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SHOPPING FROM HOME

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ABSTRACT

Conducting a new survey on the Nielsen Consumer panel we examine the impact of working from home (WFH) on shopping, finding three key results. First, WFH changed shopping modes, increasing online shopping and the fraction of trips to stores on weekdays. Second, WFH increased total spending through increased product quantity and range, tilting expenditure towards food and general merchandise and away from health and beauty products. Finally, WFH increased prices paid by shoppers and lowered price elasticities due to a move towards higher-cost products and lower deal usage. The change in prices paid is concentrated among married households, driven by a redistribution of shopping responsibility within the household, especially when the new remote worker is male. We find that remote workers engage in more shopping trips but fewer minutes of shopping. Our results suggest that shifting to remote work increases prices paid for groceries by about 1%, highlighting how WFH is impacting households, retail and inflation.

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1. Introduction

The COVID-19 pandemic drove a four-fold increase in the ability for individuals to work remotely (WFH), rising from around 7% of days in 2019 to stabilize at just above 25% of days in 2026.[1] This paper seeks to understand how households respond to shifts in working arrangements in terms of their spending decisions. Working from home entails not only changes in how households work on the production side of the economy, but also in how they consume products, shopping modalities, and responses to prices.

We commissioned three waves of new survey questions in the Nielsen household panel. These surveys elicited household-specific information about working from home, online shopping behavior, modes of shopping, and other information about household food spending. We pair these new surveys with data on household goods purchased by these households that details product-level (UPC) attributes for all retail purchases, covering about $5000 in annual household spending. This data features long household panels, allowing for the matching of spending behavior both prior to and subsequent to the survey waves we run, alongside detailed household demographic data. We can also match this consumption data to firm-side price data with which we can construct local menus of prices at a UPC level. We report three key findings.

First, shifts to working from home were accompanied by changes in household shopping modalities. Working from home is associated with sizable increases in online shopping and in the share of trips taken on weekdays relative to weekends. While online grocery spending was relatively low pre-pandemic, it surged during the early months of COVID-19 and remained at elevated levels thereafter. WFH households, in particular, exhibited a higher propensity for online grocery shopping, reflecting a broader shift toward digital convenience. They also reduce shopping expenditure and frequency on the weekend, shifting towards weekday shopping.

Second, WFH changes the volume and composition of household retail shopping. Overall spending (and quantity purchased) increases by about 10%, concentrated in food and general merchandise, while spending on health and beauty products decreases. Accompanying this overall increase in spending is an increase in the breadth of purchases, with the number of distinct products purchased increasing nearly as much as the increase in spending.

[1] Days worked from home rose from 7% pre-pandemic to around 27% post-pandemic (Barrero et al. 2026).

Finally, households who switch to WFH tend to pay higher prices than other households. This price premium is true at several levels of product aggregation, reflecting several channels. WFH households pay higher prices for the same products, buy more expensive products within a product group, buy fewer goods on sale, and have a low demand elasticity with respect to prices than non-WFH households. These price premia were observed regardless of whether the shopping was conducted online or in-store, highlighting the broader implications of WFH on price sensitivity.

We then show that price effects are driven by changes in how shopping activity is allocated across household members. In particular, we show that increases in prices paid are concentrated among married households and appear alongside a reallocation of more shopping activities to the newly remote workers who undertake larger numbers of shopping trips but spend less time shopping. These effects on prices are 3 to 5 times larger when it is the male household member who begins working remotely. These changes are persistent, potentially reflecting differences in opportunity costs of time or preferences for particular goods.

These behavioral shifts suggest a growing emphasis on convenience and accessibility, even at the expense of cost efficiency, as WFH reshapes the balance between work, home, and consumer activities. These insights contribute to a deeper understanding of the economic and social consequences of hybrid and remote work on household consumption patterns. The persistent impact on grocery spending and price premia underscores the broader implications for inflation dynamics and retailer strategies in a post-pandemic economy. As WFH remains a stable feature of many households' lives, these results highlight the need for further exploration of how remote work reshapes consumer demand, pricing structures, and market competition.

These results have several implications. One is on time-use as WFH and online shopping reduces overall driving time. These shifts also have implications for where, when, and how households shop, raising questions about the impact on the retail sector. WFH households shift their shopping preferences toward premium or convenience-oriented products, contributing to higher average expenditures. Our pricing results also connect to the inflationary pressures that emerged in the wake of the pandemic, suggesting one driver of this is lower price sensitivity of WFH households, allowing producers and retailers to increase prices.

This paper is linked to a large literature on working from home. One part of this literature has explored the diverse consequences of WFH practices. A significant segment of this research examines its influence on productivity. Research by (Emanuel & Harrington, 2023; Gibbs et al.,

2023) underscores the productivity challenges encountered in fully remote work settings, indicating it may lead to reduction in output. On the other side, hybrid work models, blending remote and in-office work, show promising outcomes for productivity (e.g. Choudhury et al., 2021), (Bloom et al., 2022) and Angelici & Profeta, 2024).

A second strand of literature examines the relationship between WFH and various broader effects, including the real estate sector, examining WFH's impact on commercial (Bergeaud et al., 2023; Ghosh et al., 2022; Gupta et al., 2022) and residential property values (Davis et al., 2021; Mondragon & Wieland, 2022). Research also probes into the significant changes WFH brings to urban development (Davis et al., 2021; Delventhal et al., 2022). Finally, a considerable amount of research investigates WFH's implications within the academic sector (Aczel et al., 2021; Corbera et al., 2020; Guy & Arthur, 2020).

A third related literature strand studies the significant role of demographics in shaping working from home (WFH) trends, with education, gender, age, and the presence of young children identified as key factors. Education stands out as the most influential determinant, with higher educational attainment correlating with increased WFH rates due to job nature and flexibility (Autor et al., 2023; Dingel & Neiman, 2020). Age influences WFH patterns in a non-linear manner, with younger and older workers less likely to work from home compared to those in their 30s and 40s, highlighting different life stage needs (Barrero et al., 2023). Additionally, having young children at home marginally increases WFH rates, though education remains a stronger predictor of WFH likelihood when controlling for other factors (Aksoy et al., 2022). Beyond demographics, WFH rates vary sharply across industries and occupations, reflecting the task content of jobs and the feasibility of performing them remotely; teleworkable jobs are also more prevalent in higher-wage segments of the labor market (Dingel & Neiman, 2020; Adams-Prassl et al., 2020; Mongey et al., 2021).

Finally, our analysis also relates to a literature on household shopping intensity and prices paid, which shows that consumers pay different prices for identical goods depending on search effort, store choice, and purchase timing (Aguiar & Hurst, 2007; Kaplan & Menzio, 2015).

The paper is organized as follows. Section 2 discusses the Nielsen data as well as describing our survey of Nielsen households. Section 3 illustrates some trends and stylized facts related to working from home. Section 4 details how working from home drove changes in both household consumption and shopping modalities. Section 5 describes effects of working from home on both price levels and price elasticities. Section 6 concludes.

2. Data

2.1 Nielsen Consumer Panel Data

The Nielsen Consumer Panel (NCP) is a long-standing panel (2004-2023) of approximately 60,000 households per year. Nielsen designs the panel to be nationally representative and works to maintain the representativeness and completeness of the panel through various incentive mechanisms and by regular adjustments in the panel composition over time. Approximately 80% of the sample is retained from year to year. Broda and Weinstein (2010) and Einav, Leibtag, and Nevo (2010) describe and perform analyses of the NCP, finding it provides largely accurate coverage of household purchases. For the purposes of our paper, we employ NCP data spanning 2016-2023.

Overall, the panel seeks to measure household spending on consumer and household goods at a product (e.g. UPC) level, with more than 11 million distinct UPCs. To do so, households use both barcode scanners and diary entries to report the prices and quantities of all household goods purchased, along with information about the shopping trips themselves (e.g. information on retailers). This panel covers the near universe of household grocery and pharmacy items as well as small electronic items, kitchenware, garden equipment, and small home furnishings. It covers approximately $5,000 per year in household spending and includes spending at relevant merchants via delivery, in-store pickup, and catalog purchases.

These purchases are categorized into multiple levels: departments (11), product groups (119) and product modules (1,582). For example, departments include ‘Dairy’ and ‘Dry Grocery’, product groups include things like ‘Crackers’, ‘Dough Products’, and ‘Fresh meat’, while product modules include ‘Paper Towels – Jumbo’, ‘Salad Dressing – Low Calorie’ and ‘Snacks – Tortilla Chips’. The underlying data is at the UPC or product level, distinguishing between, say, a 20oz bottle of Coca-Cola and a 2L bottle and a 12-pack of 12oz cans of Coca-Cola. We also develop our own measure of ‘product codes’ (with 7,646 distinct values) for analysis requiring a finer level of aggregation than product modules without consolidating across products within a given brand (eg. Coca-Cola products). This granularity and specificity at a product level helps us to understand changes in shopping behavior considering changes in prices and quantities of particular items.

As part of our analysis, we focus specifically on households that shop online for grocery items. The NCP categorizes merchants according to type and includes the category of ‘online merchant’. However, this categorization does not include delivery or curbside pickup orders from primarily non-online merchants (e.g. delivery from Safeway or Albertsons grocery stores). To this end, we directly inquire about online shopping tendencies in our survey panel of households, finding much higher levels of online grocery shopping than would be implied by direct NCP measurement.

Demographic information about each household and its members is obtained at an annual level in the NCP. This data covers occupations, income, marital status, race, gender, and age of all household members as well as some characteristics of the home.

2.2 Work From Home Consumer Survey

Nielsen's Consumer Panel enables the execution of commissioned surveys on its participants, which facilitates linking their responses to the consumption and demographic data maintained by the panel. A participant's tenure in the panel usually spans 6-8 years, providing an extensive historical view of their consumption trends prior to the survey.

We designed and commissioned three custom survey waves with questions centered on the extent to which they worked from home as well as information regarding their shopping modalities (e.g. online vs. in-person shopping). The first wave, spanning May to June 2022, had 20,569 respondents from 16,128 households. The second wave, conducted from September to October 2022, received responses from 27,500 individuals in 21,652 households. The third wave, in September to October 2023, comprised 31,806 respondents from 25,003 households. Altogether, we collected data from 33,942 households, which is around 50% of the Nielsen consumer panel households during this period.

For each wave, we asked respondents to detail the number of days they worked during specific periods and their work location—whether from home or at their employer's or client's site. In each survey, these questions covered the pre-pandemic era, the early stages of the pandemic, and the week preceding the survey. Additionally, we gathered information on the proportion of shopping they personally conducted, their industry, their preferred WFH frequency, online shopping habits, and whether they had changed employers in recent months.[2]

Within our sample, approximately 50% of the participants are employed, with males constituting 43% of the sample and the average age being 55 years.[3] Furthermore, a large portion of our respondents responded to multiple survey waves.[4] Although the household members responding may vary between waves, we can match individuals in NielsenIQ's panelists' file to survey respondents using common variables (age, sex, and employment), enabling us to match respondents across waves at a high degree of accuracy.

In each wave, respondents are asked to report days worked from home, days worked, and shopping modality in the pre-pandemic period, early in the pandemic, and at the time of the survey. We therefore have multiple responses to the same questions regarding pre-pandemic and early pandemic work and shopping modality. We find that individual responses to recall-type questions are highly consistent across waves (Appendix Figure A.2.A notes that over 80% of respondents report the exact same work modality and about 90% differ by at most 1 day). For work modality we can also validate our survey responses by comparing them with the American Community Survey (ACS). The ACS contains a question about commuting, to which people may respond that they worked at home. This question was included in the ACS prior to pandemic, so is not subject to recall concerns. We use the 2018-2019 ACS to compute WFH shares by occupation and state and compare to our data, finding a strong relationship with a slope coefficient near 1 (Appendix Figure A.2.B).[5]

Given that we have multiple responses corresponding to pre, early and post pandemic periods, and responses from multiple household members, we average across all available responses within time periods. At the individual level, we compute the average, across survey waves, of pre-pandemic and early pandemic recall responses to generate values for those periods. For post-pandemic we average "current WFH" responses across all available waves, noting our surveys ran

[2] In Appendix Figure A.1, we show the precise format of two of the primary questions from the surveys, which prompt respondents to report working locations and shopping modalities.

[3] Our primary analysis is based on data from those who are employed. Appendix Table A.1 displays a range of summary statistics for the survey respondents as compared to the broader Nielsen Consumer Panel.

[4] We have responses spanning all three waves for 5,768 NCP households, responses for waves 1 and 2 for 7,283 households, for waves 1 and 3 for 7,256 households, and for waves 2 and 3 for 16,390 households.

[5] We map ACS occupations to Nielsen occupations and assign each Nielsen individual the ACS WFH share that corresponds to their own occupation and state of residence. We then compare the ACS WFH share with that individual's own reported work modality. As the ACS question likely captures full-time WFH (see Buckman et al. 2025), we define an indicator equal to one if the NielsenIQ respondent recalled working from home full-time prior to the pandemic.

from May 2022 to October 2023, a period of relatively stable WFH after the rapid falls in late 2020 and 2021 (Barrero et al. 2025). When aggregating to the household level, we use the average WFH across up to two household heads, weighted by the average number of days worked (NielsenIQ identifies up to one male head and up to one female head for each household). Our results are robust to different approaches, such as including other adult household members, using first or last responses, or dropping individuals with inconsistent recall. Overall, the typical household has two adult members and responds in a consistent way to recall questions.

We capture online shopping in two ways. First, we ask panelists whether they usually shop online for groceries. Second, the scanner data provides the retailer "channel" for each transaction, so we can also compute the share of purchases made at online retailers. In Wave 3, we also asked panelists to select which apps they use when ordering groceries online: grocery store-specific app (e.g. Kroger, Albertsons, Safeway, Publix); Amazon Fresh/Whole Foods; third party app (e.g. Instacart); other or unknown.[6] Overall, our survey allows us a greatly expanded ability to study online-shopping behavior that is unobservable with the Nielsen data alone. We also use the survey to identify the main shopper in the household as the individual who does the most shopping. When aggregating shopping survey responses to the household level, we use the responses given by the main shopper at that wave.[7]

2.3 Nielsen Retail Scanner Data

The Nielsen Retail Measurement Services (RMS) Scanner data complements the NCP data, examining the same breadth of product sales but from the perspective of retailers rather than consumers. The RMS data is constructed from point-of-sale systems in over 40,000 individual

[6] Appendix Table A.2 and Appendix Figure A.3 show the type of online grocery shopping captured by our survey. While the Nielsen online channel classification captures third-party app and Amazon usage well, it does not capture usage of grocery store-specific apps that make up the majority of online shopping activity. In fact, the correlation of observable Nielsen online shopping with grocery store app usage is negative, consistent with households mostly utilizing one type of grocery store, either online or in-person. A transaction occurring in-person at a store is assigned the same retailer code as one that occurs through the store's app.

[7] In Wave 1, we did not ask about the share of shopping the individual was responsible for. We also did not ask who did most of the shopping during and before the pandemic. We therefore use the responses of the wave 2 main shopper for wave 1 household-level outcomes, and pre-pandemic and early pandemic recall questions. The sum of individuals' self-assessed shopping shares sometimes exceeds one (e.g. both household heads claim they did most of the shopping). We define the "main shopper" as the individual reporting the maximum share of shopping done. In the case of a tie, we assume the female head is the main shopper.

locations across about 100 separate retailers throughout the United States. These retailers cover sectors like grocery, pharmacy and drug stores, as well as other mass merchandise stores, liquor and convenience stores.

The RMS data comprises location-by-week-by-item information about product prices and quantities sold. That is, price and quantity data for over 10 billion transactions per year covering the millions of unique products (UPCs) in over 1,000 product modules that are also tracked by the Nielsen Consumer Panel. These sales are worth over $200 billion per year, making up a large portion of overall retail spending in this category (over 50% of sales in grocery and drug stores).

We utilize the RMS data to understand not only purchases by individual households but also the menu of costs that they conceivably face in their location for any given product. That is, the NCP data can show us the prices actually paid by the household, while the RMS data can show us the prices offered across different retailers in the household's area that the household, for one reason or another, chose not to patronize.

3. Trends in Working from Home

We start by examining the percentage of days spent WFH for different periods, as measured by our survey and by data from the US Survey of Working Arrangements and Attitudes (SWAA). Figure 1.A plots the fraction of days worked from home across five separate periods. Given three waves of surveys across approximately 18 months, we are able to obtain measures of working from home intensity across five distinct periods.

Before the pandemic, the average fraction of days worked from home, according to our survey, was near 10%. During the early months of the pandemic, this increased to almost 45% before stabilizing at a lower level of around 30% in 2022 and beyond. These NCP survey responses correspond well with data taken from the ATUS (for pre-pandemic estimates) and the SWAA (for the early pandemic and post-pandemic periods). Overall, our survey data track the dramatic rise and the persistence of working from home in households across the country.

Variations in WFH patterns are noticeable across different educational levels of the household head, as shown in Figure 1.B. We compare the intensity of WFH in the post-COVID period (2022-2023) among Nielsen households of different education types and as reported by

SWAA respondents, with both surveys revealing that households with less educated heads have fewer WFH days.

We also benchmark our data on WFH shares against the American Community Survey and the Current Population Survey by occupation and state. We find a very tight connection between these measures, with a 1 percentage point increase in ACS or CPS WFH predicting a 1pp increase in our Nielsen survey measure (Appendix Figure A.4). Hence, over time, education groups, occupations and income levels our NCP WFH data aligns closely with data from the ACS, CPS and SWAA surveys.

4. Working from Home, Shopping Modalities, and Consumption

4.1 Online Shopping and Working from Home

The shift in remote work drove a widespread increase in the amount of online grocery shopping done by these households after 2020. The grocery sector has long lagged other retail expenditures in the share of this spending done online. For instance, by the end of 2019, approximately 11.5% of all retail expenditures were done online. In contrast, in 2019, only about 6% of grocery spending was conducted online.[8] During the onset of the pandemic, e-commerce grew strongly overall, but with particularly rapid growth within the food and beverage sector.

We measure online shopping activity in two separate ways. First, we directly survey NCP members in each of our three survey waves. We ask a question about how the household shopped for groceries – in-store or online – in each of the reference periods in the survey (see Appendix Figure A.1 for the exact question).[9] Figure 2.A shows large changes in the propensity to shop online among all groups. In the pre-pandemic period, average levels of online grocery shopping were less than 5% for most subgroups, with only the ‘young’ (those under 50) exceeding that amount, at 6%. During the early parts of the pandemic every subgroup increased its use of online grocery shopping, with then receded somewhat during the post-pandemic period, but remained substantially higher than the pre-pandemic.

[8] https://www2.census.gov/retail/releases/historical/ecomm/19q4.pdf

[9] The survey question asks households which of three methods households utilize: in-person, online for pickup, or online for delivery. However, given the similarities in behavior among households who order online for pickup and those who order for delivery, we display results grouping together households who use either of the two online ordering options.

Figure 2.B displays the average propensity to shop online for households that worked in-person, fully remotely, or partially remotely for three periods of time. Fully or partially remote households tended to see higher levels of online grocery ordering even prior to the pandemic, with the difference between these groups and the fully in-person group growing during the pandemic. The fully working from home sub-group saw the highest average level of online grocery shopping (around 33%), while fully in-person households tended to shop online about 18% of the time during the early pandemic. Even after the pandemic, the difference in online grocery shopping persisted between these groups, with fully remote households having approximately a 50% higher level of online ordering than fully in-person households.

To focus on a more causal analysis we turn to an alternative measure of online shopping, the fraction of products bought through an 'online merchant' as categorized by Nielsen, which is available back to 2015. This measure considers shopping to be through an online channel if the retailer is entirely an online merchant.[10]

To investigate the potential shift to online shopping, we first define the share of WFH in a given period as:

$$WFH\ measure_t = \frac{sum\ of\ WFH\ days\ for\ household\ heads_t}{sum\ of\ days\ worked\ for\ household\ heads_t} \quad (4)$$

Nielsen identifies one male and one female household head (where applicable). Where male and female heads responded to our survey at least once, our WFH measure reflects their combined work arrangements. Cross-referencing information on panelists provided by Nielsen, we identify cases

[10] Appendix Table A.3 demonstrates that these self-reports of grocery shopping via app are, in general, highly correlated with observed online shopping merchant usage in the Nielsen data. We estimate: $Y_{h,t} = \alpha_h + \delta_t + \beta_1 OnlineSurvey_{h,t} + \beta_2 WFH_{h,t} + \beta_3 OnlineSurvey_{h,t} \times WFH_{h,t} + \epsilon_{h,t}$ Where the dependent variable $Y_{h,t}$ is the share of spending at retailers Nielsen classifies as "online" and $OnlineSurvey_{h,t}$ is the self-reported online shopping indicator from our survey. Households that report that they often conduct a majority of their grocery shopping via delivery or pick-up orders have a more than 100% increase in shopping done through online merchants. Excluding household fixed effects, thus relying more on cross-sectional variation, we find that the effect of such self-reports is associated with a more than 250% increase in shopping through online merchants. Appendix Figure A.5 shows the relationship between our two separate measures of online shopping (survey based and Nielsen merchant category) plotted against the fraction of days that a household works from home, conditional on household and time fixed effects. In both cases, we see strong positive relationships. Appendix Figure A.6 breaks down these trends in online grocery shopping by WFH group across categories of products. We see that the largest absolute increases in purchasing from online merchants is observed in non-perishable (and more easily transportable) categories such as general merchandise, health and beauty, dry grocery goods, and non-food grocery. However, even for categories such as produce or dairy products, we observe very large relative jumps in online shopping, especially for households engaging in remote work.

where a working household head was present and did not respond to our survey. We received responses for all working household heads in 82% of respondent households. We then calculate the change in WFH ($\Delta ShareWFH_h$) as the household's current share of days worked from home less its pre-pandemic share of days worked from home.

To investigate the impact of WFH on online shopping we run the following regression:

$$Online\_Shopping_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$$

where $Online\_Shopping_{h,t}$ is the average fraction of spending done via an online channel, as measured by Nielsen, $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home, and $\delta_h + \alpha_t$ are a full set of household and year fixed-effects. The coefficient $\hat{\beta}_t$ on $\Delta ShareWFH_h$ is allowed to vary by year and is plotted with its confidence intervals in Figure 3 left-panel.

First, we can see that there is no significant pre-pandemic correlation in online shopping propensity and the pandemic induced change in working from home. Controlling for household fixed effects removes any pre-pandemic trends in the post-pandemic change in WFH and online shopping. Second, there is a clear and highly significant jump from 2020 onwards, signifying that households which increased their level of WFH post-pandemic saw a rise in online shopping. The magnitude of this impact is large, with each day of increased remote work per week associated with 0.3 percentage point increase in online shopping, which corresponds to an approximate 10% increase relative to the baseline average level of online shopping before the pandemic.

The right panel of Figure 3 examines a different shopping mode change, which is the share of shopping trips occurring on a weekday (Monday to Friday inclusive). This also shows no pre-pandemic trend with respect to the post-pandemic change in WFH. From 2020 there is a significant jump, reflecting the shift from weekend shopping to weekday shopping. This is likely facilitated by those who are working from home having the opportunity to drive to local suburban grocery stores or accept grocery deliveries during the working week.

4.2 Working from Home and Consumption

Spending on all items covered by Nielsen, including most grocery and pharmacy items, increased by about 10% post 2020 as many consumers shifted towards home production of meals.

These changes in spending were not evenly distributed across households or across categories. To see to what extent WFH contributed to this rise in spending Figure 4 plots the annual coefficients from the regression, where $Y_{h,t}$ is either total or category level log-spending

$$Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t} \tag{1}$$

As before, α_t and δ_h represent the time and household fixed effects, respectively.

Figure 4 left-panel reports results for logged total spending as the dependent variable. First, we see that households that increased WFH intensity did not see any pre-pandemic different trends in spending. This suggests that before the pandemic groups that saw changes in their levels of working from home did not have different growth rates of spending. Second, from 2020 onwards we see a significant spending jump of 9% (9 log points) on average. This suggests aggregate spending increased by nearly 10% for a household that switched from zero remote work to full remote work from 2020 onwards. One likely explanation is WFH employees spend more mealtimes at home, so consume more food and groceries. They may also have higher spending to equip their home offices, and to more generally improve their home living conditions due to an increased amount of time spent at home.

Figure 4 right-panel displays the results from separate regressions where the dependent variables are logged spending on goods in one of the four listed categories (Non-Food Grocery, Food, General Merchandise, and Health and Beauty). Nearly all categories see an increase in expenditure - notably food, non-food grocery and general merchandise. The one notable exception being the Health and Beauty category, which drops due to large reductions in spending on beauty, cosmetics and grooming supplies, presumably because households are spending less time physically in the workplace so have fewer requirements related to their appearance.

In Figure 5 we also examine differences in the composition of products and retailers patronized by these households. These figures show annual coefficient plots from regressions of the form in (1). Figure 5 top-left panel shows that households which saw increasing WFH after the pandemic tend to purchase a greater quantity of food, which we estimated by using the subset of about half of products for which we also have a unit of weight. The magnitude of this increase is 9%, similar to the increase in overall spending. Figure 5 top-right panel shows households also buy a greater number of unique products. The magnitude of the increase is 7%, which is similar to the

9% overall increase in spending, suggesting that the rise in spending is driven in part by a larger range of purchased goods. Finally, in Figure 5 bottom left panel we see that increase in spending and number of unique UPCs purchased by a household is not accompanied by an increase in the number of retailers visited[11]

5. Effects on Price Levels and Price Elasticities

Changes in household working and shopping behavior have the potential to drive changes in the prices that households are exposed to and transact at, so we examine the extent to which WFH impacts prices paid.

5.1 Impacts of WFH on Discounts and Prices Paid

Table 2 reports results from a household-year level regression jointly investigating the impact of working from home and online shopping on a range of price-related outcome variables. In Column 1 we start with a basic price measure – the share of products sold on deals or coupons. We find that the fraction of purchases on sale or bought with coupons is significantly lower while working from home. This 'deal share' is measured as the dollar-weighted fraction of purchases made on sale or using a coupon. This coefficient on WFH of -0.844 implies that moving from fully in-person to fully-remote is associated with about 0.8 percentage point reduction in deal-share. Given that approximately 20 % of total spending was made in deal purchases before pandemic, this corresponds to a 4% decline relative to this benchmark.

In column 2, we turn to more direct measures of changes in prices paid by households. As described in Section 2.2, we can compute both the menu of prices available to households in a location as well as the prices actually paid by the household for a particular product. We use this to create a product-specific measure of price premia that we can utilize to better understand how households change shopping habits.

In particular, using the RMS data, we compute the premium that households pay over a benchmark consistent with untargeted shopping (over retailers and time) in their local area.

[11] Appendix Figure A.7 notes that we do see a temporary increase in turnover of retailers that households frequent in the months following the onset of the COVID-19 pandemic in 2020. However, the number of unique retailers they visit is not significantly affected by WFH status. Similarly, the average price level of retailers that WFH households visit is unchanged during this period.

Benchmark spending for household h over year y is created by summing over products household h purchases on trip j, and then summing over trips taken in year y:

$$Benchmark\ spending_{h,y} = \sum_{j=1}^{n_{h,y}} \sum_{u \in U_{h,j}} Q_{t_j,h,u,z_j} \times \bar{P}_{u,z_j,y(t_j)} \times \frac{\bar{P}_{u,t_j}}{\overline{P_{u,y(t_j)}}} \ (1)$$

where Q_{t_j,h,u,z_j} is the quantity of product (UPC) u purchased by household h on trip j (which takes place in week t in zip code z). $\bar{P}_{u,z_j,y(t_j)}$ is the average retail price of product u in zip code z in the calendar year of week t. As inflation is non-negligible over some years of our sample, we also multiply by $\frac{\bar{P}_{u,t_j}}{P_{u,y(t_j)}}$, where $\bar{P}_{u,t_j}$ is the average national price of product u in the week of trip j and $P_{u,y(t_j)}$ is the average national price of product u in the year of trip j.

We also calculate actual spending by household h over year y as:

$$Actual\ spending_{h,y} = \sum_{j=1}^{n_{h,y}} \sum_{u \in U_{h,j}} Q_{t_j,h,u,z_j} \times P_{t_j,h,u} \ (2)$$

We then compute the price premium as the ratio between the two measures:

$$Price\ premium_{h,y} = \frac{Actual\ spending_{h,y}}{Benchmark\ spending_{h,y}} \ (3)$$

Column (2) of Table 2 denotes the results of a regression where the dependent variable is this measure of product-specific price premium. We find that a 1 unit increase in WFH activity is associated with a 0.3 percentage point increase in prices paid for the same exact products. While households are paying more for identical products, they may also change the composition of products that they are buying towards more expensive varieties.[12]

To incorporate shifts in product choice, we also construct price premium measures that compare the prices households pay relative to the average price of products within the same product module or product group, rather than for an identical product. This allows us to investigate changes

[12] Across the board, households tend to pay less for a product than they would be expected to pay if engaging in untargeted random shopping because households tend to respond to lower prices by buying more and stocking up. Because households respond to price changes, on average the price paid relative to the average price available is less than one, indicating that consumers generally purchase items for less than the average price that product is offered at in their local area. This accords well with the literature on deals and sales (eg. Baker, Johnson, Kueng (2024)), which finds substantial stocking up and deal-seeking behavior.

in the propensity to purchase higher-priced products within a given product module or group, something that we abstract from in our price premium measure, which holds the product fixed. We can calculate this premium measure at the product group or the module level as the price of products purchased with the price of other items in the same product group.[13]

The process for calculating the product module price premium proceeds similarly. Note that this only captures product switching within groups or modules, which are still quite specific (e.g. one module is American processed cheese slices). This could involve switching to more expensive brands or smaller pack sizes with a larger unit price.

In Table 2, columns (3) and (4), we find that moving from in person to fully remote increases spending by about 1.1% relative to paying the module average unit price and over 1.5% relative to the average group unit price. Whereas our price premium measure captures paying more for an *identical* product, this shows that households pay more for *highly similar* products, as well, perhaps substituting towards higher quality products within a group or module. Combined, the two suggest a price paid of around 1% to 2%. Moreover, in these regressions, we do not observe any effects of online shopping on price premia. That is, while WFH tends to dramatically increase online shopping propensities, the effects on price premia seem to stem directly from WFH rather than any change in online shopping.[14]

Figure 6 displays figures which follow our previously-defined dynamic annual regressions for group price premia and for our measure of deal shares. We find results that are consistent with the results displayed in Table 2. In particular, the shift to working from home causes large and persistent increases in price premia and decreases in deal shopping among affected households.

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[13] For the product group price premium, we calculate the ratio as: $SpendingRatioGroup_{h,y} = \frac{Benchmark\ spending_{h,y}}{Group\ Average\ Spending_{h,y}} - 1$. We define group average spending as: $Group\ Average\ Spending_{h,y} = \sum_{j=1}^{n_{h,y}} \sum_{u \in U_{h,j}} Q_{t_j,h,u,z_j} \times \frac{\bar{P}_{u,z_j,y(t_j)}}{GroupRatio_u} \times \frac{\bar{P}_{u,t_j}}{P_{u,y(t_j)}}$ and $GroupRatio_u$ is the median of the ratio of UPC to group price, $\frac{\bar{P}_{u,z_j,y(t_j)}}{\bar{P}_{g(u),z_j,y(t_j)}}$, across store zip codes and time for each UPC.[13] Note that $Benchmark\ spending_{h,y}$ reflects the products the household actually bought, whereas $Group\ Average\ Spending_{h,y}$ corresponds to paying the group average price. That is, buying products that are more expensive than the group average pushes up $SpendingRatioGroup_{h,y}$.

[14] Appendix Figure A.7 displays dynamic versions of the individual product price premia regression and the price relative to module premia. We find results consistent with the regression coefficients in Table 2; households that shift to work from home tend to increase prices paid across both of these margins. Similarly, Appendix Figure A.8 displays the annual retailer premium coefficients, highlighting that shifts in WFH are associated with a flat trend in retailer-specific price levels. This is in contrast to the pronounced increase in per-trip spending driven by both the increased quantities of goods purchased by households as well as increases in prices paid per item.

Returning to Table 2, we investigate two potential channels of these price premia. The first relates to the 'deal potential' for products purchased by households. That is, we seek to understand the extent to which the products bought by households have the potential to be purchased during a period with a steep discount by measuring the 10th percentile of observed prices for a particular product. Products with higher 10th percentile prices (relative to their own average price level) have smaller opportunities for discounted buying than products with very low 10th percentile prices.[15] Moving from in-person to WFH increases the 10th percentile price premium by about 0.2 percentage points. In other words, households who engage in more remote work tend to purchase products where there is less opportunity for purchasing products on sale.

Finally, in column 6 of Table 2, we test whether households are shifting towards retailers with higher prices. While we previously noted little change in the number of distinct retailers frequented by WFH households, the possibility exists that households are simply shifting towards higher quality or higher amenity retailers.

We define a retailer-level price premium as follows. First, we use the RMS to compute the average price at which UPC u is sold by retailer r in year y, $\bar{P}_{u,r,y}$. We then compute each household's counterfactual spending if they had paid the retailer's annual average price for each item they purchased from that retailer:

$$Retailer\ average\ spending_{h,y} = \sum_{j=1}^{n_{h,y}} \sum_{u \in U_{h,j}} Q_{t_j,h,u} \times \bar{P}_{u,r_j,y(t_j)} \times \frac{\bar{P}_{u,t_j}}{\overline{P_{u,y(t_j)}}} \quad (6)$$

Next, we compare this with our benchmark spending measure which uses the average annual price *across all retailers* in the same 3-digit zip code:

$$Retailer\ Price\ Premium_{h,y} = \frac{Retailer\ average\ spending_{h,y}}{Benchmark\ spending_{h,y}} - 1 \quad (7)$$

[15] We compute the 10th percentile price premium for each product across all transactions, $p10_u$ (recall the price premium is expressed as a share of the benchmark price, $\bar{P}_{u,z_j,y(t_j)} \times \frac{\bar{P}_{u,t_j}}{\overline{P_{u,y(t_j)}}}$). We then compute counterfactual 10th percentile spending for each household and year as: $SpendingP10_{h,y} = \sum_{j=1}^{n_{h,y}} \sum_{u \in U_{h,j}} Q_{t_j,h,u} \times \bar{P}_{u,z_j,y(t_j)} \times \frac{\bar{P}_{u,t_j}}{\overline{P_{u,y(t_j)}}} \times (1 + p10_u)$. We then compute $PremiumP10_{h,y} = \frac{SpendingP10_{h,y}}{Benchmark\ spending_{h,y}} - 1$. This measure captures the component of the price premium that comes simply from buying products that tend to have fewer or smaller deals available.

The retailer price premium therefore captures shopping at retailers where the items purchased are, on average, priced higher than an identical item at other local retailers.[16] We find the households shifting to remote work, while paying higher prices for individual products, tend not to shop at significantly more expensive retailers.

While we can directly control for self-reported online shopping behavior and spending at online merchants in Table 2, we attempt to provide additional assurance that we are truly identifying effects of working from home on prices. Appendix Table A.4 restricts the sample to households that only shop in-person and forego shopping online altogether. As well as reporting that they usually shop in person, these households did not report using any grocery shopping apps and less than 0.5% of their spending is at online merchants. Again, we see that WFH tends to drive up the prices paid by households, reduces the number of deals utilized, and has no effect on the quality of retailer they patronize.

In Appendix Table A.5, we further condition on household age, occupation, education, race, ethnicity, high/low income and size interacted with year dummies. Our results are robust, indicating they are not driven by differential trends for household groups that are correlated with WFH. Appendix Table A.6 repeats this exercise for shopping modality and consumption outcomes and shows these results are also robust.

5.2 Changes in Consumer Price Elasticities

In addition to examining differences in levels of prices paid as households shift towards working from home, we also test directly for a difference in price elasticities for such households. Table 3 displays results from regressions of logged quantities on logged prices. We measure these quantities and prices at a product-week-WFH group level to allow for sufficient aggregation across households such that we minimize the number of weeks where the quantity purchased of a given product is zero. As we describe in Section 2.1, a 'product' is a collection of UPCs that are likely to correspond to different pack sizes and variations of the same fundamental product (e.g. diet coke).

[16] While it is in principle possible for use to compute average prices at retailer x zip code level, this dramatically increases the size of the retail price dataset, which is already very large. This is unlikely to affect our conclusions as large national retailers typically price nationally (DellaVigna & Gentzkow, 2019).

To reduce issues arising from excessive numbers of 0 purchase weeks within a product, we restrict attention to most frequently-purchased 7,646 products which account for 80% of spending.

$$Quantity_{w,i,t} = \exp\left(\delta_{t,w} + \alpha_{i,w} + \beta_1 \ln(Price)_{w,i,t} + \beta_2 \ln(Price)_{h,t} * WFH_{Group_w}\right) + \epsilon_{w,i,t} \quad (10)$$

Here, mean prices measure the average price of a given product ‘i’ in week ‘t’ for work from home group ‘w’. Work from home groups are measured using our survey responses. A WFH household is defined as one that shifts at least half of their days of work to being done at home from the pre-pandemic to post-pandemic periods. Finally, ‘Post’ is defined as the period following March of 2020. We include product group, WFH group, and weekly fixed effects. We utilize a dependent variable of quantities (rather than logged quantities), using a Poisson pseudo-likelihood regression rather than a linear regression to obtain a price elasticity. This allows us to include product-WFH group-weeks with zero sales. In columns 1-5 we restrict to products that have, on average, at least one reported sale per week in a given year.

In column 1, we highlight a strong negative relationship between prices and quantities, both within product and over time. In column 2, we note that price elasticities fell in the period following the pandemic. Households became less price sensitive, on average, to changes in posted prices for Nielsen-covered goods.

Column 3 then includes an interaction denoting whether the household shifted towards WFH in the period following the pandemic. We find a strong positive coefficient, indicating that households that shifted to WFH tended to be much less price elastic than non-WFH households across the entire sample. However, our key specification in column 4 demonstrates that this lower level of price elasticity of the WFH households is driven solely by the period in which they actually engage in remote work. Column 4 includes the triple interaction of price, WFH, and Post, testing whether WFH households *changed* their price elasticities in the period following the pandemic in which they shifted towards WFH. We find that their shift to WFH coincided with a decrease in their price elasticity, with this falling by about 0.09, or 25% on a base of 0.366 These differences in measured elasticities are large relative to the cross-sectional differences in elasticities across households with differing demographic characteristics.

Columns 5 and 6 display variants of the exercise in column 4. In column 5, we use a linear regression with $\ln(Quantity_{w,i,t})$ as the dependent variable. This drops product-WFH group-weeks with zero sales. In column 6, we relax the restriction of excluding products without at least one reported sale per week in a given year. Across both specifications, we find that shifts towards WFH tended to decrease price elasticities. The coefficients in column 5 are smaller, however, suggesting a greater price elasticity impact of WFH at the extensive margin.

Figure 7 displays the dynamic version of these elasticity results, plotting annual coefficients of the double interaction of WFH and logged prices, rather than utilizing a single indicator for the 'Post' period. We find that the WFH households have no trend in price elasticity in the years leading up to the pandemic (and to their shift towards WFH), but tend to start decreasing their price elasticity in the years following the pandemic. Finally, Appendix Table A.7 displays these estimates separately by product category. We see that perishable grocery items and non-food merchandise are driving this reduction in price sensitivity by work from home shoppers.

5.3 Shifts in Shopping within the Household

While online shopping is unable to explain the changes in prices paid and price sensitivity exhibited by WFH households, we explore another potential mechanism for these results. In Table 4, we pair our Nielsen data with data from the American Time Use Survey (ATUS) to examine the impact that WFH activity has on the allocation of shopping within married households. In columns 1 and 2, we utilize data from our survey to test whether the shopping responsibility shifted within a household as household members began to work remotely. We find that the responsibility for shopping tended to shift more towards household members who were working from home, after controlling for employment status or restricting to employed households. Column 3 shows this increase in shopping by WFH household members is driven by men, who have about 5-fold stronger relationship (total coefficient of 0.049) than women (baseline coefficient on 0.01).

Columns 4 turns to data from the ATUS, noting that WFH respondents are significantly more likely to have engaged in shopping activities on a given day. Despite this increase in shopping activity, column 5 shows that the time spent shopping, conditional on shopping, fell by 3.9 minutes for respondents who worked from home. Finally, column 6 reports results consistent with our survey data, where WFH activity is associated with increases in the probability of shopping using home delivery relative to in-person shopping.

In total, these results reflect the notion that increases in WFH tend to shift shopping activity towards the WFH worker in a household but reduces time spent shopping. A shift in the household member who does the shopping may contribute to less familiarity with prices and deals and a reduction in time spent shopping, potentially driven by higher opportunity costs of time, one factor driving up prices paid and reducing price elasticity.

Table 5 tests one element of this mechanism. We return to the setting of our Nielsen surveys and data, re-running some of our earlier specifications on spending and prices separately for single and married households. In contrast to married households, single households are mechanically unable to shift the allocation of shopping responsibility within the household. Here, columns 1-4 examine the differential impacts of WFH on price ratios and deal perceptions, finding that the entirety of the effect is found among married households. In contrast, we observe in columns 5 and 6 that both single and married households change the composition of purchases and buy a larger range of UPCs. In addition, the final two columns note that the shifts in shopping to weekdays from weekends are identical across both single and married households. Overall, while WFH affects the type of products purchased and the timing of shopping for all households, only married households see strong price impacts.

After determining that many of the effects of shopping and price outcomes are solely present for married households, we test for differences in WFH effects based on the gender of the newly WFH household member in Table 6. In columns 1-3, we note that several effects are present in household shopping and spending, regardless of the gender of the household member switching to WFH. WFH among both men and women tends to push up the number of items purchased, the variety of items, and the frequency of shopping during weekdays. In contrast, when men are the household member switching to remote work, the increase in spending is approximately triple that of when women switch, and the price impacts are five times larger. In the final column, we note that, while actual prices paid are much higher for men, they have no significant change in the perception of deals. This may be driven by the fact that these newly remote workers have less experience with such shopping trips and have different baseline expectations of deals.

6. Concluding Remarks

Our study highlights significant shifts in consumer behavior associated with increased working from home (WFH) following the COVID-19 pandemic. We find that households with higher WFH rates have increased overall grocery spending and product variety, while their choice of retailers remained relatively unchanged. This behavior indicates a strategic adjustment in consumption patterns where convenience and access to diverse products within fewer retail options take precedence. Furthermore, the increased adoption of online grocery shopping among WFH households reflects a broader trend toward digital convenience, though it often results in higher costs due to reduced sale-seeking behavior and less strategic timing of purchases.

Our results also underscore the persistent impact of WFH on consumption behavior, even as COVID-era policy restrictions have lifted. The higher prices paid by WFH households point to an important trade-off between convenience and cost-efficiency. Notably, WFH households are more likely to pay premiums on the same products compared to their in-person counterparts, driven in part by shifts toward goods with fewer price promotions.

The shifts in prices and elasticities tend to be driven by a redistribution of the responsibility for shopping within the household following the onset of remote work. Especially for men, an increase in shopping responsibilities coincides with higher spending and higher prices. The persistence of these price effects suggests that WFH households might prioritize accessibility over price sensitivity, especially as they limit their shopping trips and rely more heavily on online retail. Consequently, these shifts have potential implications for inflationary pressures in specific consumer sectors and could shape future retailer strategies and pricing models as remote work remains prevalent.

Finally, our findings contribute to a deeper understanding of how WFH reshapes not just workplace dynamics but also household consumption habits. The persistent preference for online shopping and premium products among WFH households highlights a shift in consumer expectations and preferences that retailers and policymakers may need to consider going forwards. As WFH has become a stable component of many households' lives, the intersection of work and consumption patterns continues to transform. Further research into these shifts may yield valuable insights into long-term effects on pricing trends, consumer demand diversity, and the retail landscape.

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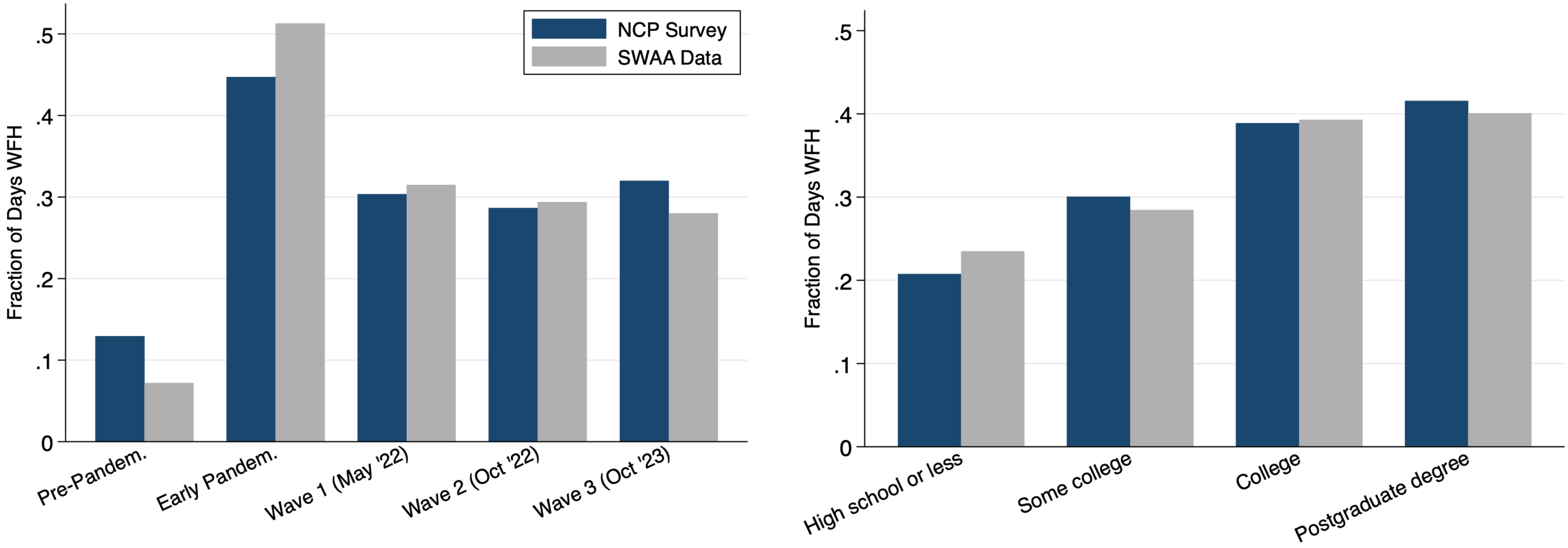
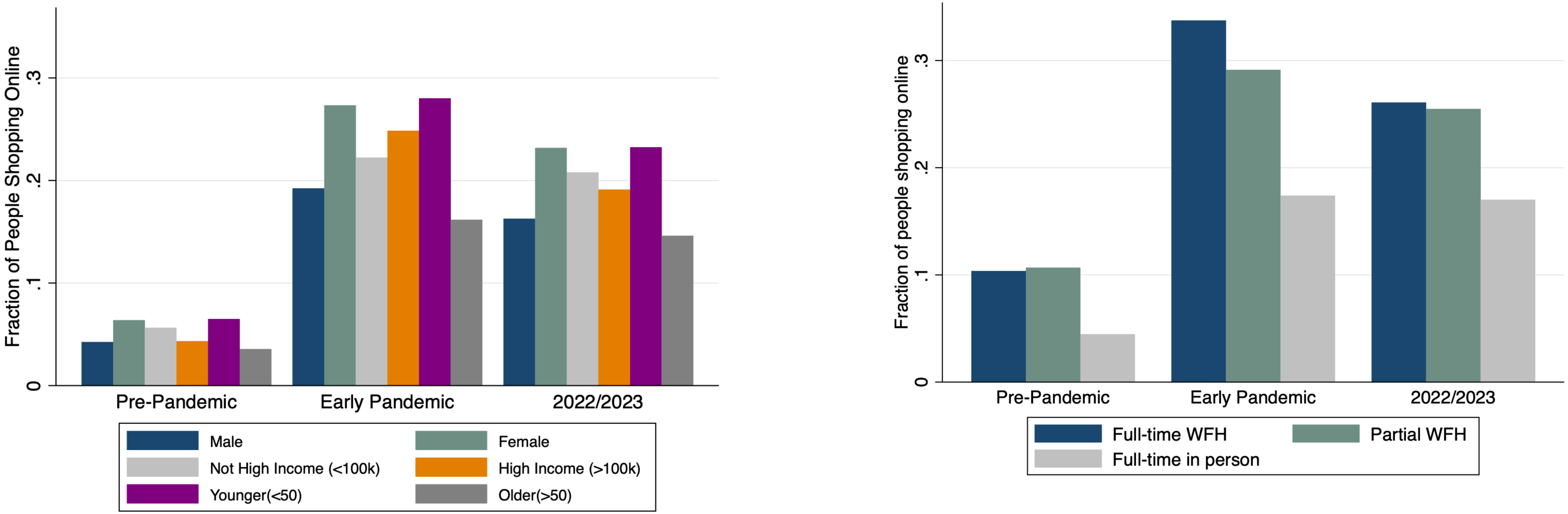
Figure 1: Work From Home Increased Post-Pandemic, Particularly for Educated Workers



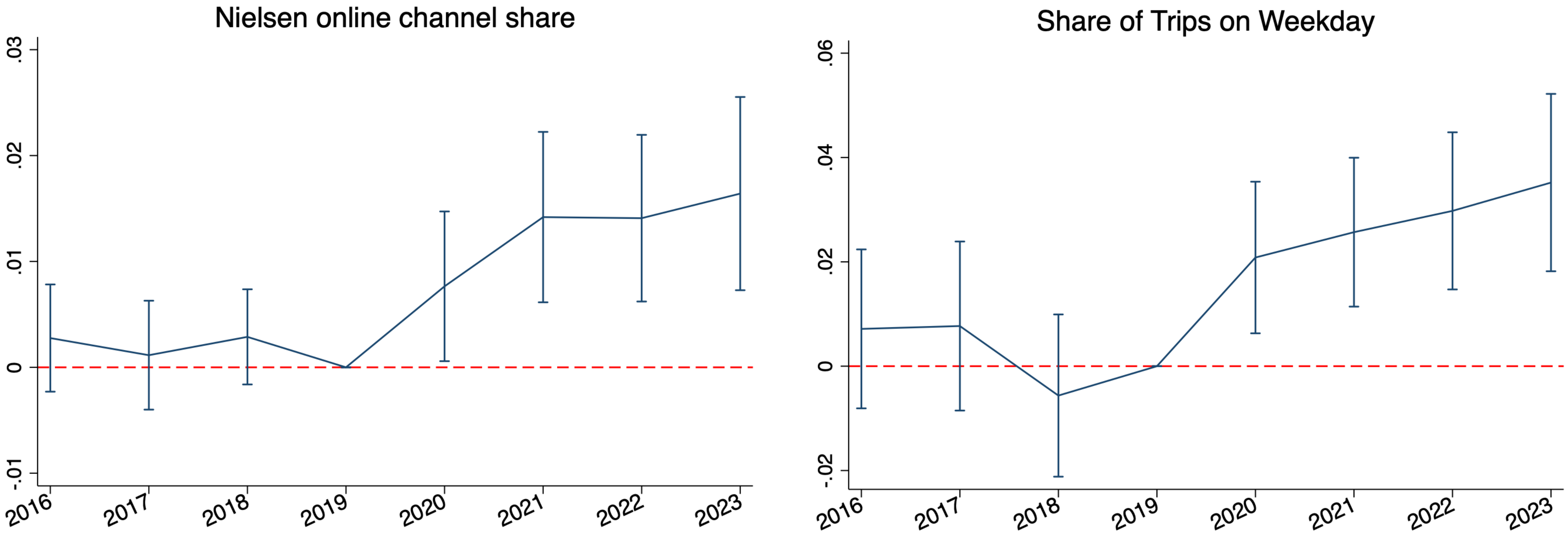
Notes: NCP (Nielsen Consumer Panel) sample surveyed individuals who worked at least 3 days per week in the relevant period. Fraction of days worked from home represents the ratio of days worked from home to the total days worked. The mean of this value is calculated across individuals, using survey weights. Individuals with inconsistent answers between survey waves are dropped. Also plotted is data from U.S. SWAA (Survey of Working Arrangements and Attitudes) for comparison. The Pre-Pandemic data point is from ATUS. The total NCP (SWAA) sample size is 20,715 (310,336) individuals for the graph on the right and 17,592 (310,336) individuals for the graph on the left. The total SWAA sample is 310

Figure 2: Online Shopping Saw a Broad Increase Post-Pandemic



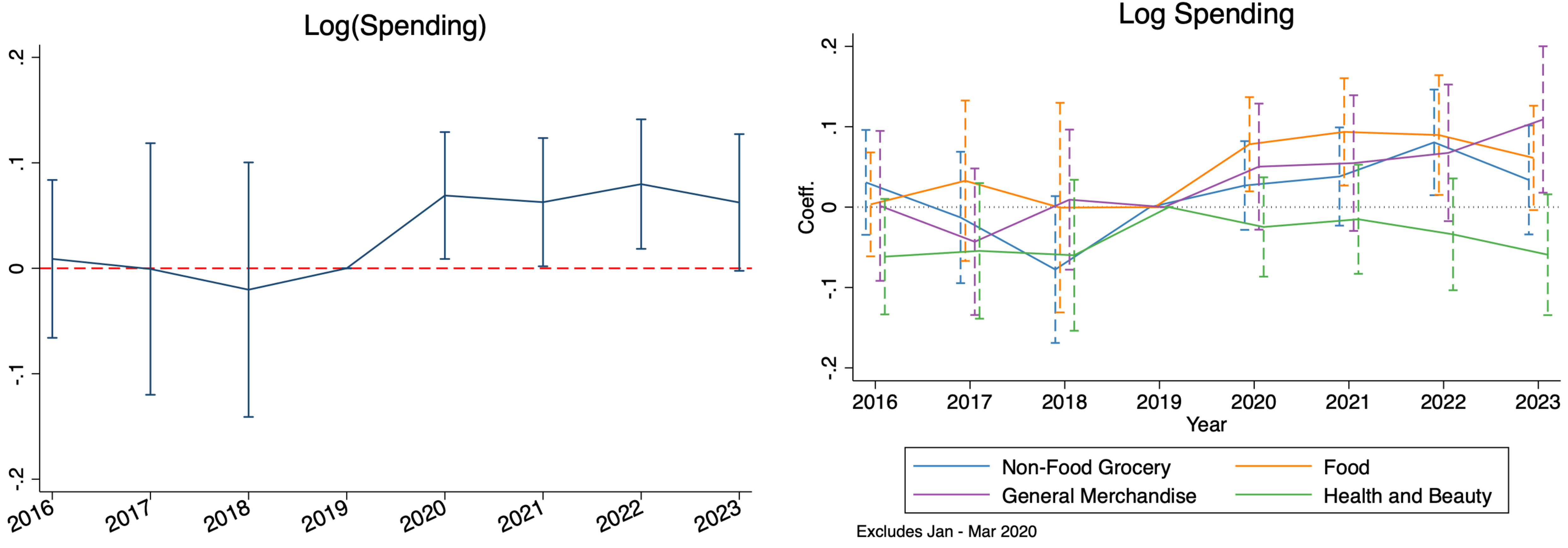
Notes: All data come from our original survey conducted on the Nielsen Consumer Panel (NCP). Online grocery shopping is based on household responses in each wave. The left panel shows subgroup averages by gender, income (high: ≥\$100k; not high: <\$100k), and age (young: <50; old: ≥50). The right panel shows averages by work arrangement (full-time WFH, partial WFH, full-time in person). Both panels are restricted to individuals who were employed; the total sample includes 17,592 individuals.

Figure 3: Working from Home Changed Shopping Mode



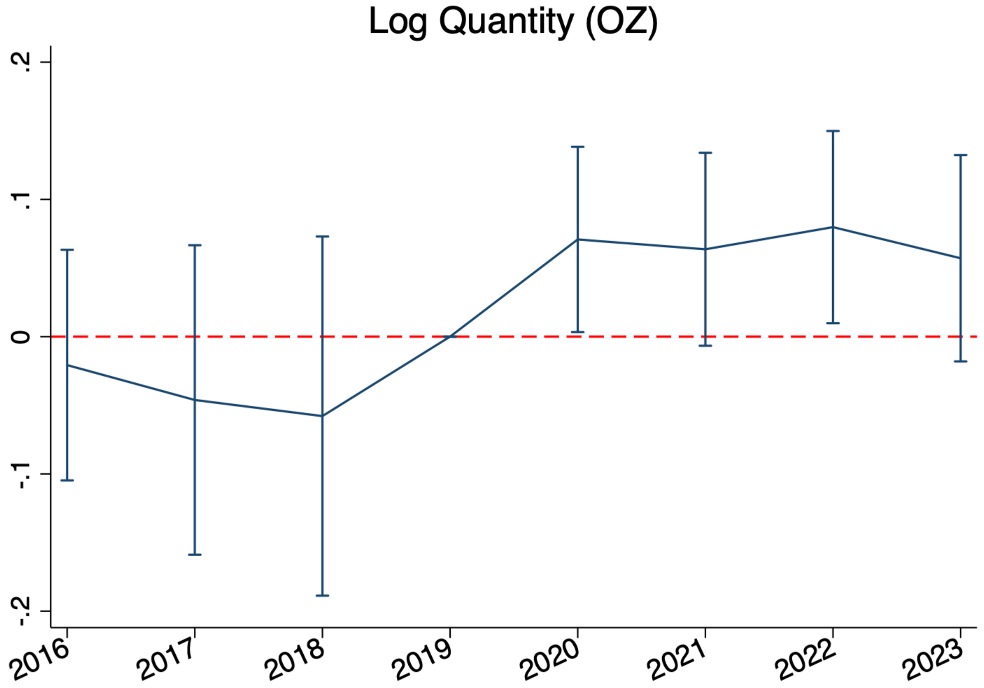
Notes: Figures plot $\hat{\beta}_t$ (and 95% confidence intervals) from $Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$. $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. We first construct current and pre-pandemic share of days worked from home for each of up to two "household heads". We then average these across household heads, weighting by the overall average number of days worked by each head. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. Average Nielsen online channel share in 2019 was 3.4%. Average weekday trip share in 2019 was 66.3%. Data from January to March 2020 is excluded. Estimates are based on 77,253 household-year observations.

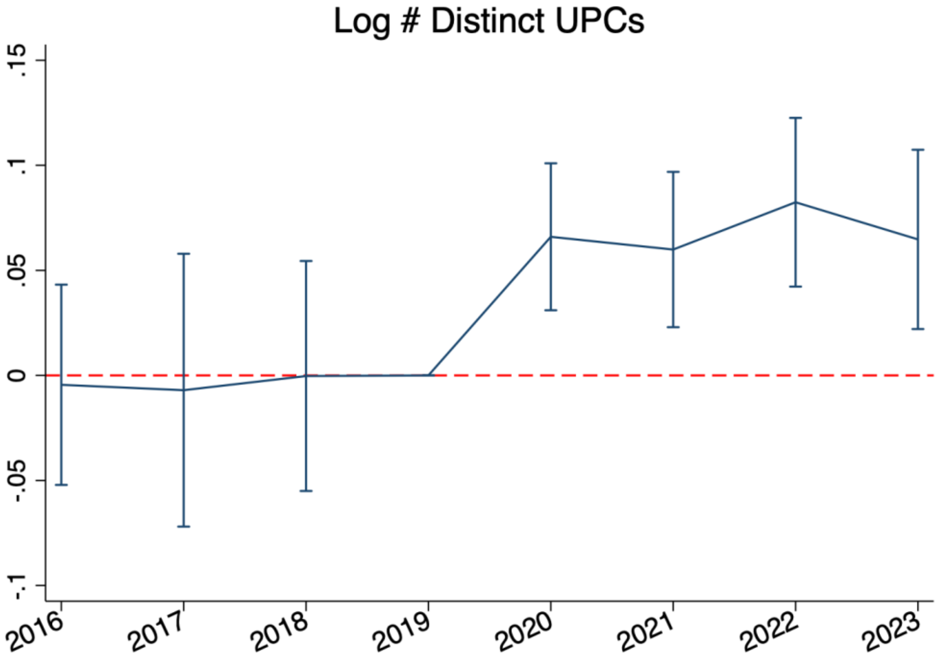
Figure 4: WFH Increased Retail Spending, Particularly and Food and Merchandise

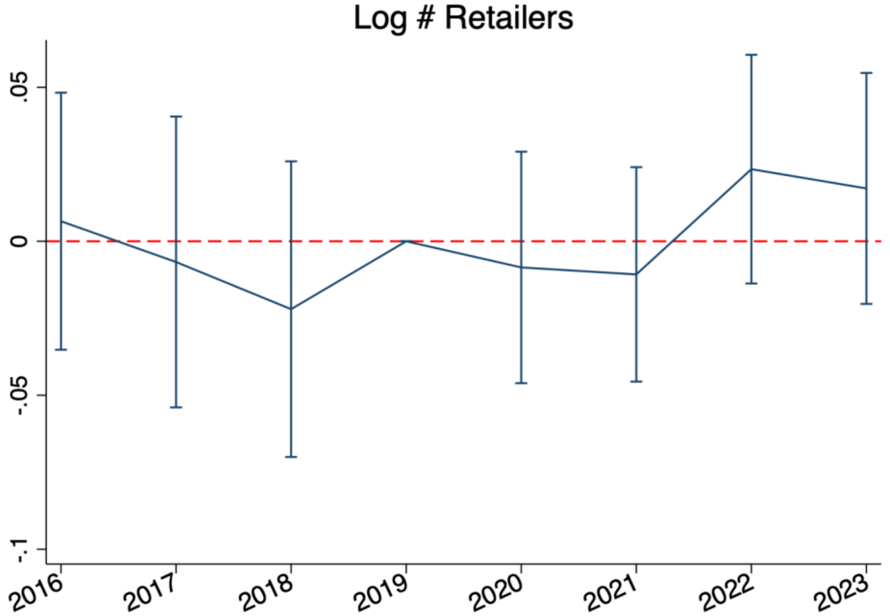


Notes: Figures plot $\hat{\beta}_t$ (and 95% confidence intervals) from $Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$. $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. Average spending per trip reflects the total spent (from the bottom of the receipt) including sales tax, delivery fees and items not covered by Nielsen. Total spending reflects the amount spent on items covered by NielsenIQ, excluding tax and delivery fees. Data from January to March 2020 are excluded. Estimates are based on 77,252 household-year observations.

Figure 5: WFH Increased Quantity and Number of Products, but Not Number of Retailers Visited

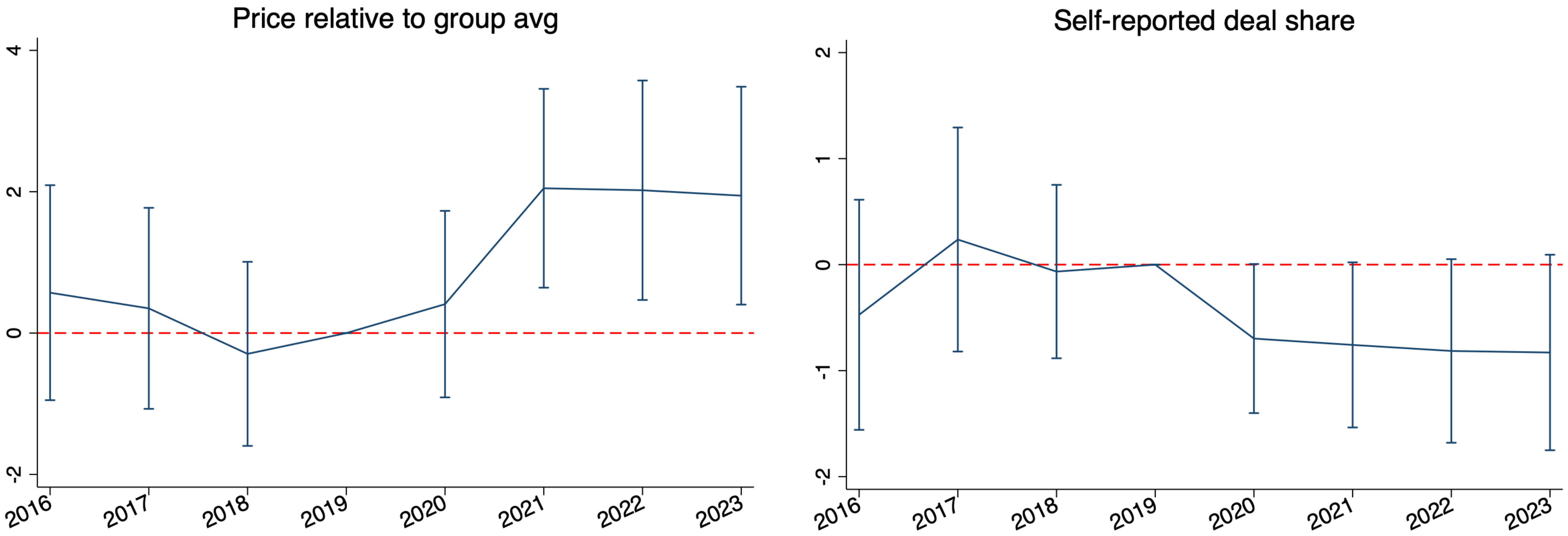






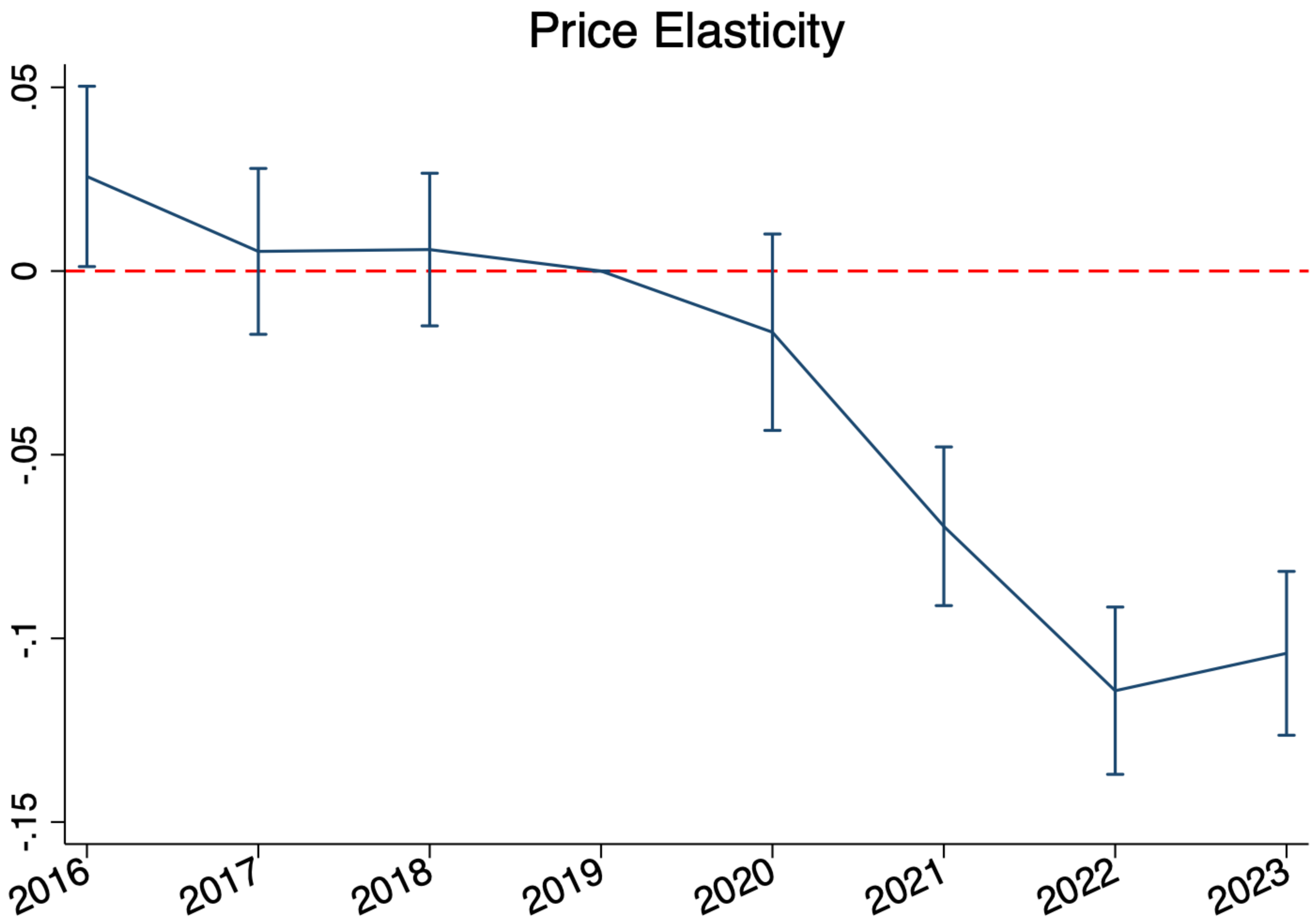
Notes: Figures plot $\hat{\beta}_t$ (and 95% confidence intervals) from $Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$. $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. We first construct current and pre-pandemic share of days worked from home for each of up to two "household heads". We then average these across household heads, weighting by the overall average number of days worked by each head. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. Data from January to March 2020 are excluded. Estimates based on 77,253 observations for the top-left and bottom graphs, and 77,230 for the top-right.

Figure 6: WFH Increased Purchases of Higher Priced Items and Decreased Deal Usage



Notes: Figures plot $\hat{\beta}_t$ (and 95% confidence intervals) from $Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$. $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. We first construct current and pre-pandemic share of days worked from home for each of up to two "household heads". We then average these across household heads, weighting by the overall average number of days worked by each head. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. We construct counterfactual spending at the average annual UPC price, and at the average annual price in the same product module and product group. We then compute 100*(spending on UPCs bought - spending at product group average)/ spending at product group average. This captures whether the household is buying more expensive types of products within a given category. Data from January to March 2020 are excluded. Estimates are based on 75,548 household-year observations for the right graph and 77,253 for the left.

Figure 7: WFH Reduced Price Elasticity



Notes: Figure displays regression coefficients of a regression where observations are WFH group-week-product groups. The dependent variable is the logged quantity of items purchased in a given week by a WFH group and while the data points plotted are the coefficients on the interaction of Ln(Price), an indicator for being a household switching to WFH post-pandemic, and an indicator for a given year. Ln(price) refers to average price of a particular product group across all measured Nielsen retailers in a given week. WFH groups are defined by work from home status in 2022 based on survey responses. 'Post' refers to the period after March 2020. Work from home households are those that increase their fraction of time working from home by 50% of total days worked. Standard errors clustered by WFH group. PPL denotes a Poisson Pseudo-likelihood regression. Estimates are based on 1,914,617 household-year observations

Table 1: Summary Statistics

	Survey Respondent Households				
	Mean	SD	10th Pctile	Median	90th Pctile
Employed	0.54	(0.50)	0.0	1.0	1.0
Age	57.86	(15.50)	35.0	61.0	76.0
Male	0.43	(0.50)	0.0	0.0	1.0
College degree (%)	0.53	(0.50)	0.0	1.0	1.0
Non-Hispanic white (%)	0.76	(0.43)	0.0	1.0	1.0
High income (>100k)	0.26	(0.44)	0.0	0.0	1.0
% WFH (if employed)	0.29	(0.41)	0.0	0.0	1.0
Change in % WFH (if employed)	0.18	(0.38)	0.0	0.0	1.0
Usually grocery shop online	0.16	(0.36)	0.0	0.0	1.0
Avg Annual Nielsen Spend	5565.78	(3115.00)	2412.0	4960.4	9411.9
Avg Trips Per Month	17.65	(10.71)	6.9	15.1	31.3
Avg Retailers Per Month	7.84	(4.01)	3.3	7.2	13.3
Number of Observations	54,874				

Notes: Displayed are selected summary statistics from survey respondents across three waves of surveys. WFH fraction is based on survey self-reports of the number of days worked from home as a fraction of total days worked per week. Online shopping reflects a self-reported indicator for whether the household typically does its grocery shopping online.

Table 2: Working from Home, Deals and Price Premia

VARIABLES	(1) Deals	(2) UPC Prem	(3) Mod. Prc Prem	(4) Grp Prc Prem	(5) 10th Pct Price	(6) Rtlr Prc Prem
WFH	-0.844***	0.322***	1.055***	1.468***	0.206***	-0.0261
	(0.298)	(0.113)	(0.269)	(0.318)	(0.0664)	(0.0694)
Online Shop	-1.071***	-0.149	-0.221	-0.206	0.118*	-0.0344
	(0.301)	(0.116)	(0.264)	(0.326)	(0.0710)	(0.0724)
Observations	73,694	66,145	66,113	66,111	66,203	66,137
R^2	0.886	0.683	0.684	0.691	0.804	0.545
Time FE	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Observations are at a household year level. Data spans 2016 to 2023. WFH is defined as a households' work from home status based on survey responses, including recall. Data from January to March 2020 are excluded. UPC Premium represents the average price the household pays for a given UPC relative to the average annual UPC price paid by all households, across all UPCs that the household buys. For columns 3 and 4, we construct counterfactual spending at the average annual UPC price, and at the average annual price in the same product module and product group. We then compute 100*(spending on UPCs bought - spending at product group average)/ spending at product group average. This captures whether the household is buying more expensive types of products within a given category. 10th Percentile Price represents the average dollar-weighted value within a household across all purchases of the 10th percentile of prices for each UPC they buy. To compute the retailer price premium we first compute the annual average price of each UPC for each retailer using the RMS. We then compute the annual average price of each UPC across all retailers using the RMS. We then compute counterfactual spending for each household under each set of prices (using only transactions for which both prices can be obtained from the RMS). The retailer premium is then (Spending at retailer average price – spending at overall average price)/spending at overall average price. Online Shop is a self-reported indicator for the household doing a majority of their shopping online.

Table 3: Working from Home and Price Elasticities

VARIABLES	(1) Q	(2) Q	(3) Q	(4) Q	(5) ln(Q)	(6) Q
ln(Price)	-0.357***	-0.369***	-0.361***	-0.367***	-0.412**	-0.358***
	(0.0497)	(0.0493)	(0.0567)	(0.0453)	(0.0120)	(0.0439)
ln(Price)*WFH			0.0523***	-0.0221***	0.0587**	-0.0214***
			(0.00109)	(0.000402)	(0.00237)	(0.000415)
ln(Price)*Post		0.0180***		0.0121	0.0134	0.0126
		(0.000705)		(0.0118)	(0.00897)	(0.0118)
ln(Price)*WFH*Post				0.0883***	0.0172***	0.0873***
				(0.00224)	(0.000262)	(0.00223)
Observations	2,787,493	2,787,493	2,787,493	2,787,493	2,034,699	3,885,177
Time FE	YES	YES	YES	YES	YES	YES
Product FE	YES	YES	YES	YES	YES	YES
WFH FE	YES	YES	YES	YES	YES	YES
Specification	PPML	PPML	PPML	PPML	Linear Reg	PPML
Pseudo R2	0.732	0.732	0.732	0.732		0.745
R^2					0.794	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are WFH group-week-product groups. Dependent variable in all columns is the quantity or the logged quantity of items purchased by a given group in a given week. In columns 1-5, products are restricted to those where the group in that year buys an average quantity above 1 during a week in the year. Ln(Price) refers to average price of a particular product across all measured Nielsen retailers in a given week. WFH groups are defined by work from home status in 2022-2023 based on survey responses. 'Post' refers to the period after March 2020. Work from home households are those that increase their fraction of time working from home by 50% of total days worked. Standard errors clustered by WFH group. PPML denotes a Poisson Pseudo Maximum Likelihood regression.

Table 4: Working from Home and Changes in Shopping Time and Responsibility

	(1) Shopping share	(2) Shopping share	(3) Shopping share	(4) 1(Shop)	(5) Shop time (mins)	(6) Delivery
WFH	0.035***	0.024***	0.010	0.021**	-3.846**	0.045***
	(5.26)	(3.46)	(1.16)	(2.25)	(-2.32)	(3.10)
Male * WFH			0.039***			
			(2.83)			
Male			-0.375***			
			(-49.55)			
Employed	-0.014***					
	(-3.19)					
Y Mean	0.72	0.70	0.70	0.09	42.18	0.09
Dataset	Nielsen	Nielsen	Nielsen	ATUS	ATUS	ATUS
Sample	Married	Married workers	Married workers	Workers with spouse	All who shopped	All
Period	2022-2023	2022-2023	2022-2023	2016-2024	2016-2024	2022-2023
N	22,881	8,911	8,911	11,475	4,246	6,650

Notes: Dependent variables are (1,2,3) Nielsen survey self-reported share of grocery shopping responsibility; (4) an indicator equal to 1 if the individual spent any time grocery shopping on the reference day; (5) For individuals who reported shopping on the reference day, the number of minutes spent shopping; (6) an indicator equal to 1 if the individual reports usually having their online grocery order delivered, or about equal between pickup and delivery; equal to 0 for people who do not usually shop for groceries online or who usually pick up their online grocery order. In Columns 1-3, WFH is the current (individual) work-from-home share. In the ATUS sample (Columns 2-4) WFH is defined as time spent working from home divided by total time spent working on the reference day. The ATUS sample is restricted to observations where the reference day is weekday. Nielsen controls in Column 1 include age group fixed effects, education fixed effects, race, ethnicity, gender and an indicator for whether household income exceeds $100,000. Nielsen controls in Columns 2-3 further include occupation and industry. ATUS controls in Columns 3 and 4 include education fixed effects, age bin fixed effects, year fixed effects, race and ethnicity and an indicator for children in the household. Column 2 additional includes hours worked bin fixed effects, occupation fixed effects and industry fixed effects.

Table 5: Working from Home By Household Marital Status

	Price Ratio		Perceived Deal		Log UPC		Weekend Shop	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH Chg	0.279	2.461***	-0.186	-1.127**	11.342***	6.478***	-0.021**	-0.021***
	(0.28)	(4.14)	(-0.27)	(-2.37)	(4.27)	(3.24)	(-2.00)	(-3.08)
Sample	Single	Married	Single	Married	Single	Married	Single	Married
N	2,869	5,994	2,945	6,065	2,945	6,065	2,945	6,065

Notes: Dependent variables are household-level changes from pre-pandemic (2016-2019) to post-pandemic (2022-2023) periods. First, we compute annual outcomes for each household. We then average the annual outcomes across years in each period and then take the difference between the two periods. For columns (1) and (2), we construct counterfactual spending at the average annual UPC price, and at the average annual price in the same product group. We then compute 100*(spending on UPCs bought - spending at product group average)/ spending at product group average. This captures whether the household is buying more expensive types of products within a given category; (3) and (4) is the percentage point change in share of items the household self-reported as "deals"; (5) and (6) is the change in log average number of distinct products purchased; (7) and (8) is the change in the share of shopping trips on weekends. WFH Chg is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. We first construct current and pre-pandemic share of days worked from home for each of up to two "household heads". We then average these across household heads, weighting by the overall average number of days worked by each head. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. Controls include age group fixed effects, occupation fixed effects, education fixed effects, race and ethnicity, and an indicator for whether household income exceeds $100,000.

Table 6: Working From Home By Gender of Switching Spouse

	(1) Log UPC	(2) Weekend Shop	(3) Log Qty	(4) Log Spend	(5) Price Ratio	(6) Perceived Deal
Male WFH Chg	8.747***	-0.021*	12.373**	11.237**	4.983***	0.143
	(2.77)	(-1.93)	(2.36)	(2.34)	(5.29)	(0.19)
Female WFH Chg	5.150**	-0.021**	10.096**	3.757	0.971	-1.781***
	(2.09)	(-2.44)	(2.47)	(1.00)	(1.32)	(-3.04)
Sample	Married HH	Married HH	Married HH	Married HH	Married HH	Married HH
N	6,107	6,107	6,105	6,107	5,994	6,107

Notes: Dependent variables are household-level changes from pre-pandemic (2016-2019) to post-pandemic (2022-2023) periods. First, we compute annual outcomes for each household. We then average the annual outcomes across years in each period and then take the difference between the two periods. Column (1) is the change in log average number of distinct products purchased; column (2) is the change in the share of shopping trips on weekends; column (3) is the change in log quantity purchased of items measured in OZ; column (4) is the change in log spending; for column (5), we construct counterfactual spending at the average annual UPC price, and at the average annual price in the same product group. We then compute 100*(spending on UPCs bought - spending at product group average)/ spending at product group average. This captures whether the household is buying more expensive types of products within a given category; column (6) is the percentage point change in share of items the household self-reported as "deals". This variable is based on the shopper's perception of whether the product was a "deal". Male (female) WFH is defined as the number days the male (female) household head worked from home divided by the total days worked by male and female household heads worked. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. We compute the change from pre-pandemic to post-pandemic analogously to our household-level measure. These variables are defined such that Male WFH Chg + Female WFH Chg = Household WFH Chg. This means the magnitude of coefficients on the gender-specific measures are comparable to our household WFH Chg estimates. Controls include age group fixed effects, occupation fixed effects, education fixed effects, race and ethnicity, and an indicator for whether household income exceeds $100,000.

APPENDIX

Figure A.1: Examples of Nielsen Survey Questions

Thinking about a typical week ***in February 2020 (pre-pandemic)***, did you work a full day (6 or more hours), and if so where?

Monday

- Did not work 6 or more hours
- Worked ***from home***
- Worked at ***employer or client site***
- Retired or not employed

For each time period, which of the following best describes your usual grocery shopping modality?

Pre-Pandemic (e.g., February 2020 or earlier)

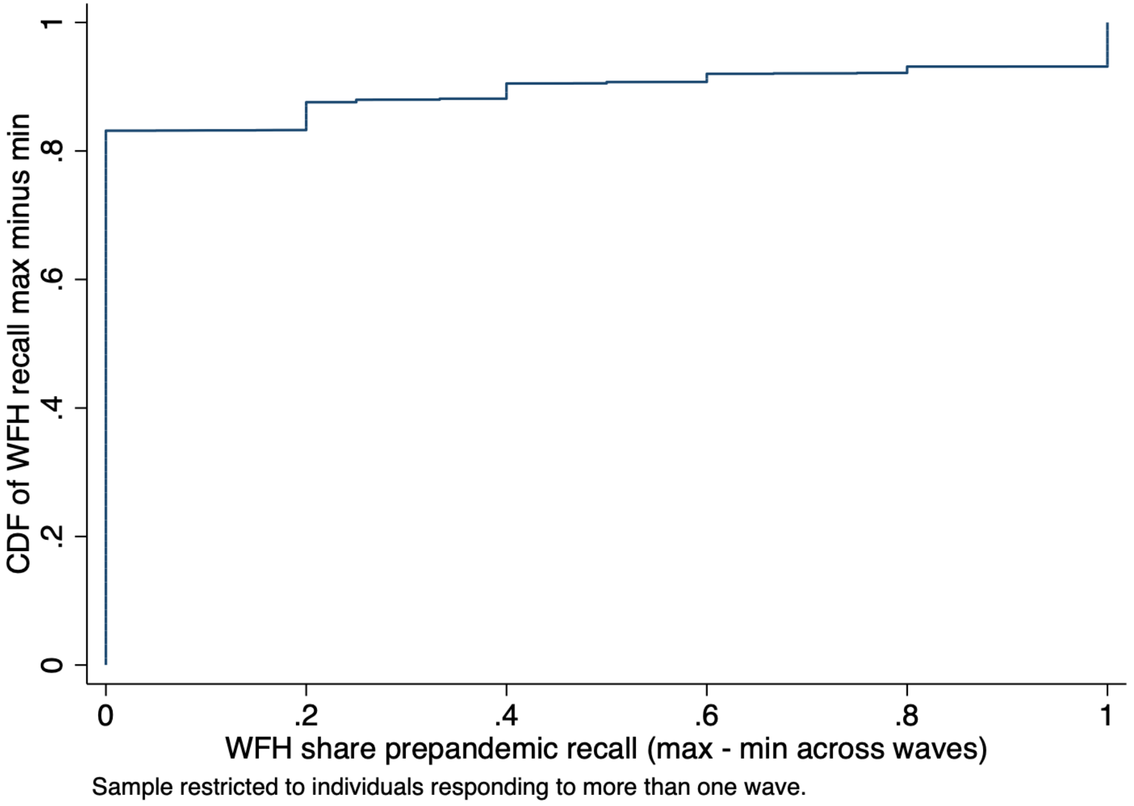
- Shop primarily in person
- Shop primarily online or via an app and use delivery
- Shop primarily online or via app and use curbside or store pickup

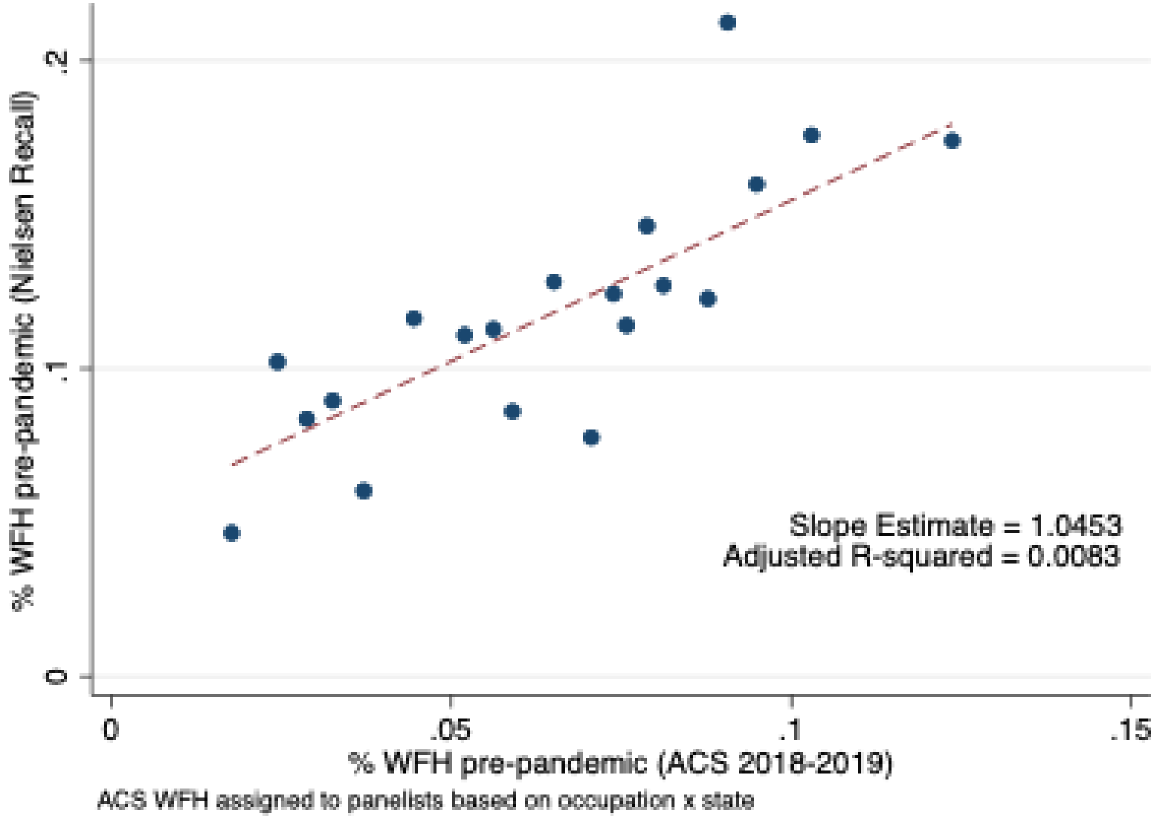
Early in the Pandemic (e.g., May 2020)

Currently (e.g., May 2023)

Notes: Both panels display examples of questions asked as part of the Nielsen Consumer Panel Survey. Top panel asks respondents the location in which they spent their working hours, if they worked a full-time job that day. This question is repeated for each day of the week for a given reference period. The top panel asks the respondent to report their preferred method of shopping for groceries (e.g. online ordering or shopping in person), for a given reference period. These questions are asked of all respondents across all waves of the survey, allowing for repeated answers to a given question.

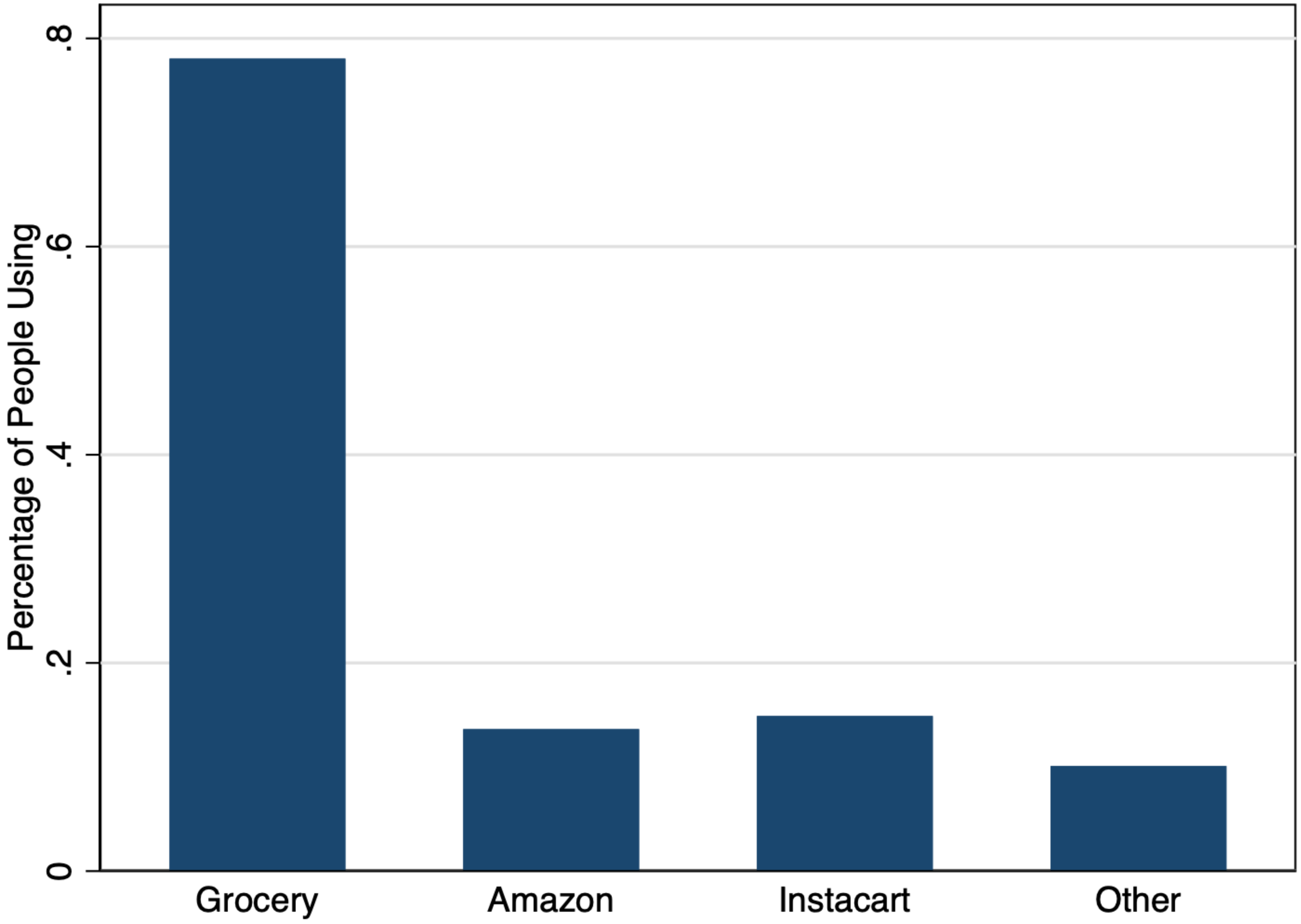
Figure A.2 Pre-pandemic recall





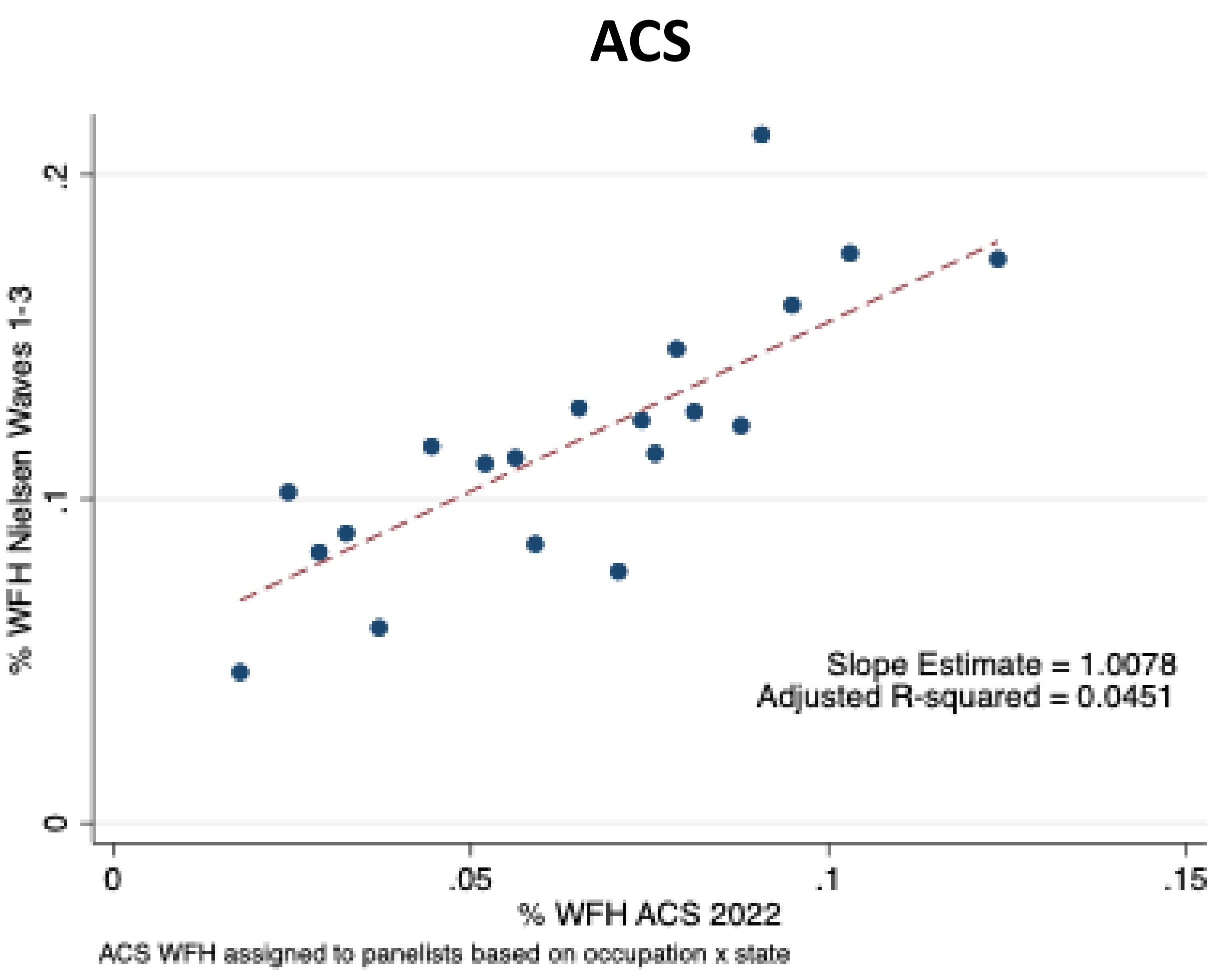
Notes: The left figure shows the cumulative frequency of (maximum minus minimum) pre-pandemic WFH shares for each individual who responded to more than one wave. A value of zero corresponds to consistent responses across multiple waves. RHS Compares individual Nielsen panelist WFH recall with the ACS. We first construct an indicator equal to one if the surveyed individual recalled working from home full-time before the pandemic. The ACS measure is based on a question about commuting to work. One of the responses is “worked at home”. We believe this aligns best with full-time WFH. We average the ACS work from home measure across people in a given state and occupation. We then regress the individual survey response on the ACS share in their state and occupation.

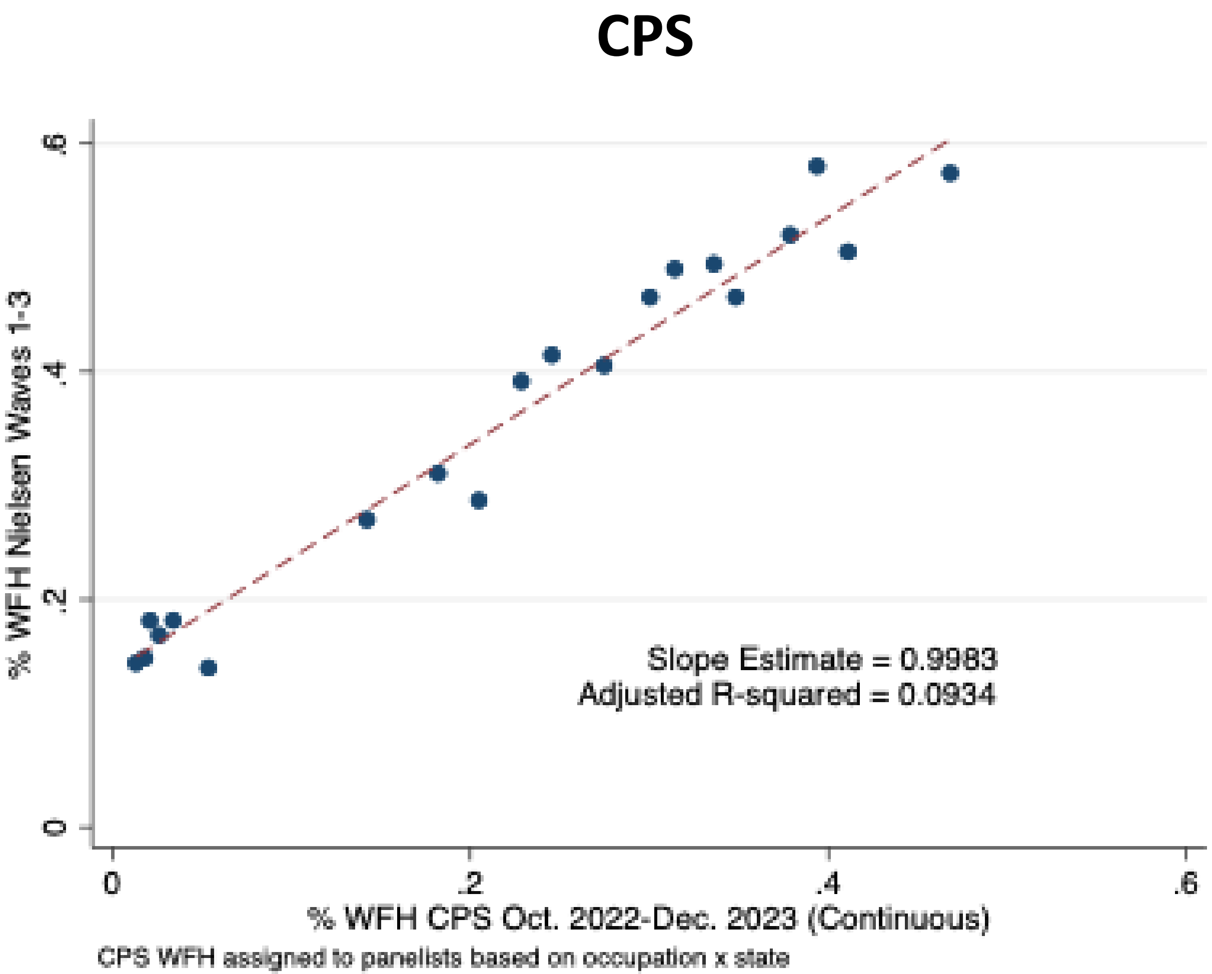
Figure A.3: Online Shopping Modality



Notes: Plotted are fractions of survey respondents who report that they shop for groceries online. Respondents are asked which modality is utilized when shopping online. Options include using an app for their grocery store, Amazon Fresh, Instacart, or another means of ordering, with respondees asked to select all that apply.

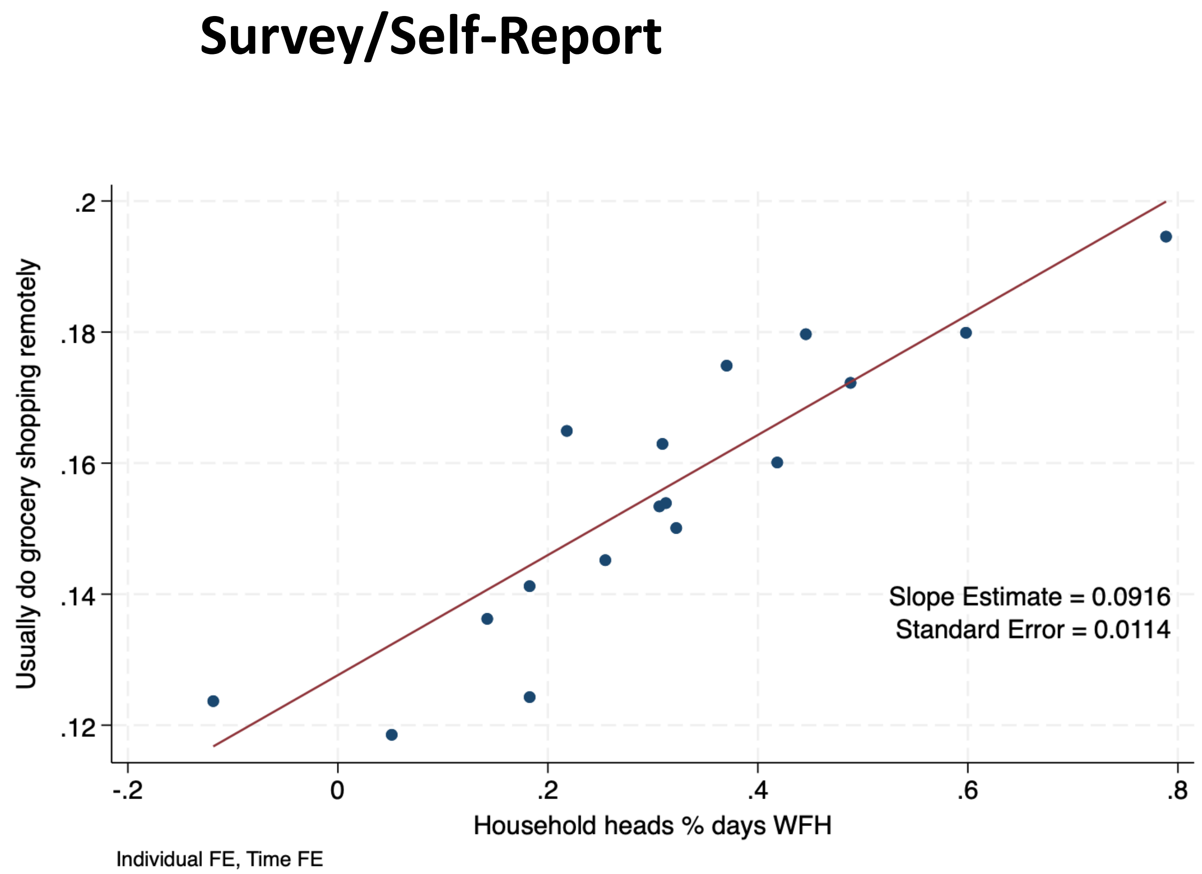
Figure A.4: ACS & CPS cross-section comparison

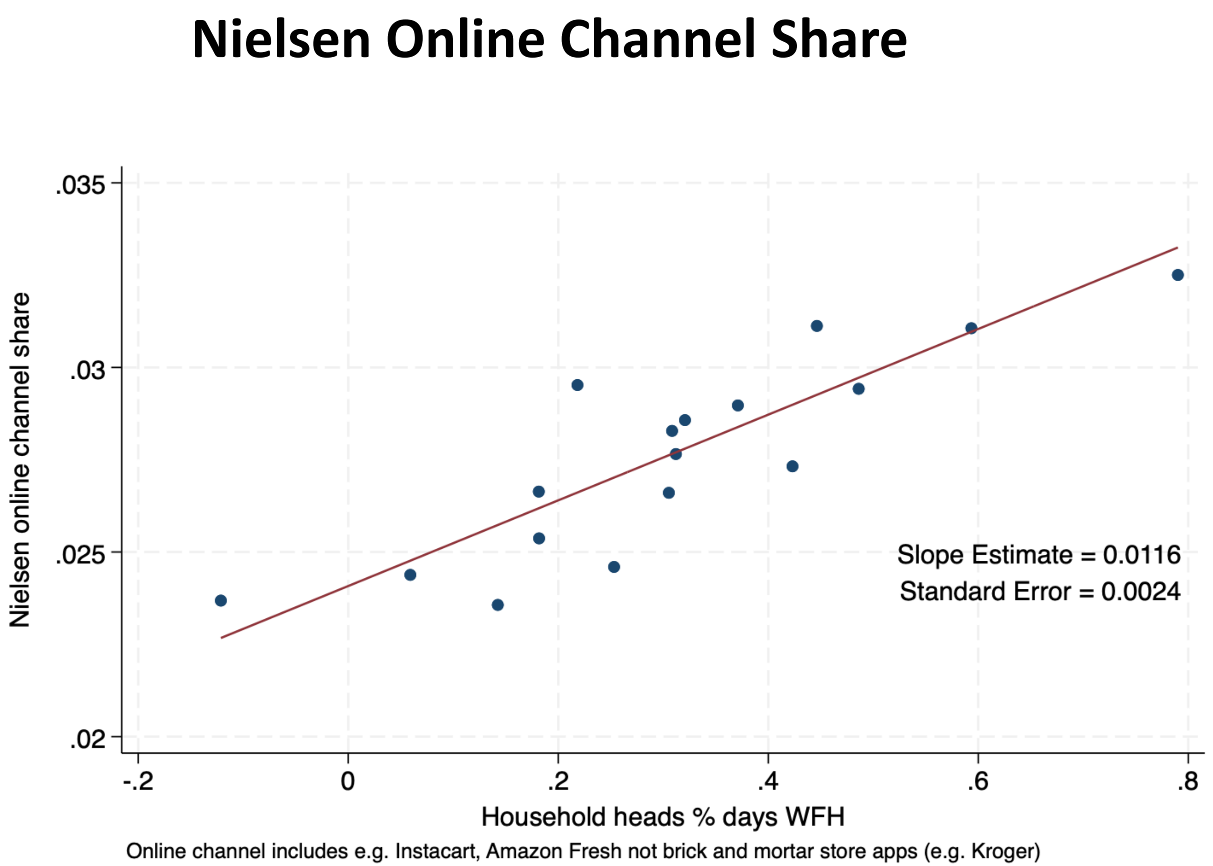




Notes: Compares individual Nielsen panelist WFH over waves 1-3 with the ACS (2022) and CPS (2022-2023). On the LHS we regress the individual survey response on the ACS share in their state and occupation. On the RHS we make a similar comparison using the CPS and a continuous WFH measure (WFH as a share of time worked).

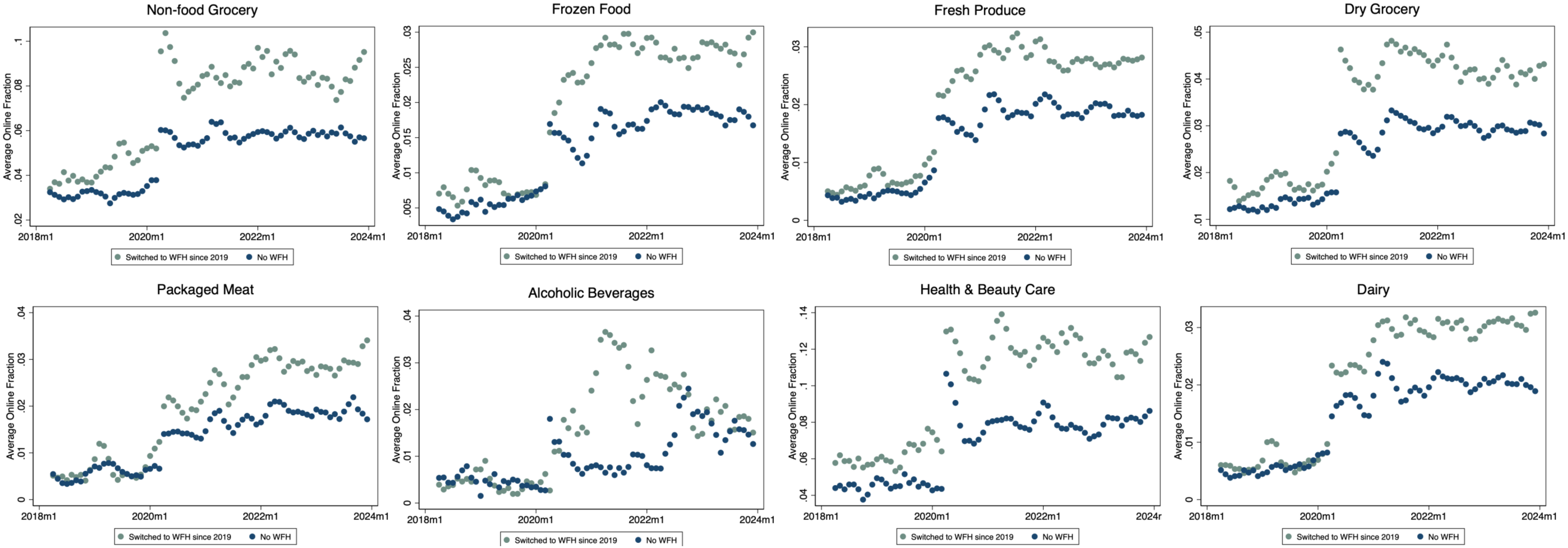
Figure A.5: Working from Home is Correlated with Online Shopping

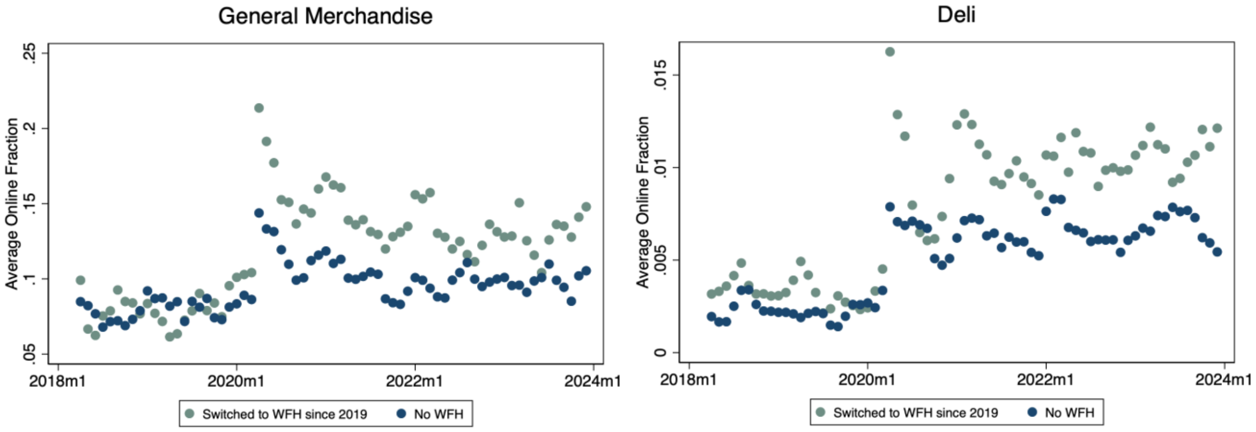




Notes: Figures depict residualized bin-scatter plots of a given variable against the fraction of days worked from home for a given household-period. Individual and time fixed effects are included. Dependent variable in the left panel is a self-reported indicator for whether the household typically shops for groceries online. In the right panel, the dependent variable is the fraction of purchases done via an online channel, as observed in the Nielsen Consumer Panel data.

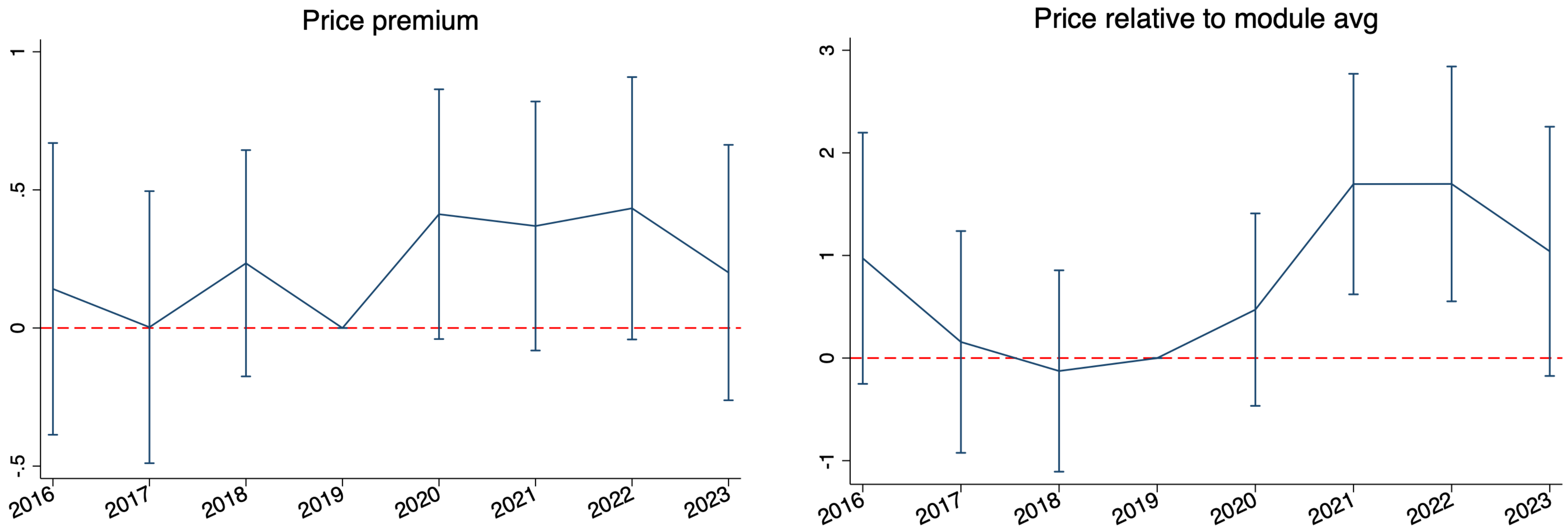
Figure A.6: Fraction Online Shopping by Category





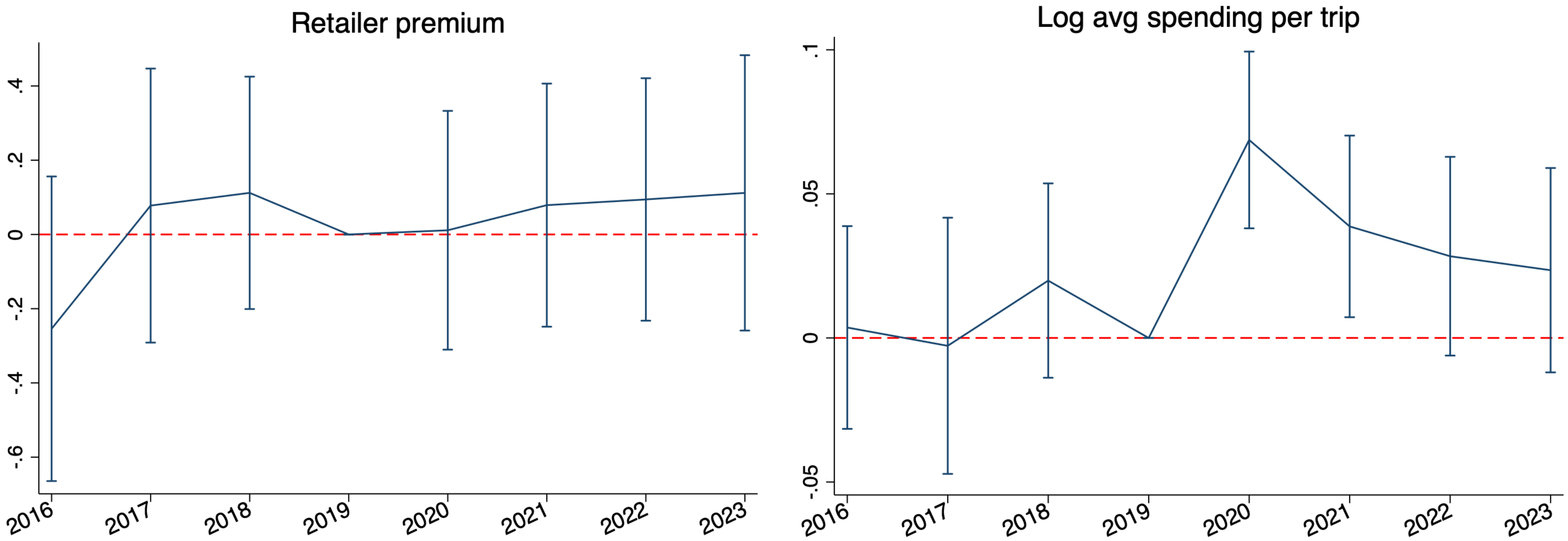
Notes: Data represent the 3-month moving average of average fraction of nominal spending on products from a given department is done via online channels. Moving averages are allowed a break in March 2020. WFH households are those who worked less than 40% of days from home in the pre-pandemic period but worked more than 60% of days from home in the post-pandemic period. ‘No WFH’ represents the group which works less than 40% of days at home in all periods.

Figure A.7: WFH Increased Prices Paid by Households



Notes: Figures plot $\hat{\beta}_t$ from $Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$. $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. We first construct current and pre-pandemic share of days worked from home for each of up to two "household heads". We then average these across household heads, weighting by the overall average number of days worked by each head. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. We construct counterfactual spending at the average annual UPC price, and at the average annual price in the same product module and product group. We then compute 100*(spending on UPCs bought - spending at product group average)/ spending at product group average. This captures whether the household is buying more expensive types of products within a given category. Data from January to March 2020 are excluded.

Figure A.8: Spending Per Trip and Retailer Premium



Notes: Figures plot $\hat{\beta}_t$ from $Y_{h,t} = \delta_h + \alpha_t + \beta_t \Delta ShareWFH_h + \epsilon_{h,t}$. $\Delta ShareWFH_h$ is defined as the household's current share of days worked from home less its pre-pandemic share of days worked from home. Current share of days worked from home, at the individual level, is the average share of days worked for home across all survey waves. Pre-pandemic share of days worked from home, at the individual level, is the average (recalled) share of days worked from home in 2019 across all survey waves. Spending reflects the amount spent on items covered by NielsenIQ, excluding tax and delivery fees. General merchandise includes items such as electronics, cookware, cameras, insecticides, lawn & garden, motor vehicle and office supplies. To compute the retailer price premium we first compute the annual average price of each UPC for each retailer using the RMS. We then compute the annual average price of each UPC across all retailers using the RMS. We then compute counterfactual spending for each household under each set of prices (using only transactions for which both prices can be obtained from the RMS). The retailer premium is then (Spending at retailer average price – spending at overall average price)/spending at overall average price. Data from January to March 2020 are excluded.

Table A.1: Summary Statistics for Survey Respondents and Non-Respondents

	Survey Respondents		Others	
	Mean	SD	Mean	SD
Employed	0.54	(0.50)	0.61	(0.49)
Age	57.86	(15.50)	51.65	(17.35)
Male	0.43	(0.50)	0.46	(0.50)
College degree (%)	0.53	(0.50)	0.58	(0.49)
Non-Hispanic white (%)	0.76	(0.43)	0.72	(0.45)
High income (>100k)	0.26	(0.44)	0.24	(0.43)
% WFH (if employed)	0.29	(0.41)		
wfh_change	0.18	(0.38)		
Usually grocery shop online	0.16	(0.36)		
Avg Annual Nielsen Spend	5565.78	(3115.00)	4408.78	(2575.05)
Avg Trips Per Month	17.65	(10.71)	12.84	(8.55)
Avg Retailers Per Month	7.84	(4.01)	6.06	(3.47)
Number of Observations	54,874		146,524	

Notes: Left two columns display selected summary statistics from survey respondents across three waves of surveys. Right two columns display values for the entire NCP population, regardless of whether they are a survey respondent. WFH fraction is based on survey self-reports of the number of days worked from home as a fraction of total days worked per week. Online shopping reflects a self-reported indicator for whether the household typically does its grocery shopping online.

Table A.2: Online Shopping Measures

	(1) Third party app	(2) Third party app	(3) Amazon	(4) Amazon	(5) Grocery app	(6) Grocery app
Grocery shop primarily online	1.7**	-0.6	0.1	-2.4***	4.1***	7.6***
	(0.8)	(0.9)	(0.8)	(0.8)	(1.0)	(1.0)
Nielsen online channel share		22.2***		24.2***		-32.1***
		(2.5)		(2.4)		(3.0)
Constant	13.7***	12.8***	13.3***	12.4***	76.6***	77.8***
	(0.5)	(0.5)	(0.5)	(0.5)	(0.6)	(0.6)
Number of Observations	7,862	7,862	7,862	7,862	7,862	7,862

Notes: This table documents the relationship between measures of online shopping obtained from Nielsen transaction data and from our survey of Nielsen panelists. Grocery shop primarily online is a self-reported indicator from our survey for whether the household typically does its grocery shopping online. Nielsen online channel share is the share of household spending at merchants Nielsen classifies as ”online”. The dependent variables capture app usage of different types and come from our survey. In columns 1 and 2, the dependent variable is 1 for households who report using a third-party app for grocery shopping, such as Instacart, and zero otherwise. In columns 3 and 4, it is 1 for households who report using Amazon for grocery shopping, and zero otherwise. In columns 5 and 6, it is 1 for households who report using a grocery store app (such as the Kroger app). The sample includes only households who responded to the app usage question in our survey.

Table A.3: Validation of Online Shopping Survey Responses

VARIABLES	(1) Online Frac	(2) Online Frac	(3) Online Frac	(4) Online Frac
Self-Reported Online Ordering	0.0254***		0.0252***	0.0189***
	(0.00272)		(0.00279)	(0.00371)
Working from Home %		0.0115***	0.00905***	0.00604**
		(0.00266)	(0.00262)	(0.00274)
Self-Reported Online Ordering * WFH				0.0135**
				(0.00557)
Observations	73,862	72,539	72,539	72,539
R^2	0.707	0.705	0.708	0.709
HH FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Each column is a separate regression, each where the dependent variable is the dollar-weighted fraction of purchases done through online channels, as measured by the Nielsen Consumer Panel (mean value of this variable is 0.03). Fixed effects are included as noted. Standard errors clustered by households. Self-reported online ordering and working from home fractions are obtained from survey responses.

Table A.4: Working from Home, Deals and Price Premia – Only In Person Shoppers

VARIABLES	(1) Deal Flg	(2) UPC Prem	(3) Mod. Prc Prem	(4) Grp Prc Prem	(5) 10th Pct Price	(6) Rtlr Prc Prem
WFH	-1.103**	0.285	1.752***	1.827***	0.292**	-0.0185
	(0.560)	(0.198)	(0.497)	(0.582)	(0.123)	(0.125)
Observations	24,812	22,177	22,357	22,321	22,184	22,169
R^2	0.903	0.699	0.691	0.689	0.811	0.546
Time FE	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are at a household year level. Sample is restricted to households that both report doing a majority of their shopping in-person and also are not observed to do more than 1% of spending at online merchants. WFH is defined as a households' work from home status based on survey responses. UPC Premium represents the average price the household pays for a given UPC relative to the average annual UPC price paid by all households, across all UPCs that the household buys. Price premium measures in columns 3 and 4 constructed as in Table 2. 10^{th} Percentile Price represents the average dollar-weighted value within a household across all purchases of the 10^{th} percentile of prices for each UPC they buy. To compute the retailer price premium we first compute the annual average price of each UPC for each retailer using the RMS. We then compute the annual average price of each UPC across all retailers using the RMS. We then compute counterfactual spending for each household under each set of prices (using only transactions for which both prices can be obtained from the RMS). The retailer premium is then (Spending at retailer average price – spending at overall average price)/spending at overall average price. Data from January to March 2020 are excluded.

Table A.5: Working from Home, Deals and Price Premia – Household by year controls

VARIABLES	(1) Deals	(2) UPC Prem	(3) Mod. Prc Prem	(4) Grp Prc Prem	(5) 10th Pct Price	(6) Rtlr Prc Prem
WFH	-0.629**	0.279**	0.890***	1.296***	0.152**	-0.0651
	(0.303)	(0.116)	(0.280)	(0.335)	(0.0694)	(0.0731)
Online Shop	-0.925***	-0.219*	-0.111	0.0732	0.0575	-0.0630
	(0.305)	(0.116)	(0.263)	(0.326)	(0.0716)	(0.0727)
Observations	73,049	65,564	65,519	65,499	65,618	65,560
R^2	0.888	0.687	0.690	0.696	0.807	0.550
Time FE	YES	YES	YES	YES	YES	YES
Household FE	YES	YES	YES	YES	YES	YES
Controls X Year	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are at a household year level. Sample is restricted to households that both report doing a majority of their shopping in-person and also are not observed to do more than 1% of spending at online merchants. WFH is defined as a households' work from home status based on survey responses. UPC Premium represents the average price the household pays for a given UPC relative to the average annual UPC price paid by all households, across all UPCs that the household buys. Price premium measures in columns 3 and 4 constructed as in Table 2. 10th Percentile Price represents the average dollar-weighted value within a household across all purchases of the 10th percentile of prices for each UPC they buy. To compute the retailer price premium we first compute the annual average price of each UPC for each retailer using the RMS. We then compute the annual average price of each UPC across all retailers using the RMS. We then compute counterfactual spending for each household under each set of prices (using only transactions for which both prices can be obtained from the RMS). The retailer premium is then (Spending at retailer average price – spending at overall average price)/spending at overall average price. Data from January to March 2020 are excluded. Household controls, including age bins, occupation fixed effects, education fixed effects, income bins, race and ethnicity, and household size, are interacted with year fixed effects. Where controls are fundamentally individual, we use information from an employed household member where present. We prioritize the female head over the male head when both heads are present and both are employed.

Table A.6: Spending, Quantities and Day of Week – Household by Year Controls

VARIABLES	(1) Log Spending	(2) Log Quantity	(3) Log UPCs	(4) Weekday Shop
WFH	0.0750***	0.0782***	0.0591***	0.0266***
	(0.0148)	(0.0171)	(0.0111)	(0.00468)
Online Shop	-0.00447	0.0133	-0.0206*	-0.00194
	(0.0147)	(0.0180)	(0.0118)	(0.00438)
Observations	73,049	73,045	73,049	73,049
R^2	0.647	0.675	0.791	0.700
Time FE	YES	YES	YES	YES
Household FE	YES	YES	YES	YES
Controls X Year	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are at a household year level. Sample is restricted to households that both report doing a majority of their shopping in-person and also are not observed to do more than 1% of spending at online merchants. WFH is defined as a households' work from home status based on survey responses. Data from January to March 2020 are excluded. Household controls, including age bins, occupation fixed effects, education fixed effects, income bins, race and ethnicity, and household size, are interacted with year fixed effects. Where controls are fundamentally individual, we use information from an employed household member where present. We prioritize the female head over the male head when both heads are present and both are employed.

Table A.7: Working from Home and Price Elasticities by Product Category

VARIABLES	(1) Health Beauty	(2) Non-Perishable Grocery	(3) Perishable Grocery	(4) Non-Food Merch	(5) Alcohol
ln(Price)	0.0277***	-0.443***	-0.337***	-0.501***	-0.198***
	(0.00414)	(0.00703)	(0.0990)	(0.00130)	(0.0605)
ln(Price)*WFH	0.00673***	-0.0230***	-0.148***	-0.0499***	-0.0187***
	(0.000492)	(4.13e-05)	(0.00165)	(0.000639)	(0.000206)
ln(Price)*Post	0.00208**	0.0200***	0.0185	0.0241***	0.0119***
	(0.000879)	(0.000323)	(0.0122)	(0.00268)	(0.00266)
ln(Price)*WFH*Post	-0.000499	-0.0318***	0.162***	0.0629***	-0.0323***
	(0.000708)	(0.000101)	(0.00188)	(0.000717)	(0.00250)
Observations	231,253	1,711,905	461,657	241,506	53,251
Time FE	YES	YES	YES	YES	YES
Product FE	YES	YES	YES	YES	YES
WFH FE	YES	YES	YES	YES	YES
Excludes	2020Q1	2020Q1	2020Q1	2020Q1	2020Q1
Pseudo R2	0.491	0.722	0.740	0.656	0.414

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Observations are WFH group-week-product groups. Dependent variable in all columns is the quantity or the logged quantity of items purchased by a given group in a given week. In columns 1-5, products are restricted to those where the group in that year buys an average quantity above 1 during a week in the year. Ln(Price) refers to average price of a particular product across all measured Nielsen retailers in a given week. WFH groups are defined by work from home status in 2022-2023 based on survey responses. ‘Post’ refers to the period after March 2020. Work from home households are those that increase their fraction of time working from home by 50% of total days worked. Standard errors clustered by WFH group. PPML denotes a Poisson Pseudo Maximum Likelihood regression.