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Sinem Hacioglu-Hoke, Leo Feler, Jack Chylak

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Lost in Aggregation: Geographic Mismeasurement of Income and Spending*

Sinem Hacıoğlu-Hoke *
Federal Reserve Board
CEPR

Leo Feler†
Numerator

Jack Chylak‡
Numerator

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Abstract

Using zip-code median income as a proxy for household income is common in economics but can mask heterogeneity and yield misleading conclusions. Using zip-code median income and self-reported household incomes from a representative panel of 150,000 U.S. households, we decompose average retail spending for 2018-2024. When using self-reported incomes, we observe substantial divergence in spending between low- and high-income households starting in mid-2021. When using zip-code aggregates as a proxy, this divergence disappears. Our findings indicate a 35 to 75 percent discrepancy between zip-code aggregates and self-reported incomes, highlighting the limitation of zip-code aggregates as a proxy for household incomes.

Keywords: Spending, Income, Heterogeneity, Zip-code Average Income
JEL Classification: E01, E2, E32

*sinem.haciogluhoke@frb.gov Web: www.sinemhaciogluhoke.com
†leo.feler@numerator.com Web: www.leofeler.com
‡jack.chylak@numerator.com

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1 Introduction

It is common in social sciences to categorize households as low-, middle- or high-income to assess the heterogeneity in, for example, consumers' spending behavior. When household incomes are not observed, a common practice is to use as a proxy the average or median income in zip codes where households live, generally obtained from population surveys. The reasons for such an approximation of household incomes using zip-code aggregates are because, first, where households live is correlated with their incomes, and second, it is rare to have access to datasets that provide information on disaggregated household incomes. In this paper, we assess whether zip-code aggregates are a valid proxy for disaggregated household incomes that accurately reflects heterogeneity in consumer behavior, using a representative panel of U.S. households with disaggregated information on household incomes.

This paper has two objectives that lead to novel contributions to existing studies that document heterogeneity in spending patterns. First, using a detailed micro dataset, we construct a measure of real average retail spending for low-, middle- and high-income households using households' self-reported incomes to construct income groups. Second, we use our micro-data to test the implications of using zip-code aggregates. Our results indicate that using zip-code aggregates as a proxy for household incomes masks heterogeneity in consumer behavior and leads to misleading conclusions about changes in consumer behavior during the post-pandemic period.

We use a panel dataset of 150,000 representative U.S. households from Numerator, a consumer data and survey company. Numerator obtains physical and online receipts from this rolling static panel of U.S. households for whom we have detailed information on household attributes. We first compare our overall measure of monthly average retail spending between 2018 and 2024 against the Census Bureau's Advance Monthly Sales for Retail and Food Services report (MARTS) to establish our measure's reliability.

Having established that the aggregated Numerator retail spending series closely matches the Census Bureau's retail sales series, we examine spending patterns based on household income. We analyze the average monthly household retail spending for low-income households ($0-$60K in annual household income), for middle-income households ($60K-

$100K), and for high-income households ($100K+) from 2018 to 2024. Published measures do not provide details on *which* consumers' spending has remained resilient in the post-pandemic period, and hence fall short of identifying vulnerabilities in the economy originating from specific groups, so our analysis fills this gap. Our results suggest that retail spending growth evolves similarly for all households before the pandemic. However, starting in mid-2021, the spending of high-income households diverges from the spending of low- and middle-income households. High-income households continue to spend strongly while low- and middle-income households' spending lags behind. This finding is supported by many analyses and can be rationalized by low-income households depleting their pandemic-era savings (Abdelrahman et al., 2024) and by the expiration of government support programs that helped low- and middle-income households during and following the pandemic.[1] Moreover, we show that this divergence is a robust finding when we decompose spending by education and simulate scenarios, using a household survey, where we control for the higher mobility between income groups in 2022 and 2023.

Instead of using households' self-reported incomes to construct income groups, we next use median zip-code incomes reported in the American Community Survey (ACS), following Chetty et al. (2023), to classify households as low-, middle- and high-income. Our analysis using Numerator self-reported income data and replicating zip-code median income aggregation is unique in allowing a direct comparison of spending measures based on disaggregated self-reported income versus aggregated proxied income. Using either method, we document similar pre-pandemic spending dynamics. However, the divergence we observe in the post-2021 spending disappears when we use aggregated zip-code median income as a proxy. Using aggregated zip-code median income, it appears that spending evolved similarly for all household income groups during the post-pandemic

[1]Such analysis of documenting the discrepancies in spending growth is sparse at best in academic platforms, mostly due to data availability to assess spending by income groups. One such analysis is Moody's Analytics', which show that top earners – the top 10% of US households in terms of earnings – drive nearly half of all consumer spending. For the details of that analysis, see https://www.wsj.com/economy/consumers/us-economy-strength-rich-spending-2c34a571?st=2odEgM&reflink=article_copyURL_share. The Moody's Analytics analysis postdates our initial analysis which shows the divergence in spending between income groups in Hacioglu Hoke et al. (2024). Another related study by the Bank of America Institute documents the slowing pace of lower-income households' spending: https://institute.bankofamerica.com/economic-insights/consumer-checkpoint-march-2024.html. Finally, Morning Consult analysis also documents slower spending by low- and middle-income households: https://pro.morningconsult.com/analysis/consumer-spending-september-2024.

period. This result contradicts our previous finding, using disaggregated self-reported household income, that higher-income households were the ones driving consumer spending in the U.S. in the post-pandemic period while low- and middle-income households pulled back.

When we look into the shares of low-, middle- and high-income households who live in low-, middle- and high-income zip codes, we find large discrepancies. In 2024, only 59% of low-income households lived in zip-codes classified as having low median household income, whereas the rest of the households living in these low-income zip-codes were actually middle- and high-income households. Similarly, only 32% of households that lived in high-income zip codes reported high incomes in Numerator data; the rest were low and middle-income households in 2024.

The use of zip code income or other household characteristics as a proxy for individual household attributes has been subject to scrutiny, particularly in the health literature. Several studies have highlighted the potential limitations of this approach. For instance, Geronimus et al. (1996) explores the challenges associated with using aggregate census-based variables as proxies for micro-level socioeconomic characteristics. Similarly, Hanley and Morgan (2008) utilizes Canadian administrative data to demonstrate the significant variability between household-level income and area-based income measures. More recently, Buajitti et al. (2020), also drawing on Canadian data, advises caution when employing area-level data as indicators of individual socioeconomic status. In the field of economics, Geronimus et al. (1996) stands out as one of the few studies to critically examine the use of zip-code level measures as proxies for household characteristics. Their findings suggest that using aggregate proxies may overstate the impact of socioeconomic factors on health outcomes while inadequately addressing confounding variables between socioeconomic characteristics. These studies collectively underscore the importance of carefully considering the limitations and potential biases when using aggregate data to represent individual-level socioeconomic information.

Our analysis builds upon recent studies that examine consumer spending patterns during and after the pandemic using private-sector data (see Vavra (2021) and Brodeur et al. (2021) and the references therein). At the onset of the pandemic, the Economic Tracker developed by Chetty et al. (2023) provided important, innovative, and timely high-frequency estimates of spending contributions from different income groups from 2020 onward. Their analysis, which uses credit card spending data, illuminated potential economic risks and proxied income using median zip-code income from the ACS. Another notable study by Cox et al. (2020) documents the heterogeneous effects of the pandemic on households using bank account data. Their analysis of spending by income quartiles offers insights into expenditure differences during the pandemic's early stages. However, as the authors acknowledge, their study was limited by the unavailability of micro-data on income at the time of writing, necessitating the use of publicly available data to simulate income changes in the pandemic's initial months.

Our research contributes to this growing body of literature in several ways. First, we utilize a new micro dataset that directly captures households' self-reported incomes and observed spending. Second, we explore spending changes across income groups over an extended period, encompassing both pre- and post-pandemic time frames. Third, we compare the implications of using disaggregated self-reported household incomes to construct income groups versus using proxied income based on zip code data to assess how spending changes for low-, middle-, and high-income households. Furthermore, our analysis can be updated weekly, similar to Chetty et al. (2023)'s approach, allowing for a near real-time assessment of spending dynamics. These unique features enable us to readily detect changes in spending patterns by different income groups with greater accuracy during a time when the economy and consumer spending behaviors are being affected by various shocks.

The rest of the paper proceeds as follows. Section 2 provides the details of the Numerator data and the reliability of our spending measure. In Section 3, we construct the seasonally-adjusted real average retail spending measures for low-, middle-, and high-income households by self-reported income groups between 2018 and 2024, and provide additional evidence for the robustness of the divergence in spending. Section 4 instead uses zip-code level aggregation to decompose spending by income. In Section 5, we quantify the reported versus zip code income discrepancy and Section 6 concludes. We provide additional analyses and robustness checks in the Online Appendix.

2 Data

The Numerator data contain 150,000 panelists who self-identify as the primary shopper in the household and whose transactions are continuous and complete for a period of at least 12 months. These 150,000 panelists are selected from more than 1 million panelists in a way that is demographically and nationally representative. Numerator provides weights for households to ensure a match with Census demographic data and to ensure their detailed purchases, when summed by retailer or manufacturer, align with quarterly earnings reports of major retailers and consumer packaged goods companies.

Numerator collects data from households in several ways using a mobile phone app. First, consumers can upload pictures of their paper receipts. Second, they can allow Numerator to scrape their emails for digital receipts. Third, users can link loyalty and membership accounts so their transactions are automatically recorded.[2] Numerator collects survey information on household income, zip code, age, education, household size, race/ethnicity, and various other measures. Panelists' identifiable information is anonymized.

The Numerator data allow for 16 income groupings based on panelist's self-report income.[3] All panelists are resurveyed about their household income approximately every 12 months and often more frequently if panelists report life events, such as job changes, when prompted approximately every 3 months. Panelists report any changes to their income group when they are re-surveyed. Although there may be a lag in detecting changes in household income, frequent surveys provide confidence that the margin of error in accounting for changes in household income is within reasonable limits.

To establish the reliability of the average retail spending measure we construct using Numerator data, we compare it against official statistics published for retail spending. Every month, the Census Bureau publishes the MARTS report to provide an estimate of retail sales and food services spending. To prepare the MARTS report, the Census Bureau collects the dollar value of sales directly from retailers by fielding establishment-

[2]Numerator collects these data from households using a mobile phone app called Receipt Hog. Panelists are rewarded directly with coins and with virtual spins of a slot machine that also rewards coins, which panelists can redeem for gift cards or for cash through PayPal. On average, Numerator rewards panelists approximately $43 per year for providing their purchase information and completing surveys.

[3]The income groups start with <$20K and go up to $100K with $10K increments. After $100K, they increase with $25K increments up to $250K with the last group being $250K+.

level surveys and estimating total results and the results by the relevant three-digit North American Industry Classification System (NAICS) categories.

The Numerator panel data include information on households' purchases from paper receipts, online receipts, and transaction records. The purchase information contains the quantity and price of each item purchased, the overall total on the receipt, and where and when the purchase took place. These details allow us to classify households' spending into the relevant three-digit NAICS categories for retail sales categories to construct a spending measure comparable to the Census Bureau's retail sales measure in the MARTS report.[4] Note that our measure excludes spending on motor vehicles and parts, a spending category Numerator data do not capture.

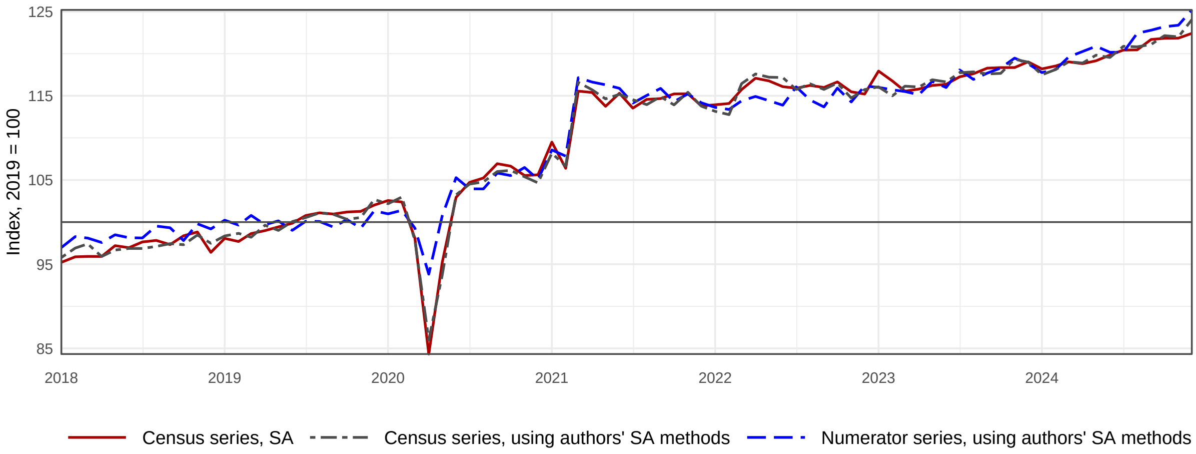
Figure 1 compares how the retail spending measure we construct using Numerator data compares with the Census Bureau's published series. The red line indicates the Census Bureau's published seasonally adjusted total retail sales excluding motor vehicles and parts. The blue dashed line is the retail spending measure we construct from the Numerator data, which we seasonally adjust using the Census Bureau's X13-ARIMA-SEATS package.[5] The gray dash-dotted line is the non-seasonally adjusted Census series that we then seasonally adjust using the same X13-ARIMA-SEATS methodology we use for Numerator data. The purpose of the gray line is to show that our seasonal adjustment methodology aligns closely with the Census methodology, and therefore, the differences between the Numerator seasonally-adjusted series and the official Census seasonally-adjusted series is not due to differences in seasonal adjustment.[6] The correlation be-

[4]These 11 spending categories are Furniture & home furn. stores (NAICS 442), Electronics & appliance stores (NAICS 443), Building material & garden eq. & supplies dealers (NAICS 444), Food & beverage stores (NAICS 445), Health & personal care stores (NAICS 446), Gasoline stations (NAICS 447), Clothing & clothing accessories stores (NAICS 448), Sporting goods, hobby, musical instrument, & book stores (NAICS 451), General merchandise stores (NAICS 452), Miscellaneous store retailers (NAICS 453), Non-store retailers (NAICS 454), and Food services & drinking places (NAICS 722). According to the Census Bureau, the MARTS report covers firms classified in the Retail Trade and Food Services sectors as defined by the North American Industry Classification System (NAICS). Retail Trade, as defined by NAICS sectors 44-45, includes establishments engaged in selling merchandise in small quantities to the general public, without transformation, and rendering services incidental to the sale of merchandise. Food and drinking services to final consumers, subsector 722, is also included in the survey. More information on how the data are collected is available at https://www.census.gov/retail/how_surveys_are_collected.html.

[5]In addition, due to a change in Numerator methodology starting in April 2021, we apply a fixed level-correction to the Numerator series for April 2021 and onward. This level-correction is equivalent to a fixed-effect that accounts for the change in Numerator's methodology.

[6]It is not entirely possible for us to replicate the Census Bureau's seasonal adjustment methodology.

Figure 1: Real retail sales, total excluding motor vehicles and parts, constructed using Census Bureau estimates and Numerator panel data



Note: The solid red line is the Census Bureau's seasonally adjusted retail sales series excluding motor vehicles and parts. The dashed blue line is the retail spending measure we construct using the Numerator data, which we seasonally adjust. The dashed gray line is the non-seasonally adjusted Census series that we then seasonally adjust. The data are monthly from January 2018 through December 2024. Authors' seasonal adjustment method uses X13-ARIMA-SEATS. Inflation adjustment uses the chain indexed PCE deflator for goods and food services excluding motor vehicles. All three lines are indexed to 100 in 2019.

tween the Numerator series and the Census Bureau's official seasonally adjusted retail sales series is 0.94 in levels and 0.83 when looking at monthly percent changes. Figure 1 and the correlation of Numerator's retail spending measure with the officially published retail sales measure allow us to verify that the bottom-up construction of the Numerator data, captured from household purchases, closely matches the top-down construction of the Census Bureau's retail sales series, captured from surveys of retail and food service establishments. Appendix A provides additional figures and reports correlations for sub-spending categories.

Retail sales subcategories are seasonally adjusted separately, sometimes even at a more granular level, and then combined to sum to the total retail sales series published by the Census Bureau. This is the main reason why we perform our own seasonal adjustment. Due to the time span of the data and the reasons explained above, we can get close to but cannot fully replicate the officially published seasonally adjusted retail sales series. More information on the Census Bureau's seasonal adjustment can be found at `https://www.census.gov/retail/marts/www/timeseries.html`.

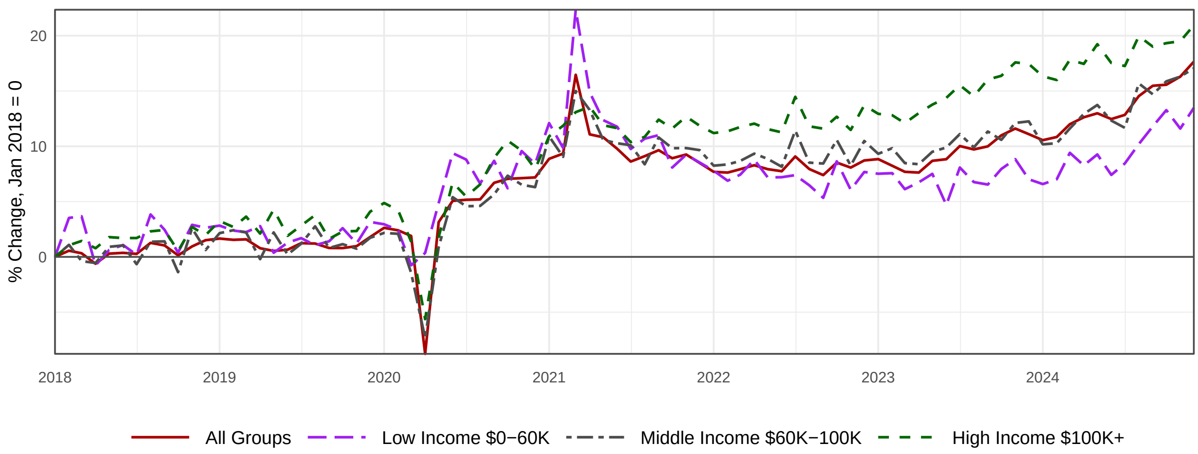
3 Spending by self-reported income

This section reports our findings on average retail spending by income. Using the categorical income groups recorded in Numerator data, we decompose retail spending, the blue line in Figure 1, into spending by low-, middle-, and high-income households. We then provide additional evidence for the validity of the divergence in spending between high- vs low-income households.

3.1 Average household spending by income

Figure 2 reports growth since January 2018 in average monthly household spending, adjusted for inflation and seasonality, overall and by three income groups: low ($0-$60K in annual household income), middle ($60K-$100K), and high ($100K+).[7]

FIGURE 2: Growth of average retail spending decomposed by household income



Note: The data are monthly from January 2018 through December 2024. All series are adjusted for inflation using the chain indexed PCE deflator for goods and food services excluding motor vehicles and are shown as growth relative to January 2018. All series are seasonally adjusted using X13-ARIMA-SEATS. Solid purple, dash-dotted gray and dashed green lines plot the spending by low-, middle- and high-income households.

The growth in average household retail spending is similar across all income groups in the pre-pandemic era. During the onset of the pandemic, all households' spending declined. Various studies, e.g. Cox et al. (2020), show that spending declined due to

[7]We select the cutoffs for low-, middle-, and high-income groups based on the following Census Bureau report that is based on 2022 incomes: `https://www.census.gov/library/publications/2023/demo/p60-279.html`. Minor modifications to these income groupings do not change our qualitative results.

the direct effects of pandemic rather than a loss of income. Following the decline in the beginning of the pandemic, average household spending for all income groups bounced back, reaching levels higher than pre-pandemic levels as households spent pent-up savings and government-provided stimulus payments.

During the pandemic recovery period and shortly thereafter, low-income households appeared to benefit more from pandemic-era stimulus. In percentage terms, low-income households increased their spending by more than middle and high-income households in 2020 and early 2021. The large jump in the average spending of low-income households in early 2021 coincides with the last stimulus program which provided more stimulus, as a percentage of their income, to low-income individuals. The finding that middle- and high-income households did not increase their spending as much as low-income households around the time of the last stimulus program in March 2021 is consistent with Chetty et al. (2023)'s findings.

Despite similar pre-pandemic and early-pandemic trends, the spending behavior of low- and high-income households starts to diverge in mid-2021. Between mid-2021 and mid-2023, middle- and high-income households maintain or increase their real average spending; low-income households reduce their real average spending compared with mid-2021 levels. Since mid-2023, low-, middle-, and high-income households have all been increasing their real average spending. As of December 2024, real average spending by low-income households is up 13.5% relative to January 2018; spending by middle-income households is up 17.0%, and real average spending by high-income households is up 20.9%.

While our analysis does not offer evidence for the differences in spending we observe for low-, middle-, and high-income households, we offer a few hypotheses for why these differences may have emerged. First, low-income households depleted pandemic-era excess savings earlier as documented by Abdelrahman et al. (2024). Second, government support programs–such as SNAP emergency allotments, enhanced unemployment insurance, and enhanced child tax credits that disproportionately benefited low-income households–expired and no longer provided a boost to these households' spending. Third, high-income households might have experienced a wealth effect as their homes and investments increased in value, while also receiving more interest and investment income during periods of higher interest rates, providing a stimulus for sustained levels of spending.

Note that our analysis and inflation adjustment likely under-counts the extent to which low-income households experienced inflation. Cavallo and Kryvtsov (2024) document that the prices of products low-income households tend to purchase increased at a faster pace. If there were heterogeneity in households' inflation experience, with low-income households experiencing higher inflation, low-income households' spending after the appropriate inflation adjustment would be lower than what our analysis has shown, which supports a wider divergence in spending.

3.2 Robustness Checks: Spending by Education, Survey Evidence, and Simulation

To support our results on the divergence of spending across income groups, we provide additional evidence in this subsection. First, Numerator data contain several different household attributes we could use to decompose retail spending. Among a few attributes that were explored in Hacioglu Hoke et al. (2024) is education. One benefit of decomposing retail sales by education rather than income is that education, which is regarded as a good proxy for income (see Card (1999)), remains broadly stable over a relatively short period of time, whereas household incomes increase with inflation between 2018 and 2024. The stability of the education groups over time allows us to check whether our results based on household income might have just been driven by compositional changes in income groups (e.g., if more households become high-income over time and fewer households remain low-income, that affects the composition of households in each income group and their average monthly retail spending).

In panel A of Figure 3, we show the average household retail spending by education. Education is based on the self-reported level of education of the primary shopper of a household in Numerator panel data. Our results for education are broadly similar to our results for household income, with households with lower education levels (high school completed or less) experiencing a pullback in real average household spending on retail goods and food services between mid-2021 and mid-2023, similar to households with lower-income levels, while households with middle- and higher-education levels (some college or undergraduate degree and some graduate school or graduate degree) showing resilience and sustaining higher levels of retail spending on goods and food services since mid-2021.

In addition, to overcome the rigidity in reporting of income groups over time, Numerator conducted a survey on a smaller representative set of Numerator panelists to gauge the compositional changes in income groups. The survey asked panelists their annual incomes in 2019 and 2024 as well as a multiple choice question for whether they and their household earn more, less, or about the same income in 2024 compared with 2019. After the data cleaning steps outlined in Appendix B, the final dataset has 5,644 respondents with reliable data on nominal incomes. We classify survey respondents as high-, middle-, and low-income consistent with the categorization we use for Figure 2 and calculate the percentage of respondents who stay in the same income bucket or move up or down in income buckets between 2019 and 2024.

The share of respondents in each income bucket in 2019 and 2024 is reported in Table B.1. While most respondents remain in their original income buckets, we also observe upward and downward movement across buckets. If respondents move across buckets, the biggest moves are to the nearest bucket, not across multiple buckets. Given inflation and wage gains, it is not surprising that we observe upward movement in income buckets. However, we also observe some downward movement, and using respondent commentary entered while completing the survey, we see that most of the downward movement is due to older respondents retiring during the pandemic.

We next proceed to a simulation exercise, the purpose of which is to assess what would happen to Figure 2 if we could observe changes in household incomes in the year these changes happen and reassign households into new income buckets. Unlike education levels, which remain fairly constant across panelists over time, the self-reported household incomes of panelists change over time, but our data only allow us to see their most recently reported household incomes. To simulate what would happen if we could observe panelists' incomes changing, we conduct a simulation exercise. First, we use the survey results reported in Table B.1 as an estimate for how income buckets would have changed between 2019 and 2024. Second, we artificially move panelists between income buckets in proportion to the changes in Table B.1. We take each panelist's spending for the entire period. We then take a randomly selected high-income panelists and reassign them to be middle-income in proportion to the share of high-income panelists in 2024 who were middle-income in 2019. We repeat this step for all other shares reported in the table. Once we move the appropriate share of randomly selected panelists to their reassigned income buckets, we recalculate the seasonally and inflation-adjusted average spending of low-, middle- and high-income households. We repeat this simulation 1,000 times. We then calculate confidence bands by taking the range of the 10^{th} and 90^{th} percentiles of spending across simulations.[8]

In panel B of Figure 3, we overlay the confidence bands of the simulation exercise for average spending by household income in 2024 on our main results from Figure 2. While moving panelists across income buckets changes the levels of average spending by household income, it does not change the finding that there is a divergence in the average spending of low- and high-income households. This suggests the divergence we observe is not likely to be caused by mis-measurement of households moving between income buckets. Even when we simulate for these movements between income buckets, we still observe a similar divergence in average spending between low- and high-income households.[9]

4 Spending by zip code income

Numerator data provides us with a unique advantage of exploring whether using zip code-level income as a proxy for household income leads to similar results. In this section, we apply zip code-level aggregation to Numerator's spending data to compare the results for spending by reported income in the previous section. The analysis of spending by zip code-level income follows Chetty et al. (2023).

Chetty et al. (2023) link zip codes of card transactions to the median household income in zip codes reported in the 2014-2018 ACS.[10] They then split the sample between high-

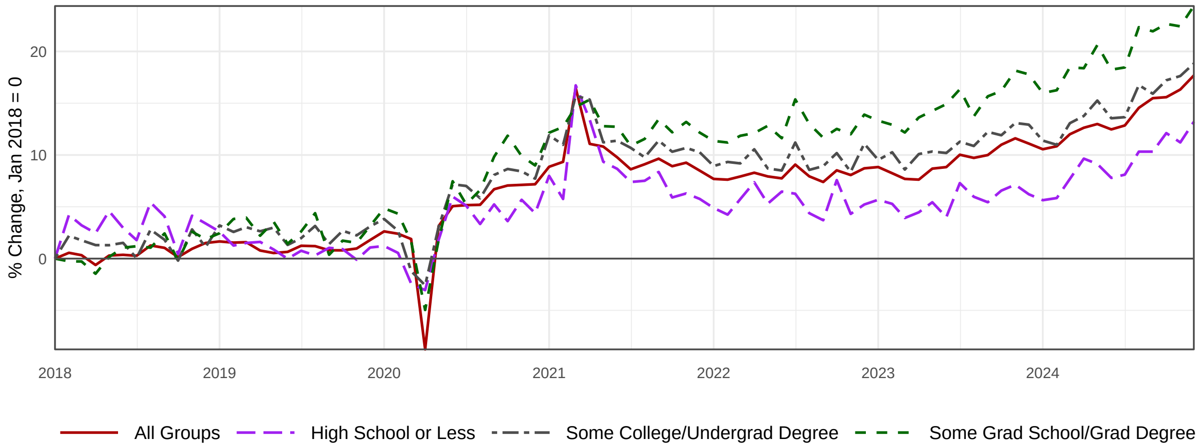
[8]We also experiment with taking the minimum and maximum across simulations. Taking the minimum and maximum does not change our conclusions.

[9]For readability, we show the confidence bands for 2024, which indicate that the divergence between low- and high-income groups still exists in 2024. When we look at the entire period and not just 2024, the conclusion holds that the divergence patterns using this simulation exercise look similar to our main results reported in 2.

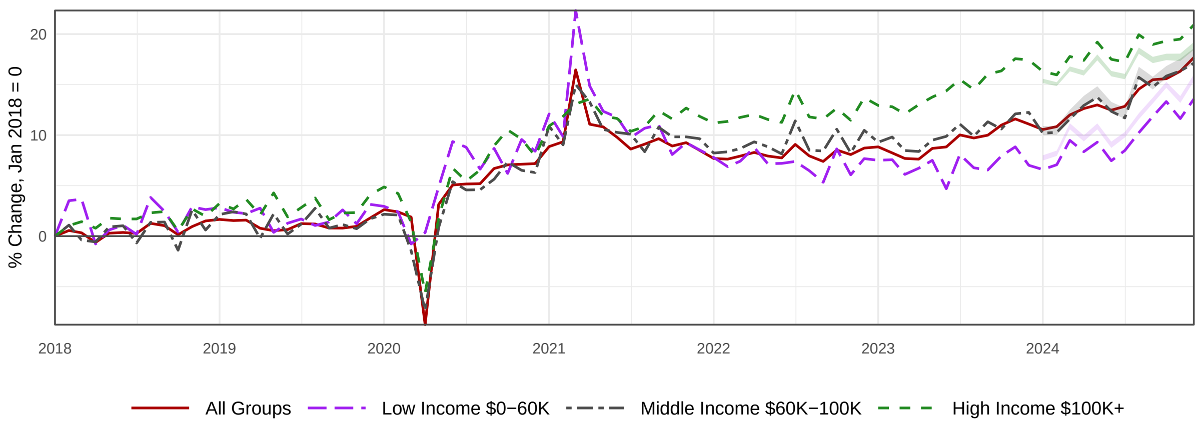
[10]The 5-year American Community Survey data cover all geographic units whereas the 1-year estimates only account for areas with at least 65,000 people.

Figure 3: Spending by education and simulation results for shifts across income groups

(A) Growth of average retail spending decomposed by education



(B) Growth of average retail spending decomposed by household income with simulated confidence bands based on the survey results



Note: The data are monthly from January 2018 through December 2024. All series are adjusted for inflation using the chain indexed PCE deflator for goods and food services excluding motor vehicles and are shown as growth relative to January 2018. All series are seasonally adjusted using X13-ARIMA-SEATS. The confidence bands show the range of the 10th and 90th percentile of spending across simulations that is designed based on the survey results reported in Table B.1. Solid purple, dash-dotted gray, and dashed green lines show spending by low-, middle- and high-income households.

(household income greater than $78,000 per year), middle- (household income between $46,000 and $78,000 per year) and low-income households (household income less than $46,000 per year). The dollar values for annual income correspond to the top, middle two, and bottom quartiles of median household income. Chetty et al. (2023) discuss that, although zip codes are a strong predictor of income in the U.S., they are not a perfect proxy for income (see also Chetty et al. (2020)).

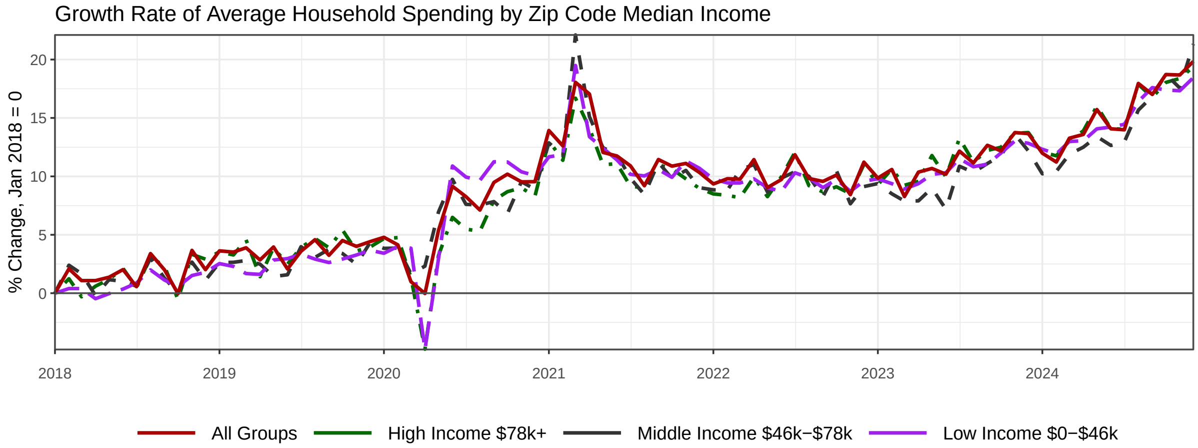
To replicate a similar analysis using Numerator data, we aggregate households' spending by the income groups that are given by zip code level median income. We map Numerator panelists' zip codes to the real median household income over the preceding 12 months from 2014 to 2018 in zip codes reported in the 2014-2018 ACS. The ACS publishes household income by 5-digit ZIP Code Tabulation Area (ZCTA). We use a crosswalk to match 5-digit zip codes to ZCTA.[11] For consistency with Chetty et al. (2023)'s analysis, we define the income groups in a similar way, i.e. high- (household income greater than $\$78,000$ per year), middle- (household income between $\$46,000$ and $\$78,000$ per year) and low-income households (household income less than $\$46,000$ per year). Appendix C compares Numerator spending series based on zip code aggregation with Chetty et al. (2023).

Figure 4 reports the average household spending when we use zip code aggregation instead of using panelists' self-reported household income. The spending patterns are similar to those reported in Figure 2 until roughly mid-2021, including the pre-pandemic period. The final stimulus check in March 2021 leads to a bigger jump for lower-income households. However, the divergence starting in mid-2021 between low- and high-income households, evident in the analysis in Section 3, disappears at the zip code level. Note that the income group categorization we use in the previous section is only slightly different than Chetty et al. (2023)'s, and reassuringly, the findings in this section do not change when we use the same income groups as in the previous section, as Figure C.2 shows.

The difference in spending patterns between self-reported income versus zip code median income decompositions makes a difference in macroeconomic deliberation. For instance, as the VAR analysis in Appendix D shows, the responses of high- vs low-income households to an uncertainty shock paints different pictures depending on which income measure is used. In summary, being able to analyze the heterogeneity in spending responses to any economic shock is crucial for accurate and timely policy responses.

[11] The crosswalk from ZCTA to zip codes is from UDS Mapper. Source: https://www.graham-center.org/maps-data-tools/uds-mapper.html

Figure 4: Growth Rate of Average Household Spending by Zip Code Median Income



Note: The data in the top panel are monthly from January 2018 through December 2024; lower panel from January 2024 through 2024. All series are adjusted for inflation using the chain indexed PCE deflator for goods and food services excluding motor vehicles and are in percent changes compared to January 2018. All series are seasonally adjusted using X13-ARIMA-SEATS. Solid purple, dash-dotted gray, and dashed green lines show spending by low-, middle- and high-income households.

5 Reported versus zip code income discrepancy

We can classify households low-, middle- and high-income based on their zip codes using the median zip code income information in ACS as in Section 4 and also based on the self-reported income group. In this section, we use these classifications in combination and calculate the shares of households that report having low-, middle- and high-incomes and live in low-, middle- and high-income zip codes.

Table 1 reports the discrepancy between the zip code implied income versus Numerator income groups. The first column specifies zip code income group and the second column shows the Numerator self-reported income groups. Values in other columns are the shares of households living in the low-, middle-, high-income zip codes in the first column who report the income groups in the second column in Numerator data. In summary, when the first and the second column do not match, the shares show the error that zip code-level income aggregations makes for each group. The ‘correct’ shares are in green shades.

Different dates in columns reflect the vintages of the data we use to calculate the reported versus zip code-level mismatch. As the Numerator panel rotates, we expect changes in the shares of households living in different zip-code areas. More importantly, since the Numerator panel is benchmarked to the ACS to construct a representative US panel, changes in the shares reflect population changes, rather than any specific feature of the data. The last panel of the table is the sum of the non-shaded rows providing the total discrepancy between the zip code aggregated income versus self-reported income groups.

Table 1: The discrepancy between the zip code implied income vs reported income groups, share as percent

Zip code Income	Reported Income	2018	2019	2020	2021	2022	2023	2024
Low	Low	71.7	71.2	67.7	66.2	58.8	56.6	58.7
	Middle	19.8	19.4	21.3	21.3	25.0	25.9	26.7
	High	8.5	9.4	11.0	12.5	16.2	17.4	14.6
Middle	Low	59.4	59.4	57.4	57.1	49.7	47.7	47.9
	Middle	27.3	26.7	27.4	26.8	29.5	29.9	30.8
	High	13.3	13.9	15.2	16.1	20.8	22.4	21.2
High	Low	43.4	43.7	42.2	42.8	37.8	35.6	36.6
	Middle	30.8	30.1	30.7	30.2	31.3	31.1	31.1
	High	25.9	26.2	27.1	27.0	30.9	33.2	32.2
Discrepancy	Low	28.3	28.8	32.3	33.8	41.2	43.4	41.3
	Middle	72.7	73.3	72.6	73.2	70.5	70.1	69.2
	High	74.1	73.8	72.9	73.0	69.1	66.8	67.8

Notes: The table calculates the share of Numerator panelists that live in low-, middle- and high-income zip codes in column 1 and reports the incomes in column 2 for three income groups: low ($0-$60K in annual household income), middle ($60K-$100K), and high ($100K+). Numerator income information updates periodically. The calculation of the shares in columns are based on yearly average of data between 2018 and 2024. The green shades indicate when zip code income groups match Numerator income groups, i.e. unshaded rows indicate the discrepancy between zip code aggregates and self-reported income groupings. Discrepancy is the sum of the unshaded rows for each income group. Due to rounding, some columns might not sum exactly to 1.

Based on Table 1, in 2024, only 59% of low-income households live in low-income zip codes, whereas nearly 27% that live in low-income zip codes are actually middle-income households, and almost 15% are high-income households. This is a change from 2018 when the share of low income households living in low income zip codes was much higher at almost 72% and the share of high-income households living in low-income zip codes was 8.5%. Similarly, in 2024, only 32% of households that live in high-income zip codes report high income in Numerator data, while the rest are low and middle-income households, whereas in 2018, nearly 26% of the high income households lived in high zip code areas.

Although there are year over year changes in the shares, the most significant change happens in 2022. With wage increases starting in 2022, households start becoming wealthier and the share of low-income households declines while the share of high income households' increases. The share of middle-income households remains fairly stable over time across most zip codes except those in low income areas where they have been on the rise. The discrepancy panel of the table provides a summary of these observations. Low income households are more likely to live in low income zip codes. But for households that self-report middle and high incomes, throughout 2018-2024, their self-reported household income grouping and their zip code median income grouping do not match.

These results point to conclusions that remained underrated until now. First, even before the pandemic-led demographic changes, there is a discrepancy in zip code implied versus self-reported income. In other words, even in 2018 which the latest ACS covers, zip code-income is not a sufficiently good proxy for self-reported household income. Second, income composition in zip codes changes over time. The scenarios that lead to such a discrepancy are not difficult to come by. Households start earning more but do not move to a higher income zip code. High-earners in high-income zip codes retire and start receiving a fraction of what they used to make as income. Households with middle to high income may live in low-income areas where houses are more affordable with the prospect of these areas gentrifying in the future.

In summary, survey-based zip code-level median income masks considerable heterogeneity in self-reported household incomes, which is important when trying to understand the spending behaviors of different types of consumers. Moreover, the ACS we use, also used in Chetty et al. (2023), reports median zip code income for the 2014-2018 period. The characteristics of U.S. households and the landscape in rural and urban areas have changed significantly during this period. All of these factors we discuss throughout the paper collectively indicate that zip code-level income is far from being a good proxy for household income and hence for gauging heterogeneity in consumer behavior.

6 Conclusion

The analysis in this paper has two objectives. First, we construct novel spending measures for low-, middle-, and high-income households using micro-level household retail spending data from 150,000 representative U.S. households. We validate our overall measure using officially published statistics. We regularly update our measure to track the state of the U.S. consumer. Second, and more importantly, our analysis attempts to document the discrepancy in using reported household income groups versus zip code median incomes as a proxy for household income levels. The latter masks the heterogeneity in spending that arises in the post-pandemic period. Using self-reported household incomes, we observe that starting in mid-2021, low-income households' spending slows while high-income households drive the strength in spending. Our analysis calls for caution in using zip code-level median income as a proxy for household income and highlights the importance of using alternative datasets with micro-level information to more accurately account for consumer heterogeneity.

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Online Appendix

A Benchmarking Numerator to MARTS

Numerator retail spending data allow us to decompose aggregate retail spending to 12 categories reported in the US Census Bureau's Monthly Sales for Retail and Food Services (MARTS) report. These categories are spending in 3-digit North American Industry Classification System (NAICS) level for the sectors listed in Table A.1. Hacioglu Hoke et al. (2024) establishes the reliability of Numerator's retail spending measure.

According to the U.S. Census Bureau:

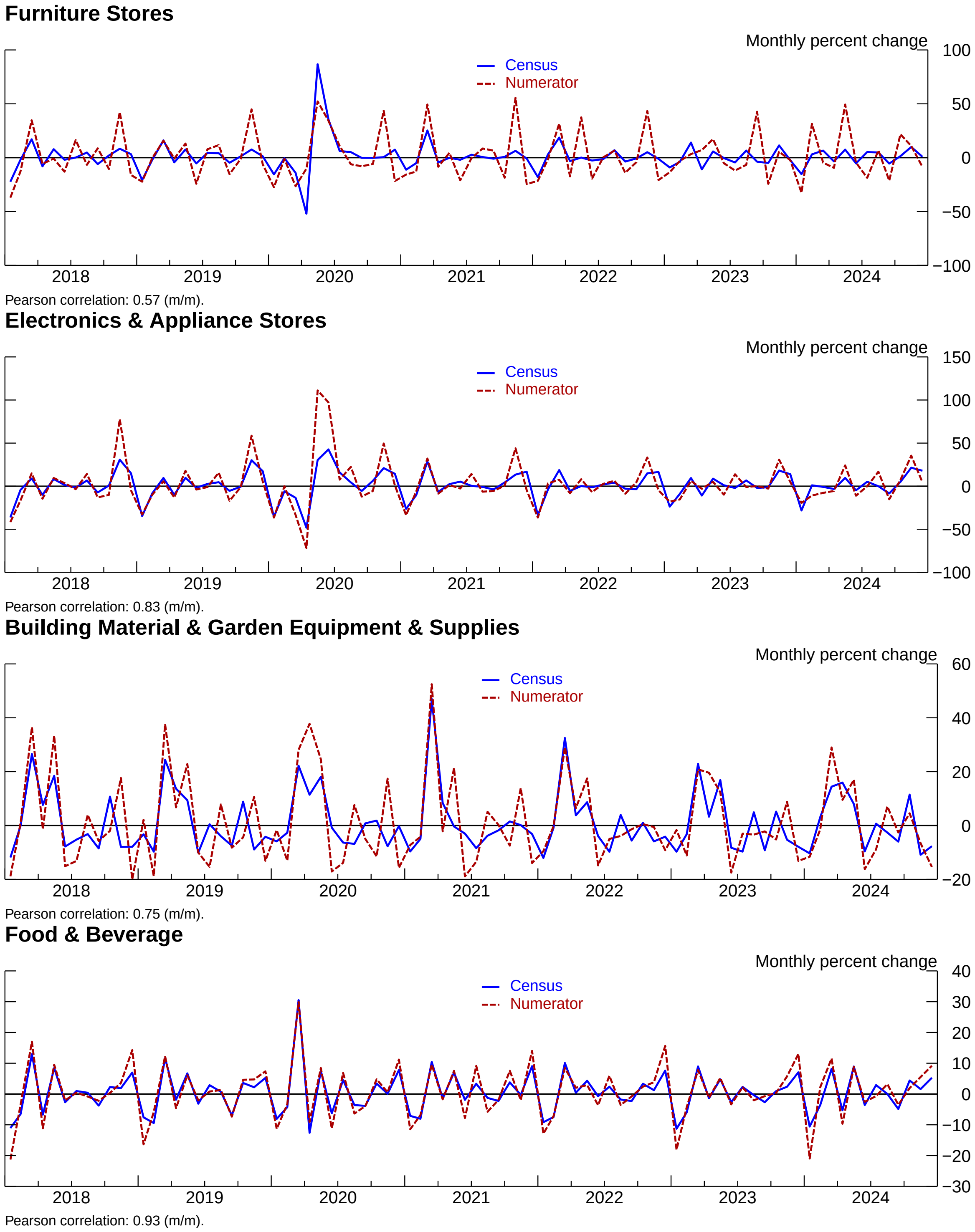
> MARTS covers firms classified in the Retail Trade and Food Services sectors as defined by the North American Industry Classification System (NAICS). Retail Trade, as defined by NAICS sectors 44-45, includes establishments engaged in selling merchandise in small quantities to the general public, without transformation, and rendering services incidental to the sale of merchandise.
>
> Two principal types of establishments classified in retail trade can be distinguished: i) Store retailers operate fixed point-of-sale locations, located and designed to attract a high volume of walk-in customers. They have extensive displays of merchandise, use mass-media advertising to attract customers and typically sell merchandise to the general public for personal or household use. Some store retailers also provide after-sales services, such as repair and installation; for example, new automobile dealers; ii) Nonstore retailers also serve the general public, but their retailing methods differ. Such methods include paper and electronic catalogs, door-to-door solicitation, in-home demonstration, "infomercials," selling from portable stalls or through vending machines. Food services, as defined by NAICS subsector 722, include establishments that prepare meals, snacks, and beverages to customer order for immediate on-premises and off-premises consumption.

Figure A.1 shows the month-over-month changes of Numerator and MARTS series for the 12 spending categories reported in Table A.1 and reports their correlations.

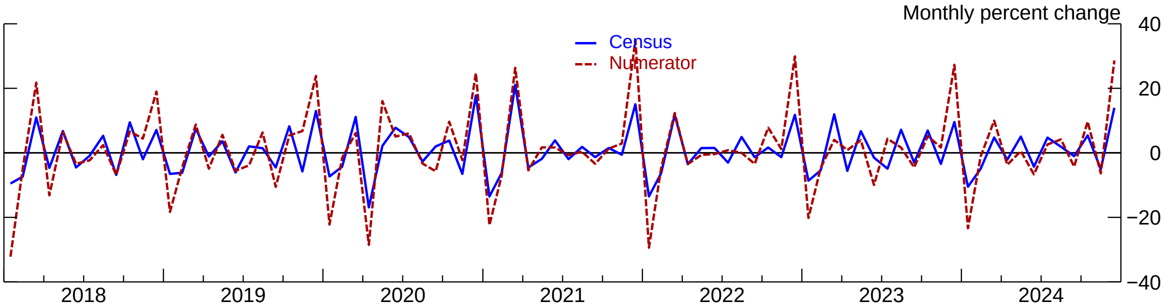
Table A.1: Spending categories at 3 digit NAICS level

NAICS	Spending Type
442	Furniture & home furniture stores
443	Electronics & appliance stores
444	Building material & garden equipment & supplies dealers
445	Food and beverage stores
446	Health & personal care stores
447	Gasoline stations
448	Clothing & clothing accessories stores
451	Sporting goods, hobby, musical instrument & book stores
452	General merchandise stores
453	Miscellaneous store retailers
454	Non-store retailers
722	Food services & drinking places

Figure A.1: Comparing Numerator spending categories with Census Bureau's MARTS

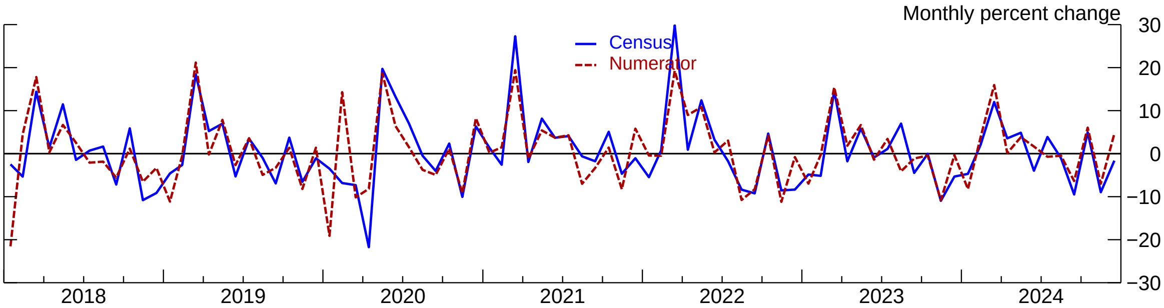


Health & Personal Care Stores



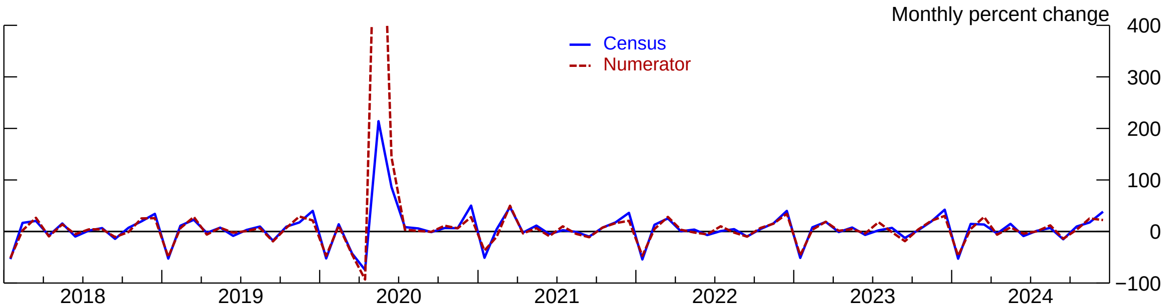
Pearson correlation: 0.85 (m/m).

Gasoline



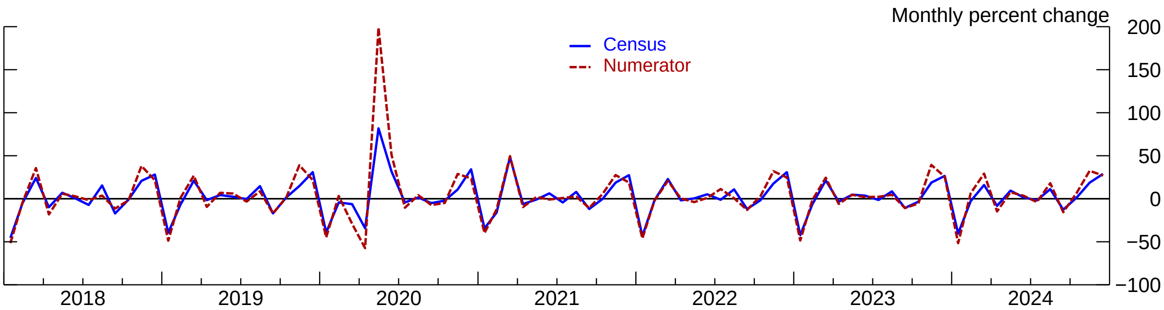
Pearson correlation: 0.76 (m/m).

Clothing & Clothing Accessories



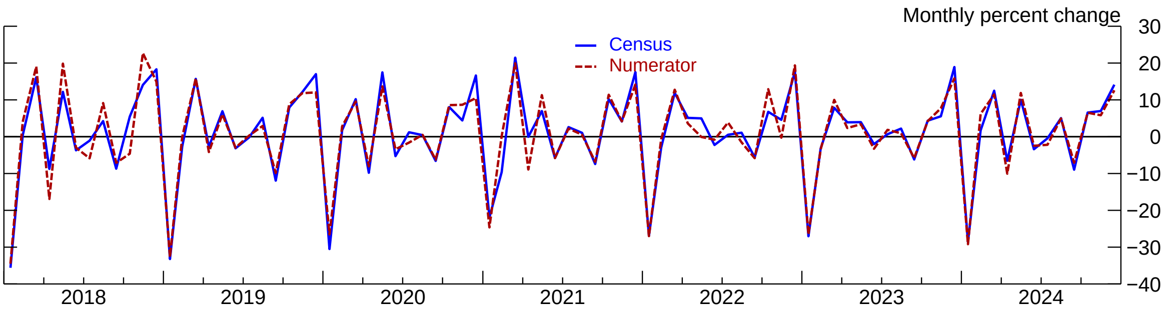
Pearson correlation: 0.82 (m/m).

Sporting, Hobby, Music, & Book Stores



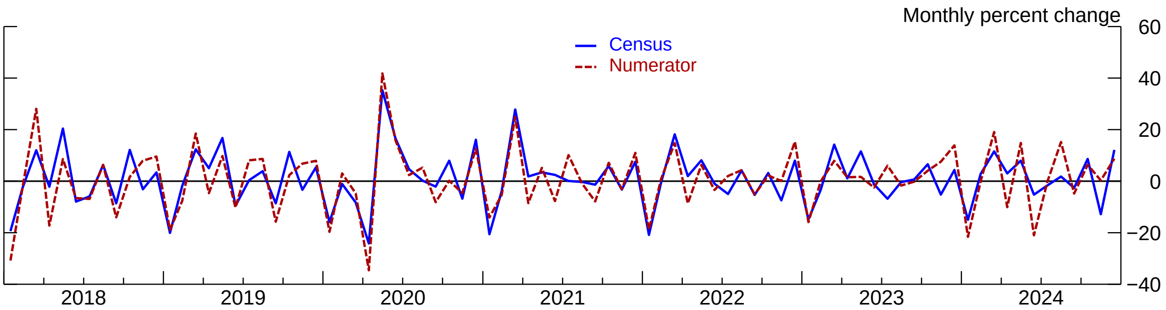
Pearson correlation: 0.9 (m/m).

General Merchandise Stores



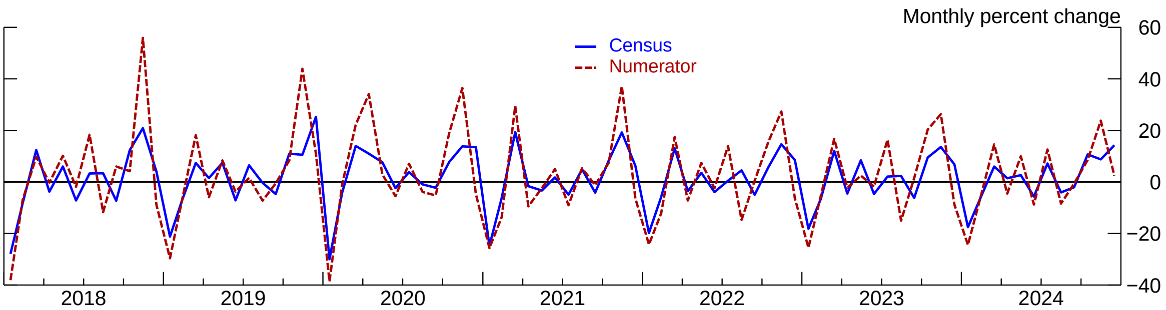
Pearson correlation: 0.96 (m/m).

Miscellaneous Store Retailers



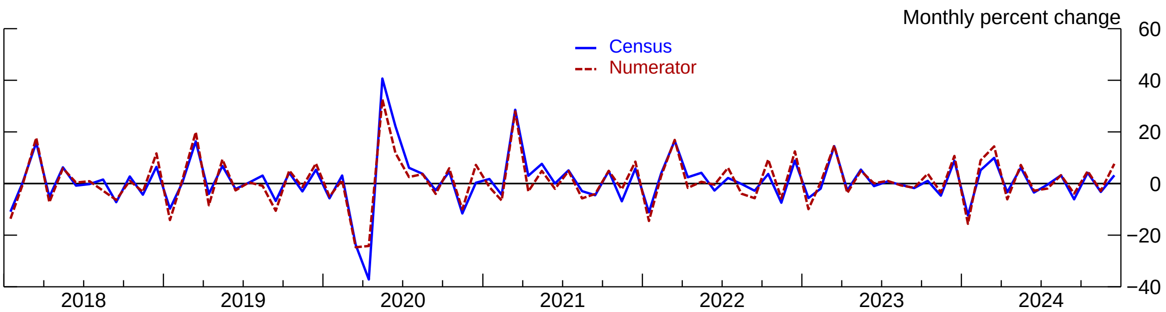
Pearson correlation: 0.81 (m/m).

Non−Store Retailers



Pearson correlation: 0.79 (m/m).

Food Services & Drinking Places



Pearson correlation: 0.94 (m/m).

Note: Monthly percent change for Census series in solid blue and Numerator series in dashed red. The data are monthly from January 2018 through December 2024. Not seasonally adjusted. Pearson correlation between the two series are reported below each figure.

B Survey Data and Results

Numerator conducted a survey among its panelists that helps us address potential concerns related to the construction of the income buckets in Section 3. First, a test wave was run on 100 panelists on October 25-28, 2024 to gauge the appropriateness of the questions and the validity of respondents' answers. Numerator subsequently adjusted the survey questions. We do not use any responses from this test wave in our analysis. Then the first wave of the survey was fielded to a random representative subset of 10,000 Numerator panelists on October 28, 2024, and 4,600 panelists responded by November 3, 2024. The second wave started with 10,000 different Numerator panelists on November 12, 2024 and concluded on November 19, 2024 with 4,618 responses. Overall, the survey received 9,218 responses, and the spending and income results were re-weighted to ensure representativeness.

The survey consisted of 13 questions and a commentary box and incorporated questions to understand the change in household incomes from 2019 to 2024. The four questions from the survey that help us in our analysis are:

1. *Do you and your household earn more, less, or about the same income now compared with 2019?* Respondents chose from three options: 'We earn more now'; 'We earn about the same now'; 'We earn less now'.

2. *About how much do you and your household earn now per year?*

3. *About how much did you and your household earn per year in 2019?*

4. If panelists chose not to provide an estimate for their incomes in 2019 and 2024, they were asked the following question: *Can you please provide a rough estimate of how much you think your household income changed between 2019 and today? Please use the sliding scale below to indicate your best guess for the percentage increase or decrease in your household income between 2019 and today.* They could respond by sliding a button along a bar to select a positive or negative percent value in 10% increments from -100% to +100%.

Among the 9,218 responses received, there were inconsistent entries for household incomes that are outlined below. Once we clean the data for these inconsistencies, the final dataset has 5,644 respondents' income information alongside all the other household characteristics Numerator data records for these households.

- **Missing zeros:** Reporting \$150,000 for 2024 income but \$147 for 2019 income. Similarly if 2024 and 2019 income are, e.g., \$50 and \$48. As long as the 2024 income provided by the panelists is consistent with the categorical bin information Numerator records for panelists, and their qualitative answer is also consistent with their entry, we corrected for the missing zeros.

- **Missing zero:** Reporting \$28,500 for 2024 income but \$2,400 for 2019. As long as the 2024 income provided by panelists is consistent with the categorical income group information Numerator records for panelists, and their qualitative answer is also consistent with their entry, we corrected for the missing zero.

- **Reporting an additional zero:** Reporting \$1,000,000 for 2024 income while reporting \$76,000 for 2019 income. As long as the 2024 income provided by the panelists is consistent with the categorical income group information Numerator records for panelists, and their qualitative answer is also consistent with their entry, we corrected for the additional zero.

- **Inconsistent incomes:** If either 2019 or 2024 income is reported, and the other income is missing but the percent change in income is provided with the information on if they earn more, less or the same now, we applied that percent change to their reported income to fill in the missing income. We performed this correction in very rare occasions when all other survey responses were consistent.

- **Erroneous or misleading entries:** If 2024 and 2019 incomes are inconsistent or they do not seem to reflect respondents' approximate income levels (e.g., reporting a number like \$123,456 or reporting \$3,000 for 2019 and then \$85,000 for 2024), and if information on how much they earn now and their income bucket do not give us a way to estimate their incomes, we eliminated these users.

- **Outliers:** After all these cleaning steps, we look for outliers in percent change in income between 2019 and 2024 and eliminate survey respondents who are below the

5% and above the 95% percentiles. We eliminate survey respondents that report earning more in 2024 with negative percent change in nominal income, and similarly eliminate respondents that report earning less in 2024 with positive percent change in nominal income. For respondents that report earning the same, we eliminate those whose income changes are anything aside from the 0-5% range to account for the small changes that might have affected these households' incomes which they neglected to report in the qualitative question of earning more, less, or the same.

Table B.1 presents the share of respondents in each income group in 2019 versus 2024. For example, 90.5% of the respondents who were high income households in 2019 remained high income in 2024 while 19.5% of middle-income households moved to high income in 2024. As expected, most of the respondents stay in the income bucket they are originally in but there is both upward and downward movement across buckets. If respondents move across buckets, the biggest moves are to the nearest bucket, not across multiple buckets. There is also some downward movement, and we can infer a couple of reasons using the commentary respondents provide while completing the survey. Most of the downward movement is associated with older respondents who retired during the pandemic period, followed by a small fraction of respondents who reported job losses.

Table B.1: Shares of respondents in each income group in 2019 versus 2024

2019 \ 2024	High Income	Middle Income	Low Income
High Income	90.5	9.5	0
Middle Income	19.5	70.0	10.5
Low Income	<0.1	9.4	90.5

Notes: Share of respondents in each income group in 2019 vs 2024 for three income groups: low ($0-$60K in annual household income), middle ($60K-$100K), and high ($100K+). Information on annual income in 2019 and 2024 collected by the custom survey run by Numerator in October and November 2024. Final data set has 5644 respondents' reliable nominal income information.

Note that younger respondents, such as those in early or mid 20s in 2024 record big jumps in their incomes over the five year horizon during which we explore the change in income using the survey. This is because these respondents probably got their first jobs upon graduating high school or college between 2019 and 2024. To address the big shift in their income bins, we check if our results look similar when we exclude Gen Z. In this case the dataset comprises 5,510 respondents. The differences in the results are negligible.

C Replicating Chetty et al. (2023)

Replication documentation for the Economic Tracker from Chetty et al. (2023) can be found at https://github.com/OpportunityInsights/EconomicTracker/tree/main/docs. The Economic Tracker uses aggregated and anonymized purchase data from consumer credit and debit card transactions from Affinity Solutions which is available starting on January 13, 2020. Spending by consumer zip code income relies on matching the zip codes they live in with the measured median household income provided by surveys. To replicate Chetty et al. (2023)'s analysis, we use Table S1903 from the 2018 American Community Survey, which contains the real median household income over the preceding 12 months from 2014 to 2018.[12]

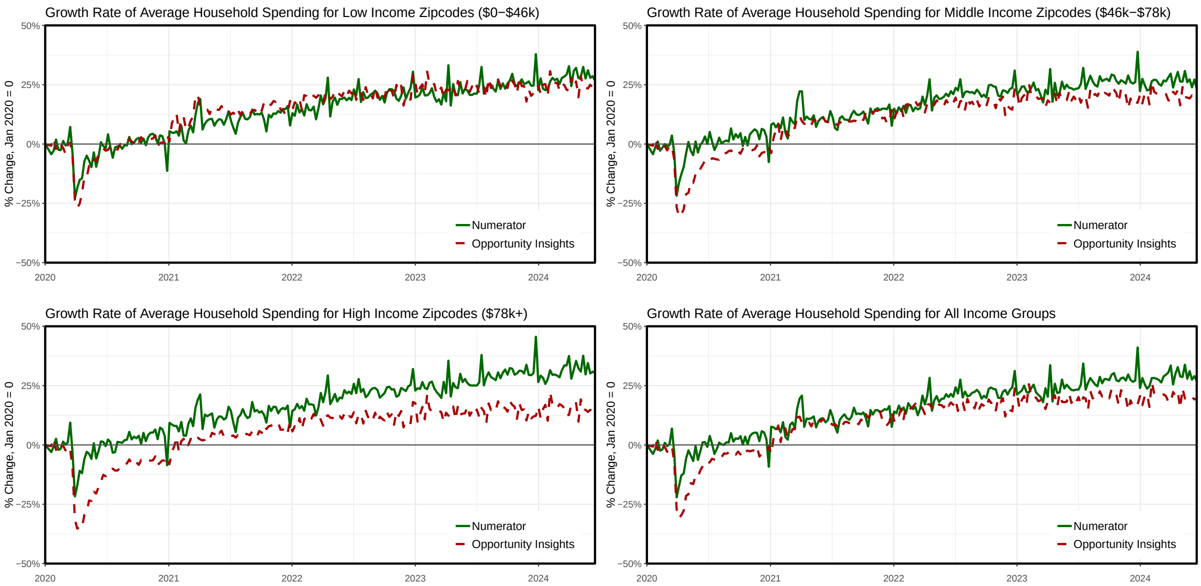
The American Community Survey publishes household income by 5-digit ZCTA instead of 5-digit zip code. We use a ZCTA to zip code crosswalk to identify the income levels that correspond to panelists' zip codes. The income groups in Chetty et al. (2023)'s analysis are slightly different from our original analysis. To replicate their results and compare how Numerator's zip code level income measures perform in comparison, we use Chetty et al. (2023)'s income group classification:

- High Income (top quartile of median household income; approximately greater than \$78,000 per year)
- Middle Income (middle two quartiles of median household income; approximately between \$46,000 per year and \$78,000 per year)
- Low Income (bottom quartile of median household income; approximately less than \$46,000 per year)

[12] The 5-year American Community Survey data cover all geographic units whereas the 1-year estimates only account for areas with at least 65,000 people.

The Economic Tracker is in weekly frequency until May 2024, so we construct weekly average spending measures using Numerator data through May 2024 to compare both spending spending measures. Figure C.1 shows the weekly Numerator spending series and the Economic Tracker spending series for different income groups and for all income groups combined when households are grouped based on zip code income. The Numerator and Economic Tracker series are very close for low-income households. There are differences for middle- and high-income households and overall spending which generally emerge in the post-2022 period. Note that Numerator only captures retail sales and food

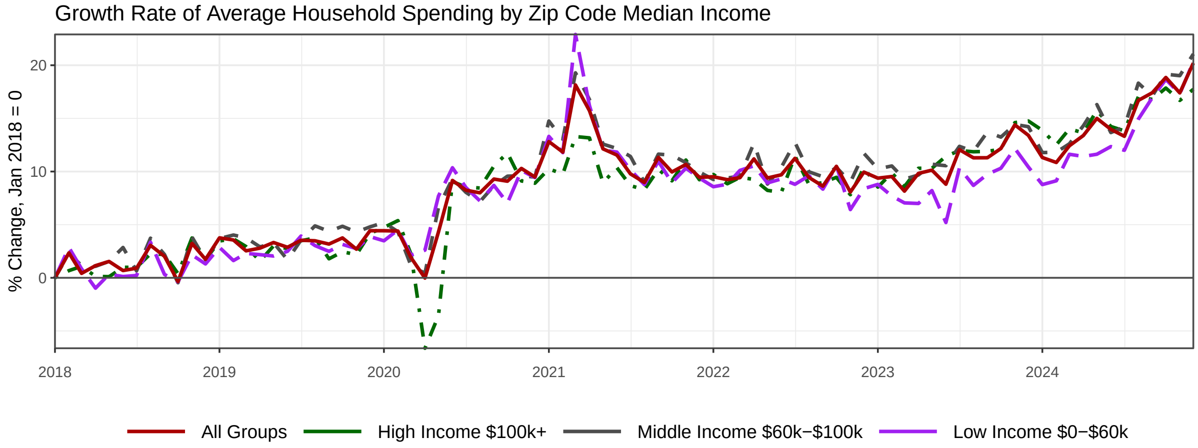
FIGURE C.1: Growth Rate of Average Household Spending by Zip code Income



Note: The data are non-seasonally adjusted, weekly from January 2020 through June 2024 and presented in percent changes compared to January 2020 as in Chetty et al. (2023). The data start from January 2020 due to the availability of the Opportunities Insight series. Red dashed line indicates the percent change in spending implied by Opportunity Insights. Green solid line indicates the percent change in spending implied by Numerator. Top left: low-income zip codes ($0-$46K); top right: middle-income zip codes ($46K-$78K); bottom left: high-income zip codes ($78K+); bottom right: all income groups.

services whereas card spending should also capture a broader array of services spending.

FIGURE C.2: Average household spending by zip code using the income classification in Section 3



Note: The data are monthly from January 2018 through December 2024. All series are adjusted for inflation using the chain indexed PCE deflator for goods and food services excluding motor vehicles and are in percent changes compared to January 2018. All series are seasonally adjusted using X13-ARIMA-SEATS. Solid purple, dash-dotted gray and dashed green lines show spending by low-, middle- and high-income households.

D Responses of spending to uncertainty shocks

Does it matter if we disregard the heterogeneity in spending? Yes. Different income groups adjust their spending in different ways in response to various economic and financial shocks. In this section, we demonstrate how spending responses of different income groups vary with uncertainty shocks.

We use a structural vector autoregression (SVAR) where we identify an uncertainty shock using Jurado et al. (2015)'s three-month-ahead real uncertainty measure by Cholesky decomposition. We have seven variables in a monthly VAR for the 2018-2024 period that includes the following: the term premium; industrial production; consumer price index; unemployment rate; house price index; average household spending by low-, middle-, high-income households, and the uncertainty index. Uncertainty is ordered last. All the variables except average household retail spending and the uncertainty index are from FRED. [13]

[13] The variables from FRED have the following mnemonics: term premium (10-year Treasury yield (DGS10) minus two-year Treasury yield (DGS2)), industrial production (INDPRO), consumer price index (CPIAUCSL), unemployment rate (UNRATE), and house price index (CSUSHPISA). The uncertainty index was downloaded in March 2025 from https://www.sydneyludvigson.com/

Figure D.1 presents the responses of low-, middle-, and high-income households' average spending to a 1 percentage point increase in uncertainty. The top panel reports the impulse response functions of the spending measures based on reported income in Numerator data, as in Figure 2. The bottom panel reports the results based on zip code-level income, as in Figure 4.

All households' spending declines after an increase in uncertainty. In the top panel, where we use the spending by reported income, the decline in spending by low-income households is much smaller in magnitude than that of middle- and high-income households. At the trough, spending by low-income households declines by 2.5 percentage points, whereas other households' spending declines by 10 percentage points. This is intuitive, as low-income households cannot cut back on spending as much, since most of their consumption basket constitutes essential items. This result is also in line with our observation during the pandemic, shown in Figure 2, that the biggest decline in spending is by middle- and high-income households (see also Cox et al. (2020) and for evidence in other countries Hacıoğlu-Hoke et al. (2021)). While higher-income households can cut back on larger shares of non-essential goods or simply postpone their spending, low-income households restore their level of spending more quickly. As the effect of uncertainty dissipates, spending by all households increases, although low-income households are the ones who restore their level of spending more quickly compared with other households.

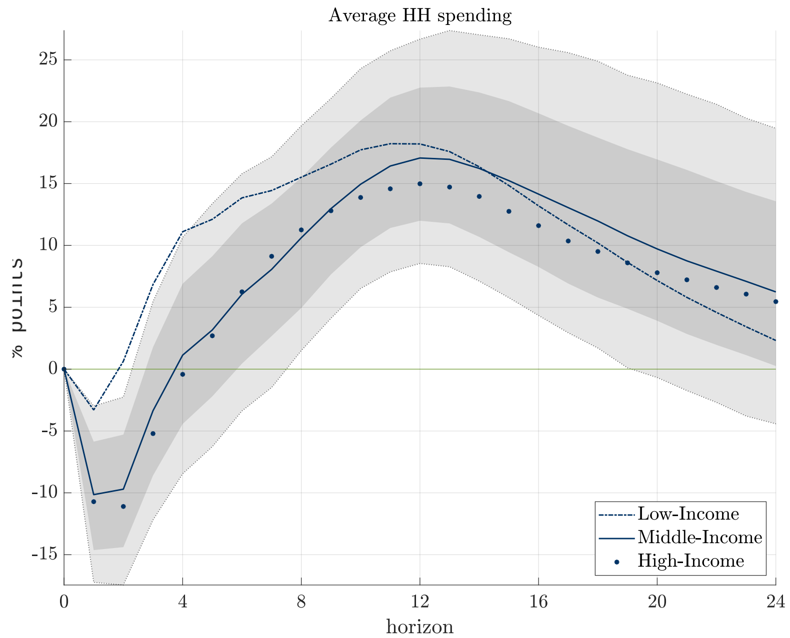
The bottom panel of Figure D.1, where we use spending by zip code-level income, provides mixed signals. First, the spending response of middle-income households is not significant for eight to nine months after the uncertainty shock. This result is at odds with the notion that consumers respond to uncertainty shocks. Second, the decline in the spending of low-income households is quite large and is almost the same as the decline in spending by high-income households. Given that low-income households do not have the level of income that would allow them to cut back spending as much as high earners, this result by itself emphasizes the importance of accurately gauging the heterogeneity

`macro-and-financial-uncertainty-indexes`. Industrial production, consumer price index and average household spending enter the VAR in log levels and rates, and the uncertainty index enters in levels. Using the term premium, instead of short-term interest rates, helps with the identification for the near zero-lower-bound period.

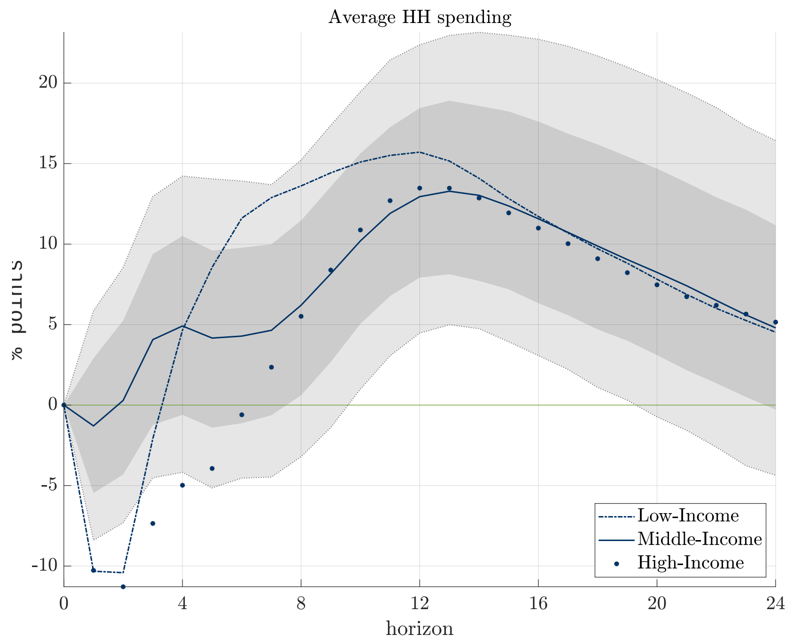
in spending by income groups. In summary, being able to analyze the heterogeneity in spending responses to an economic shock is crucial for accurate and timely policy responses.

FIGURE D.1: Impulse Responses of Spending by Low-, Middle-, High-Income Households to an Uncertainty Shock

Top Panel: Average Spending in based on Reported Income as in Figure 2



Bottom Panel: Average Spending based on Zip Code as in Figure 4



Notes: Monthly SVAR from 2018 to 2024 using 6 lags. Identification uses Cholesky decomposition where the uncertainty index is ordered last. Responses of average household spending to an uncertainty shock that increases uncertainty by 1 percentage point. Dark shaded areas denote 68% and light shaded areas denote 90% posterior credible sets. VARs include the following variables: the term premium, industrial production, consumer price index, unemployment rate, house price index, average household spending by low-, middle-, high-income households and uncertainty. The VAR includes pandemic dummies from March through August 2020, in the spirit of Cascaldi-Garcia (2022). Top Panel: Average Spending is based on Reported Income as in Figure 2. Bottom Panel: Average Spending is based on Zip Code as in Figure 4.