismatch
Recreation	N/A	N/A	--	N/A	Category mismatch
Public transportation	-0.70	-0.46 ✓	+0.24	PCE	Category mismatch

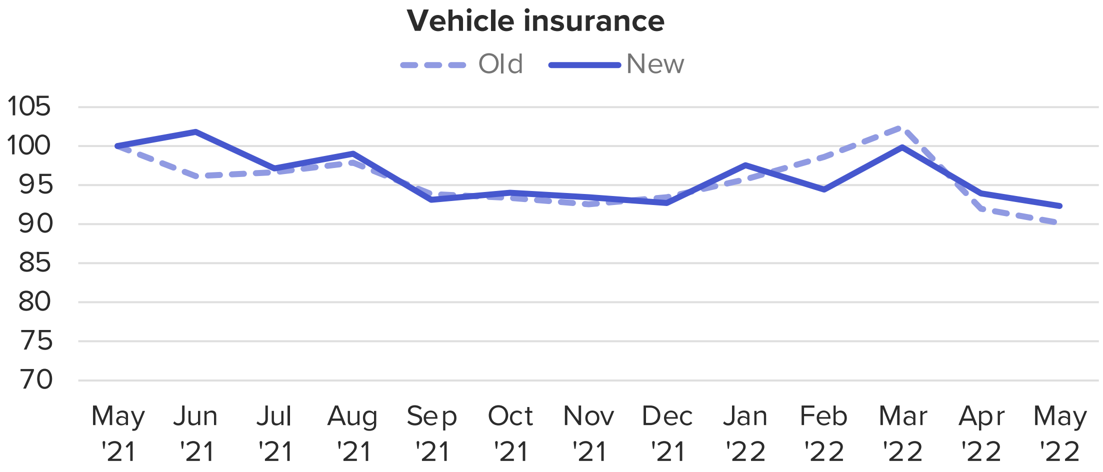
Certain categories did not have an appropriate benchmark series, most often because the category definition was not well aligned with our data.

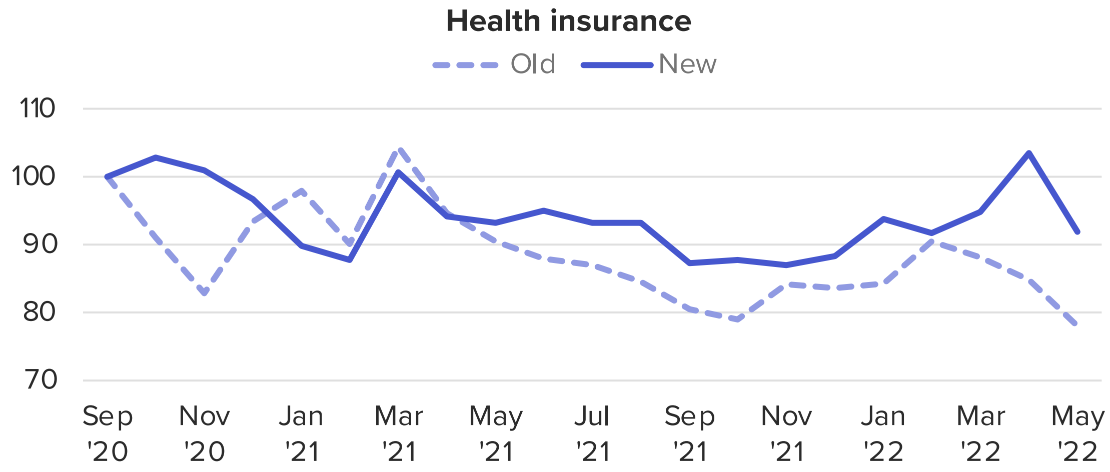
KEY

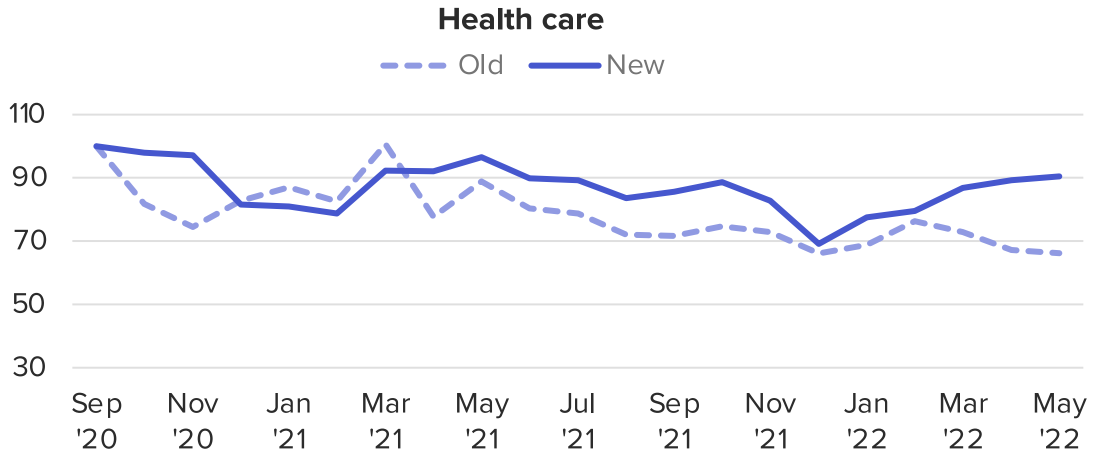
<0	0-0.49	0.50-0.74	0.75+	✓
Negative	Weak	Moderate	Strong	Better fit

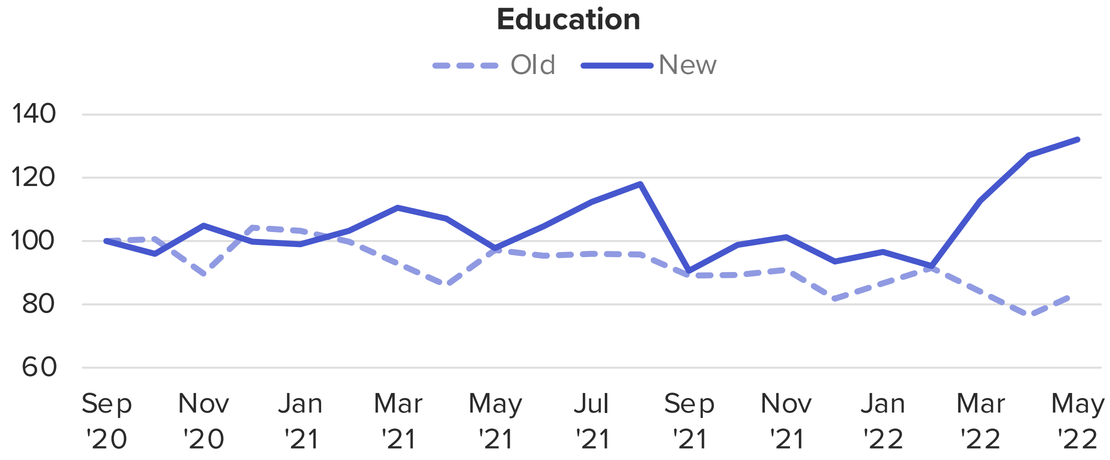
Old vs. new methodology

Note difference in scales across charts



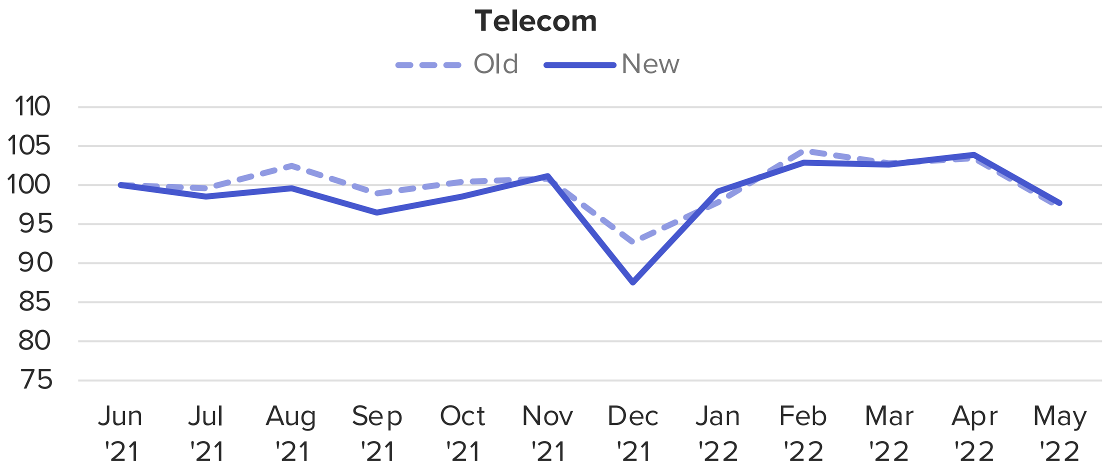


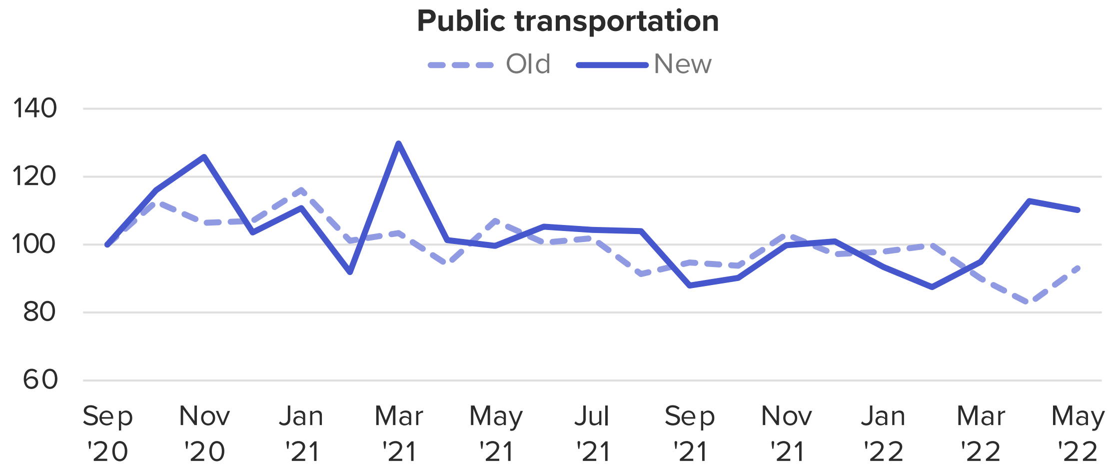




Old vs. new methodology

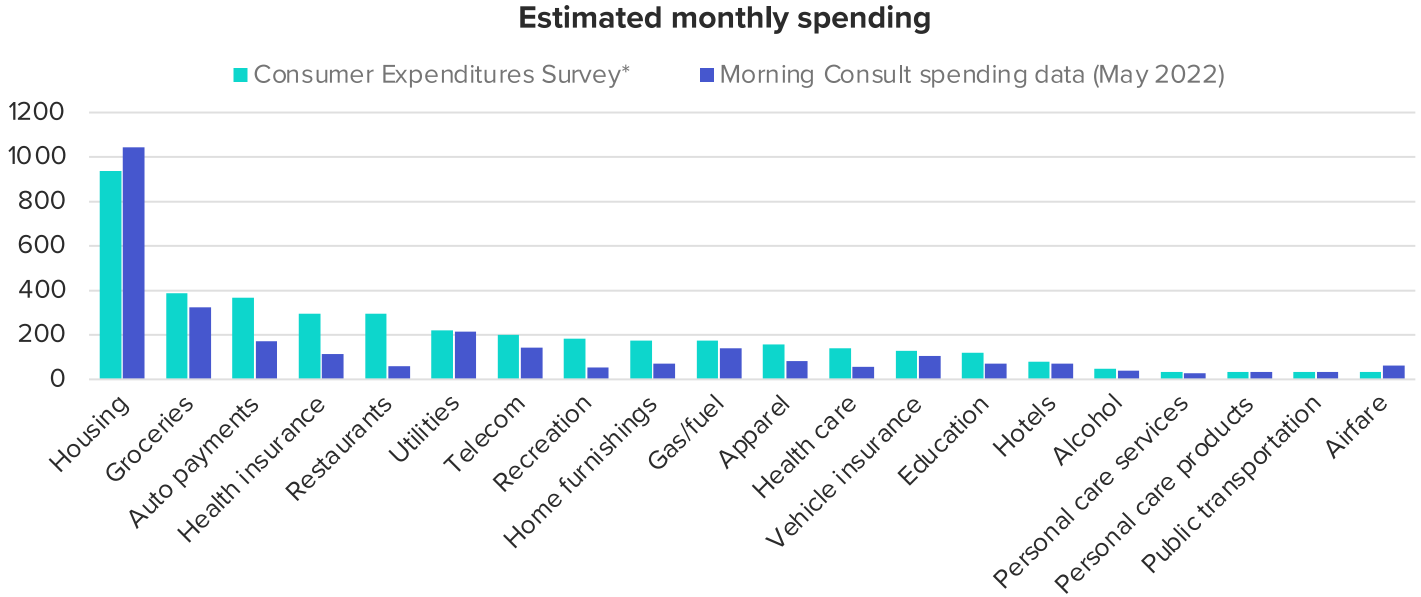
Note difference in scales across charts





Note: Historical trend for Personal care products, Personal care services and Recreation categories was unaffected by the methodology revision.

Spending levels and allocations resemble government data on consumer expenditures



The Bureau of Labor Statistics' Consumer Expenditures Survey is the most comparable dataset to Morning Consult's consumer spending data in structure. The spending levels and allocations per category are relatively consistent across both surveys. However, the CEX survey is only released on an annual basis and with several months' lag. As such, the time periods being compared in the graph and accompanying table are not in alignment, potentially explaining some of the discrepancies. Additionally, while the most recent available data is from 2020, we used 2019 spending levels instead in order to eliminate the pandemic impacts. Price-level changes since 2019, however, remain, potentially still influencing the comparison.

*Data from 2019, since more recent 2020 data was heavily impacted by the pandemic

Category	CE Allocation	MC Allocation
Housing	23%	36%
Groceries	10%	11%
Auto payments	9%	6%
Health insurance	7%	4%
Restaurants	7%	2%
Utilities	5%	7%
Telecom	5%	5%
Recreation	5%	2%
Home furnishings	4%	2%
Gas/fuel	4%	5%
Apparel	4%	3%
Health care	3%	2%
Vehicle insurance	3%	4%
Education	3%	2%
Hotels	2%	2%
Alcohol	1%	1%
Personal care services	1%	1%
Personal care products	1%	1%
Public transportation	1%	1%
Airfare	1%	2%

SECTION 2

APPENDIX

Additional context for methodology revision

MOTIVATION

Our former method of calculating consumer spending based on pre-specified spending levels from our survey has differed from official statistics since the fall of last year. Initially, we could explain this by the fact that our data is not seasonally adjusted, but it became increasingly clear that inflation caused our assigned spending ranges to be less representative of the average consumer. We addressed these concerns with the following solutions. This same change in methodology will be applied across demographics for both U.S. and international spending surveys.

PURPOSE

Revise the methodology underlying the construction of our consumer spending data in order to benchmark it with official statistics (PCE, MARTS), make it more robust to inflation and lay the groundwork for applying seasonal adjustments in the future. Our chosen course of action consisted of a mix of survey design changes, a novel benchmarking procedure relying on robust statistics in order to match average levels of household spending and variation over time, and simple seasonal adjustment procedures.

NEW METHODOLOGY

The old way vs. the new way

Feature	Old methodology	Weakness	New methodology	Improvement
Data sources	• Multiple-choice response data • Static midpoints corresponding with each spending range from the multiple-choice data	• Multiple choice levels & midpoints are static (do not change when price levels shift) • Upper bound "midpoint" is not a midpoint — arbitrarily assigned and likely inaccurate • Most categories do not include an "I did not buy __" option, so doesn't account for nonbuyers • Grocery, restaurant and alcohol categories split the sample into weekly or monthly — spending levels per month are difficult to calculate from weekly data	• Open-end response data • Multiple-choice response data (for nonbuyers) • Asks all respondents about monthly spending, no longer splitting sample between weekly and monthly	• Open end response data is robust to inflation (midpoints aren't static; maximum bucket isn't capped) • All categories have an "I did not buy __" option, so nonbuyers are assigned a spending value of 0 • Allows for consistent time period reporting (monthly for all categories)
Spending estimate	• Weighted average of midpoints & corresponding share of adults selecting a given option	• More like a median than a mean; does not allow for any outliers and flattens out potential variation over time and across demographics	• Trimmed mean (2.5%, 5% or 10%) • Zeros are removed, and nonbuyers are calculated based on the share who selected "I did not buy __" for a given category	• Trimmed mean removes extreme outliers while allowing for more variation, reflecting a truer average (not median) • Nonbuyers are reliably counted
Benchmarking	• Mixed results, not very strong correlation with MARTS/PCE overall	• Spending data integrity is difficult to defend when it doesn't align well with official data sources • Spending data likely cannot be used for forecasting if it doesn't have a relationship with official data sources	• Virtually all categories with reasonable MARTS/PCE benchmarking series were improved in new methodology • MARTS/PCE relationships were used as basis for identifying robust statistic (trimmed mean) to use	• Improved correlations help validate our data • Improved correlations improve the prospects for using our data to forecast other data sources in the future

NEW METHODOLOGY

Method #1

Categories: *auto payments, *vehicle insurance, *gas/fuel, housing, public transportation, airfare, hotels, Education, apparel, home furnishings, groceries, restaurants, alcohol, health insurance, health care, utilities, telecom

Steps:

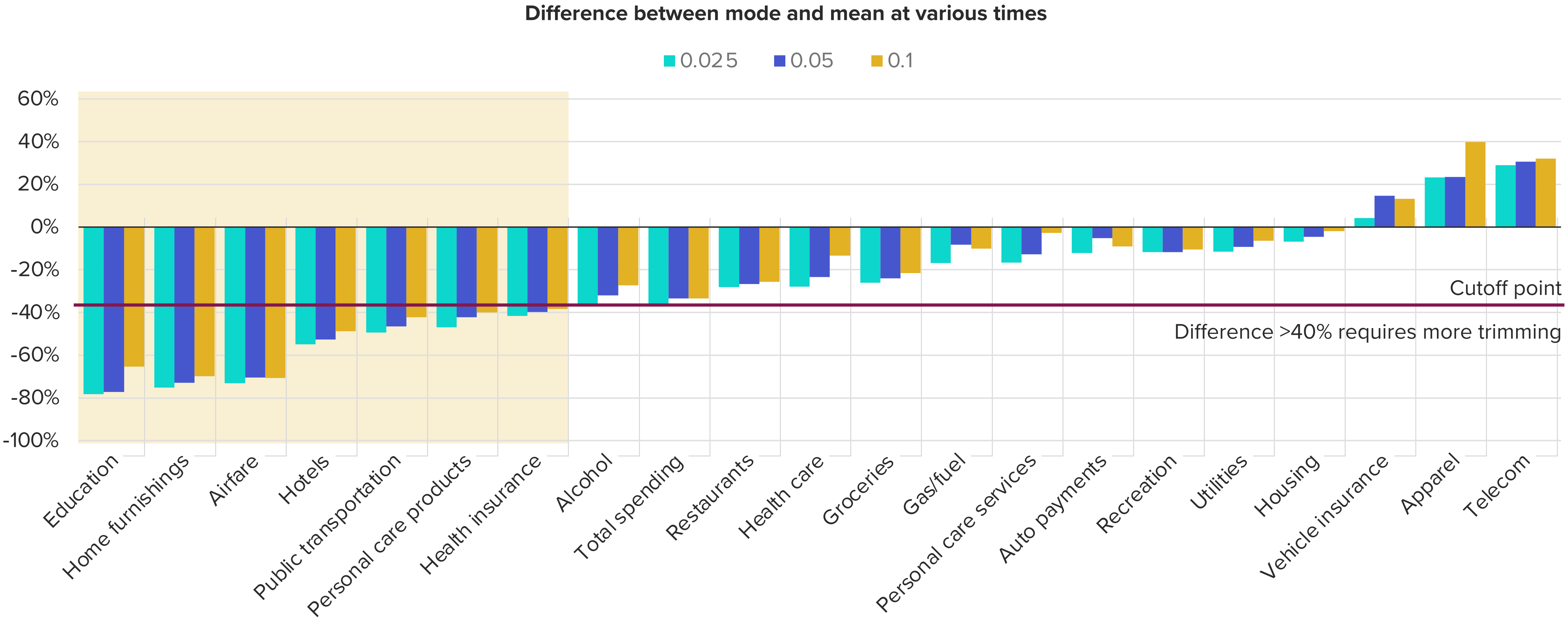
1. Eliminate responses of 0 or less than 0 from the raw response data.
2. Calculate trimmed mean (2.5%, 5% or 10% depending on category distributions) .
3. From the multiple-choice responses for the same category, the share of adults who spent money on this category is calculated by taking 1-[share who selected “I did not spend money on ___”].
4. The trimmed mean is multiplied by the “buyers only” share to reflect average spending on this category across all adults.**

**These categories subsequently require additional steps described in Method #2*

***Except for auto categories, which still reflect vehicle owners only and require further modification on next step*

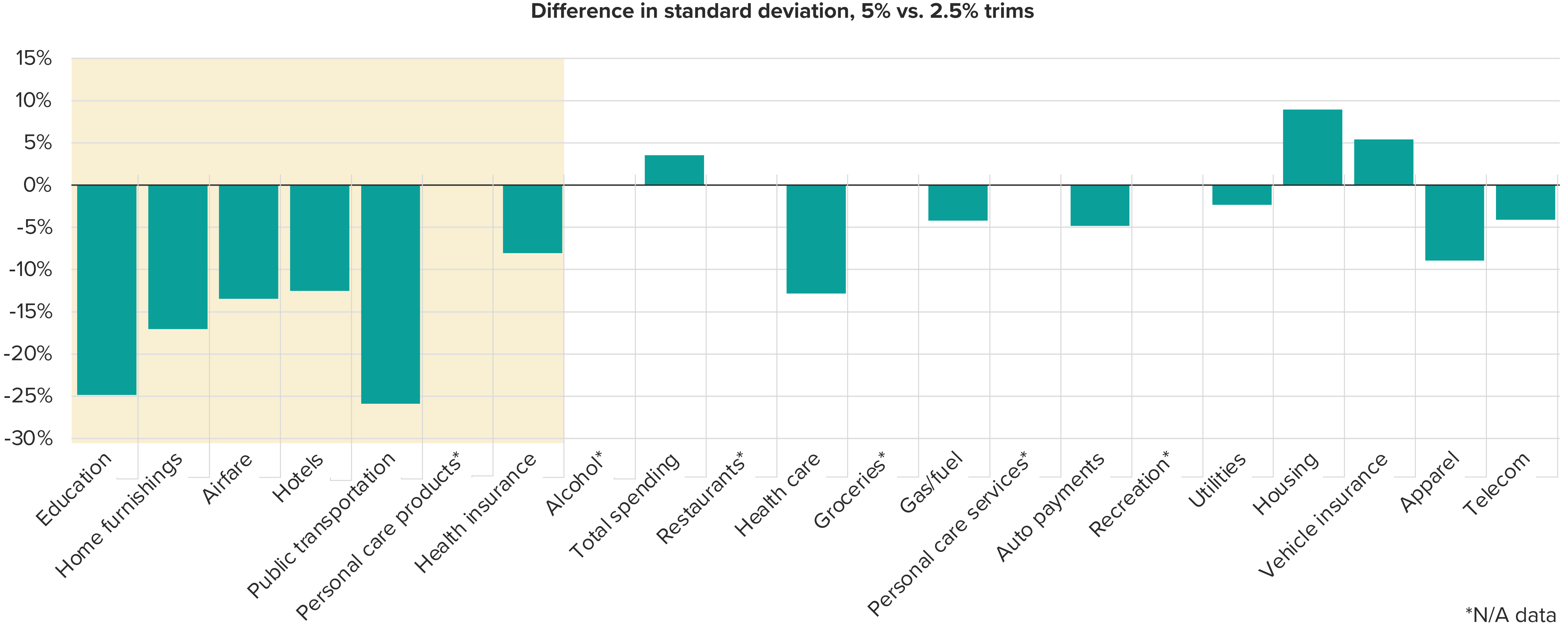
Trim selection per category: Mode vs. mean & volatility reduction

Similar categories show up as benefiting from more trimming in terms of volatility and mode/mean comparison



Trim selection per category: Mode vs. mean & volatility reduction

Similar categories show up as benefitting from more trimming in terms of volatility and mode/mean comparison



*N/A data

NEW METHODOLOGY

Method #2

Categories: auto payments, vehicle insurance, gas/fuel

Steps:

1. The auto category questions are only asked among U.S. adults who said their household owns at least one vehicle. These spending estimates must therefore be modified to reflect all adults.
2. Take the share of vehicle owners (i.e., share of sample who answered the vehicle-related questions) from the following multiple-choice question: “Does your household own at least one car, truck or SUV.”
3. Multiply the trimmed means for auto-related categories calculated in Method #1 by the share of adults who said their household owns vehicles in order to estimate spending on these categories across all adults.

Method #3

Categories: total income, total spending, recreation*

Steps:

1. Eliminate responses of 0 or less than 0 from the raw response data (note: this applies only to total income & total spending).
2. Calculate trimmed mean (2.5%).

Reasoning: These categories do not have a corresponding multiple-choice value identifying “I did not spend money on __”. For total income and total spending, all respondents should supply a nonzero response. For recreation, zero responses are acceptable (it’s possible some respondents spent $0 on recreational activities in a given month, but unlikely that respondents earned or spent $0).

Reconciling historical data when trends were broken due to survey revisions

	Situation #1	Situation #2	Situation #3	Situation #4
Description of trend break	• None	• Missing nonbuyers' share response option prior to 4/22	• Missing nonbuyers' share prior to 4/22 • Respondents split by monthly/weekly prior to 5/22	• Missing open-end response option prior to 5/22
Applicable categories	• Total income, total spending, auto payments, vehicle insurance, utilities, housing	• Gas/fuel, public transportation, airfare, hotels, education, apparel, home furnishings, health insurance, health care, telecom	• Groceries, restaurants, alcohol	• Recreation, personal care products, personal care services

Reconciliation method #1

Categories: auto payments, vehicle insurance, gas/fuel

Differences from current methodology:

- None. The survey questions for these categories did not require any changes in order to align with the current methodology, so we can generate historical data through the new process without breaking trend.

Reconciliation method #2

Categories: gas/fuel, public transportation, airfare, hotels, education, apparel, home furnishings, health insurance, health care, telecom

Differences from current methodology:

- Prior to April 2022, these categories did not have a multiple-choice option for “I did not spend money on __” included in the survey, so the current method for eliminating non-buyers cannot be applied.

Steps:

1. Eliminate responses of 0 or less than 0 from the raw response data.
2. Calculate trimmed mean (2.5%, 5% or 10% depending on distribution).
3. Use the monthly percentage changes (from historical start date through April 2022) to impute historical spending estimates that align with the levels generated by the new methodology at the series breakpoint (April 2022).
4. Example: March 2022 imputed value = March 2022 old methodology value / April 2022 old methodology value * April 2022 new methodology value.

Reconciliation method #3

Categories: groceries, restaurants, alcohol

Differences from current methodology:

- Prior to April 2022, these categories did not have a multiple-choice option for "I did not spend money on ___" included in the survey, so the current method for eliminating non-buyers cannot be applied.
- Prior to May 2022, respondents were split for each of these categories based on a sorting question asking whether they preferred to submit total spending on a monthly or weekly basis.

Steps:

1. Apply Method #2 to all categories' historical data; this results in two historical series for each category — a monthly and weekly spending estimate.
2. Modify each "weekly" series to reflect a "monthly" estimate for those respondents by dividing each value by 7 and multiplying times the number of days in the corresponding month.
3. Identify the optimal weighting mix of "weekly" (modified to a monthly estimate) and "monthly" responses that maximizes correlation with the Census Bureau's nonseasonally adjusted retail sales for the corresponding category. To do this, calculate composites for different weights of monthly and weekly data and select the one with the highest correlation to government data.
4. Use the top-performing composite as the imputed historical spending value for each category.

Reconciliation method #4

Categories: recreation, personal care products, personal care services

Differences from current methodology:

- Prior to May 2022, these categories did not have open-end response options in the survey, so trimmed means could not be calculated.

Steps:

1. The only available history for these categories is spending estimates based on the weighted average of midpoints from the multiple-choice survey data.
2. Using the old methodology (midpoints method), calculate spending estimates through May 2022.
3. Use the resulting percentage changes to append history prior to May 2022 that aligns with the May 2022 level generated from the new methodology.

Summary of method & reconciliation approaches per category

Category	Method	Reconciliation approach	Series start date	New method transition point
Housing	1	1	Sep 2020	N/A
Groceries	1	3	Sep 2020	May 2022
Auto payments	2	1	Sep 2020	N/A
Health insurance	1	2	Sep 2020	Apr 2022
Restaurants	1	3	Sep 2020	May 2022
Utilities	1	1	Sep 2020	N/A
Telecom	1	2	Jun 2021	Apr 2022
Recreation	3	4	Dec 2021	May 2022
Home furnishings	1	2	Jun 2021	Apr 2022
Gas/fuel	2	2	Sep 2020	Apr 2022
Apparel	1	2	Jun 2021	Apr 2022
Health care	1	2	Sep 2020	Apr 2022
Vehicle insurance	2	1	Sep 2020	N/A
Education	1	2	Sep 2020	Apr 2022
Hotels	1	2	Jun 2021	Apr 2022
Alcohol	1	3	Feb 2021	May 2022
Personal care services	1	4	Oct 2021	May 2022
Personal care products	1	4	Oct 2021	May 2022
Public transportation	1	2	Sep 2020	Apr 2022
Airfare	1	2	Jun 2021	Apr 2022
Total spending	3	1	Sep 2020	N/A
Total income	3	1	Sep 2020	N/A

REPORT AUTHORS

SCOTT A. BRAVE
Lead Consumer Spending Economist

KAYLA BRUUN
Economic Analyst

LEARN MORE
MorningConsult.com

FOLLOW US
@MorningConsult

MEDIA & SPEAKING INQUIRIES
press@morningconsult.com

ECONOMIC INTELLIGENCE

Data intelligence on key economic indicators

Morning Consult's SaaS platform tracks key economic indicators including consumer sentiment, spending, labor conditions and more.

MCEI DATA INTELLIGENCE CAPABILITIES

Economic Intelligence collects over 15,000 daily responses on key global macroeconomic indicators including:

- Personal finances
- Buying conditions
- Business conditions
- Employment status
- Employment type
- Labor market sizing
- Future price increases
- GDP expectations
- Pricing effect
- Supply expectations
- Demand expectations
- Ability to pay

Key use cases

TRACK GLOBAL CONSUMER CONFIDENCE

Track global consumer confidence to better understand and forecast spending.

MONITOR LABOR & EMPLOYMENT CONDITIONS

Compare labor market conditions across and within countries to identify job seekers with appropriate skill sets.

TRACK INFLATION EXPECTATIONS

Track inflation expectations and their impact on consumer spending and buying habits.

UNDERSTAND HOUSING MARKET

Track housing supply and demand, including buying and renting trends and consumers' ability to make payments.

Available in 44+ countries

MORNING CONSULT®