Household Cost Indexes: Prototype Methods and Results[1]

Robert S. Martin, Joshua Klick, William Johnson, Paul Liegey[2]

June 1, 2023

CONFERENCE PAPER/PRELIMINARY

Abstract

We estimate a family of price indexes known as Household Cost Indexes (HCI) using U.S. data. HCIs aim to measure the average inflation experiences of households as they purchase goods and services for consumption, and similar indexes are produced in the United Kingdom and New Zealand. These differ from the Bureau of Labor Statistics' headline Consumer Price Index (CPI) products in two main respects. First, the upper-level aggregation of the HCIs weights households equally, unlike most headline CPIs which implicitly give more weight to higher-expenditure households. Second, the HCIs use the payments approach to value owner-occupied housing services explicitly using household outlays. In contrast, the U.S. CPIs use rental equivalence. The HCI for all urban consumers has an average 12-month change of 1.51% over December 2011 to December 2021, compared to 1.86% for the CPI-U. The bulk of the difference is due to the payments approach.

Key Words: Price index; inflation; democratic aggregation; payments approach

JEL Codes: C43, E31

[1] We thank Anya Stockburger, Robert Cage, Thesia I. Garner, and many others at the Bureau of Labor Statistics for helpful comments and guidance.

[2] Division of Price and Index Number Research (Martin), Division of Consumer Price Indexes (Klick, Liegey), Division of Price Statistical Methods (Johnson), Bureau of Labor Statistics, 2 Massachusetts Ave., NE, Washington, DC 20212, USA. Emails: Martin.Robert@bls.gov, Klick.Joshua@bls.gov, Johnson.Bill@bls.gov, Liegey.Paul@bls.gov

1. Introduction

This article estimates Household Cost Indexes (HCIs) using U.S. data. Similar price indexes are already produced in the United Kingdom (Office for National Statistics, 2017) and New Zealand (Statistics New Zealand, 2020). HCIs measure the change in cash outflows required, on average, for households to access the goods and services they purchase at a constant quality. Like the headline and subpopulation Consumer Price Indexes (CPIs) produced by the Bureau of Labor Statistics (BLS), the HCIs aim to capture price change for consumer goods and services. However, the HCIs differ in two important methodological respects from the CPIs. First, the upper-level aggregation of the HCIs weights households equally, whereas the CPI market baskets implicitly give higher weight to higher-expenditure households.[3] Second, the HCIs use the payments approach to value services from owner-occupied housing, using outlays on mortgage interest, property taxes, and the full reported value of insurance, appliances, maintenance and repairs (i.e., what the household pays and when they pay it). The CPIs, in contrast, use an implicit measure of owner-occupied housing consumption called rental equivalence, and all other goods and services are valued using acquisition prices and expenditures (i.e., when the household acquired or took possession of the good). For HCIs in principle, the payments approach should be applied more broadly, but this paper focuses only on owner-occupied housing. We are ignoring household outlays for the purchase of vehicles and other durable goods and instead are including the full acquisition expenditures for these regardless of financing; including these in an HCI is left for a future study.

[3] Households are still weighted by their sampling weight so that averages represent the population.

We compute an HCI for the urban U.S. population covering the period December 2011 to December 2021. The HCI is based on the Lowe (modified Laspeyres) formula using average annual household weights with about a two-year lag. From December 2012 to December 2021, we find an average twelve-month inflation rate of 1.51 percent for the HCI-U, compared to 1.86 for the CPI-U and 1.73 for the Chained CPI-U. We find that empirical differences between the HCIs and CPIs are primarily due to the HCI's use of the payments approach, which we estimate subtracts 0.39 percentage points per year on average relative to an index that uses rental equivalence. This difference reflects both a lower weight for owner-occupied housing in the HCI as well as lower inflation in explicit housing costs when compared to owner's equivalent rent. In contrast, we estimate that equal household weighting increases the index only about 0.05 percentage points per year on average compared to an index which uses the standard expenditure weighting, but otherwise uses the same methodology as the HCI.

CPIs are used in a wide variety of economic applications—as an overall macroeconomic indicator, to deflate national accounts, to adjust marginal tax rates, and measure changes in the cost-of-living representative of the entire economy. In such applications, measuring the change in purchasing power of the average dollar of expenditure using an implicit consumption concept like owner equivalent rent may be appropriate. In other cases, such comparing the economic conditions of population subgroups, a measure tied to explicit outlays may be attractive. One index cannot usually satisfy all needs, and in this sense the HCIs can provide useful complimentary information about the average household inflation experience.

2. Literature Review

Current BLS CPI methodology is based on market-level expenditure weights and the rental equivalence approach to owner-occupied housing (Bureau of Labor Statistics, 2020). Household-weighted aggregation and the payments approach differ substantially from current BLS CPI methodology, though neither is new to the price index literature. Astin and Leyland (2015) propose using these methods to better capture the inflation experiences of households. They argue such a measurement is more credible for indexing monetary values, while a traditional CPI is superior for macroeconomic analysis and inflation targeting. Based in part on their research, the Office of National Statistics developed a set of HCIs for the United Kingdom (Office for National Statistics, 2017). Statistics New Zealand publishes a similar set of indexes called the Household Living-Costs Price Indexes. Research on a similar set of indexes for the U.S. began with Cage, et. al. (2018).

Household-weighted aggregation (also known as democratic aggregation) has been considered at least since Prais (1958). The topic has been developed and reviewed in Pollak (1989), National Research Council (2002), International Labor Organization (2004, Chapter 18), Ley (2005), and Martin (2022), among others. Spending patterns differ across the distribution of total expenditure. To the extent that these differences coincide with expenditure categories that have higher or lower inflation than average, a household-weighted index will differ from a traditional expenditure-weighted one. Equally weighted indexes have been studied with U.S. data in Kokoski (2000) and Hobijn, et. al. (2009). The latter is notable for statistically matching the interview and diary components of the Consumer Expenditure Survey (CE), and we follow many aspects of its approach. Our paper also builds on work from Cage, et. al. (2018) and Martin (2022), the latter of which finds that household-weighted aggregation adds about 0.08 percentage points per year to inflation measured by a Lowe-type CPI from December 2001 to June 2021.

The payments approach to owner-occupied housing has been discussed at least since the 1989 version of the International Labor Organization (ILO) CPI manual (as cited by Goodhart, 2001), and much of our initial approach follows the 2004 version (International Labor Organization, 2004, Chapter 10). The payments approach to owner-occupied housing focuses on the month-to-month outlays by households rather than an upfront purchase price (the acquisition approach) or the implicit consumption value (the use approach).[4] In addition to the HCIs for the United Kingdom and New Zealand, the payments approach is also used in the CPI for Ireland (Central Statistics Office, 2016). Mortgage interest is also included in the housing component of the CPI for Canada (Statistics Canada, 2019), and was a part of the U.S. CPI housing component prior to 1983 (Gillingham and Lane, 1982). Diewert and Nakamura (2009) contains a conceptual comparison of the payments approach against other methods like the user cost approach and rental equivalence, while Garner and Verbrugge (2009) compare methods empirically using the CE.

Astin and Leyland (2015) argue that the payments approach is superior for comparing household inflation experiences and escalating payments. They make the case that because rental equivalence is not tied to explicit outlays, an index which includes it as a large

[4] Rental equivalence and user cost are both flavors of the use approach.

component may be less tethered to the actual price movements that affect household budgets. For some subpopulations, there can be large differences between implicit rents and explicit cash flows. For instance, in Cage et. al. (2018), the subpopulation of households which receives at least 50% of its before-tax income from Social Security has higher relative expenditures on shelter (35-39%) when measured using rental equivalence than the overall urban population (32%), but lower relative expenditures when measured using payments (16-23%). This is because these households are disproportionately likely to be owner-occupiers without mortgages, meaning their explicit housing outlays are limited to items like property taxes, insurance, and maintenance.

Astin and Leyland (2015), as well as ILO (2003) advocate such an index for escalation purposes, but this position is not universally held. Diewert and Shimzu (2021) argue "it is not an index that can measure household consumption of the services of durable goods because it focuses on the immediate costs associated with the purchase of durable goods and ignores possible future benefits of these purchases." The payments approach has also been criticized in Goodhart (2001), Poole, Ptacek, and Verbrugge (2005), and elsewhere on the basis that it doesn't reflect consumption in an economic sense. We agree that a flow-of-service method like rental equivalence is more appropriate for a macro-focused CPI or a representative consumer's cost-of-living index (See, e.g., Diewert 1976). However, we study the HCIs as complementary series intended to capture explicit outlays of households rather than the implicit consumption prices (in an economic theoretic sense) reflected in a traditional CPI, though initially the distinction is limited to owner-occupied housing. The objective of our paper is primarily to compare owner-occupied housing and household aggregation methods.

3. Methods and Data

Our methods for this paper are preliminary and based on utilizing existing BLS surveys or publicly available data sources. Like the CPIs, the HCIs are constructed in two stages. First, basic indexes are constructed for item-area strata (e.g., coffee in Washington, DC). These are then aggregated using expenditure weights from the CE. As our initial version only applies the payments approach to owner-occupied housing, the elementary indexes and underlying household expenditures used in upper-level aggregation are largely the same. See Bureau of Labor Statistics (2020) for more details. For housing, the owner equivalent rent elementary indexes are replaced with indexes for property taxes, mortgage interest, and property management services. In addition, we use the full reported value of household expenditures on household appliances, maintenance and repair, and insurance when constructing upper-level aggregation weights. Finally, we estimate equally weighted averages of household expenditure shares based on matched CE Interview and Diary data and use these in the second-stage aggregation.

3.A. Payments Approach Item Structure and Elementary Indexes

The payments approach for owner occupied housing reflects the housing-related cash outflows of households. Compared to the CPI, the HCI item structure excludes owner's equivalent rent and includes three additional expenditure classes—property taxes, mortgage interest, and other primary residence expenses. The payments approach also removes several adjustments CPI makes to other category weights, which we discuss more later in this section. Within property taxes and mortgage interest, we create new elementary item indexes representing primary residences. These also serve as proxies for secondary residences. In the CPI, the price index for owner's equivalent rent of primary residences (numbered "01") also serves as the proxy for the unpriced item (numbered "09") representing secondary residences. A further item classification (see

Table 1 for details) for other primary residence expenses consists of ground rent, parking, and property management services. This category comprises less than one half of one percent of the overall index weight, and we provisionally measure its price change using the producer price index for final demand property management services as a proxy. Finally, our objective, where possible, is to limit expenditures to those pertaining to primary residences and vacation homes and exclude investment properties.

The rest of this section details the construction of the property tax and mortgage interest payment indexes. We follow what is (to our knowledge) international practice by including the interest component of mortgage payments (excluding second mortgages or home equity lines of credit) and excluding the portion that goes toward principal reduction (and by this reasoning down payments and cash purchases). From the 2004 ILO manual, only the interest portion is considered a pure cash outflow; the principal portion immediately shows up on the household's balance sheet as an increase in assets, so it may be considered more like an investment with a potential future return (International Labor Organization 2004, Chapter 10). This view is not universal (see Astin and Leyland, 2015). However, including mortgage principal presents additional technical challenges.[5]

Also following international practice, the mortgage interest and property tax payments indexes derive conceptually from two sources of potential change: a rate (an interest rate or an effective property tax rate) and the base to which the rate is applied (the debt level or the

[5] The most straightforward method to estimate the proportional impact of changing interest rates on mortgage principal payments would involve plugging in aggregate (i.e., average) interest rates into a nonlinear function. In the sense of measuring a change in average payments across households, the potential bias of such a plug-in procedure from Jensen's Inequality is unknown.

dwelling value). Changes in rates alone do not capture changes in purchasing power (International Labor Organization 2004, Chapter 10). Some users could be concerned about allowing the effects of home prices given these could be associated with (eventual) financial returns to households. In our view, there is a tradeoff between representing the explicit outlays of households and controlling for investment using economic theory. Indeed, as noted by Poole, Ptacek, and Verbrugge (2005), adjusting housing payments to account for investment results in the user cost approach, which is another implicit housing cost concept. Empirically, Garner and Verbrugge (2009) show that user costs can differ greatly from explicit payments.[6] Our initial strategy, following international practice, aims to exclude the investment aspect of housing ownership by excluding mortgage principal. Appendix A shows the decision to indirectly include home prices is significantly inflationary for the housing payments indexes and suggests the decision to exclude mortgage principal is somewhat deflationary.

Finally, our preliminary results compute a single set of payments approach elementary item indexes representing the U.S. urban population. We leave it to future research to extend these methods to create elementary indexes by CPI geographic areas.

3.A.1. Mortgage Interest Payment Index

The mortgage interest payments index measures the proportional change in the interest payment amount that would occur holding fixed the financing conditions—such as the loan term and proportion of principal remaining. We aim to follow the recommendations in the 2004 ILO manual (Chapter 10), which is to use both a representative basket of interest rates

[6] Garner and Verbrugge (2009) also find that user cost measures based on different underlying assumptions can differ greatly from each other and from implicit rents.

and a debt index, which holds “constant the age of the debt” between index periods (International Labor Organization 2004, Chapter 10). Payments in each period are determined by transactions occurring at many previous points in time, as mortgage loans are long-term contracts. Consequently, our index is based on weighted averages of interest rates and house prices corresponding to loans or debt of different ages. A fixed-basket approach has the advantage of being feasible with aggregate interest rate and house price data, but the disadvantage of not being micro-founded.[7]

Similar to Canada (Statistics Canada, 2019), we define the index as the product of a debt index (which is influenced by home prices) and an interest rate index which compare payments in the comparison period t against the reference period s.[8] The index is based on the model of a thirty-year fixed rate mortgage, which dominates the U.S. market (about 75% of existing loans as reported in the CE).[9] It is written:

$$P_{MIP} = P_D P_r, \tag{1}$$

where P_D is the debt index and P_r is the interest rate index. They are written

$$P_D = \frac{\prod_{j=0}^{\bar{\theta}} H_{t-j}^{\psi_{bj}}}{\prod_{j=0}^{\bar{\theta}} H_{s-j}^{\psi_{bj}}} \tag{2}$$

and

[7] We considered such a micro-founded approach which could, for example, average proportional changes in rates actually paid by households between the reference and comparison periods without fixing the loan age. Such an approach may be more appropriate for the U.S. market, which is dominated by 30-year fixed rate mortgages. However, basing such an approach on CE interest rate microdata misses any variation which occurs when a consumer unit moves from one house to another since consumer units are not followed.

[8] While our debt index is similar to the housing component of Canada’s mortgage interest index, their interest rate component is based on unit value-like averages using administrative banking data.

[9] We ignore preferential treatment of mortgage interest in the tax code.

$$P_r = \frac{\prod_{j=0}^{\theta-1} r_{t-j}^{\varphi_{bj}}}{\prod_{j=0}^{\theta-1} r_{s-j}^{\varphi_{bj}}}. \tag{3}$$

The indexes measure change from period s to period t by weighting past home prices (relative to a common base) and interest rates according to the relative importance of loans or debt initiated in those months to the index periods t and s.[10]

In these expressions, H_τ is a home price index for month τ, r_τ is an average interest rate for month τ, ψ_{bj} is the population-weighted proportion of mortgagor-month observations with debt of age j (measured as the number of months since the property was acquired), and φ_{bj} is the population-weighted proportion of mortgagor-month observations with current loans of age j (measured as the number of months since the first payment) during the reference period b. The ψ and φ parameters differ due to refinances. We use the proportion of mortgagors (rather than the proportion of debt, which is closer to what Statistics Canada uses) in keeping with the equal-weighting objective of the HCI. The parameter θ equals 360 to reflect the number of potential payments in a thirty-year loan, while $\bar{\theta}$ is set higher to allow for acquisition periods to be earlier on refinanced properties. While not well bounded in theory, we set $\bar{\theta}$ equal to 408 to accommodate the beginning of our house price indexes in January 1975. This covers about 97.5% of observations in our sample. We evaluate adjacent months t and s. We set b as the fourth quarterly lag of the quarter containing month t. This reflects a realistic production constraint for using CE data to construct the weights while keeping them as current as possible. We use CE microdata on mortgage expenses and keep those observations with 30-

[10] While the product of two geometric means with identical weights could be written as one geometric mean, writing the index as a product of two components makes for convenient discussion and analysis.

year fixed rate first mortgages on primary residences. We drop loan records that likely pertain to non-housing expenditures (second mortgages and home equity lines of credit).

We use monthly averages of the weekly 30-year fixed mortgage rate averages from the Freddie Mac Primary Mortgage Market Survey (PMMS), which are available only for the U.S. market. We also use the Federal Housing Finance Agency's (FHFA) All Transactions House Price Index. This index is quarterly, and we interpolate monthly values using the natural spline in SAS's PROC EXPAND. The FHFA's purchase only house price index is monthly and superior conceptually for a debt index representing past home purchases. However, this series only goes back to 1991, and would not be long enough to cover all loan ages in our sample.

3.A.2. Property Tax Payment Index

The property tax payment index measures the change in average property tax payments for households. Our proposed method attempts to hold the aggregate quality of the housing stock constant and uses annual data from the CE.[11] Let $X_{s,t}$ and $V_{s,t}$ denote proportional growth in population aggregates for property tax payments and owner-occupied housing unit values between years s and t, and let $H_{s,t}$ be a constant-quality home price index between years s and t. We use timeseries representing the entire U.S. and leave it for future research to extend the method to geographic areas, which require more granular tax data than we currently have. We compute the following:

$$P_{PTP} = \frac{X_{s,t}}{V_{s,t}} H_{s,t}. \quad (4)$$

[11] The CE asks homeowners the annual property taxes owed on their primary residence and adjusts these amounts if the property is partly used as a business. The CE also asks the consumer unit to estimate the market value of their primary residence. Investigating potentially more timely sources of property tax data is a task for future research.

Our method is similar to that of Statistics Canada and the Office for National Statistics, which compute unit value indexes, or ratios of average property tax payments, though they do so for different geographic areas. Let $N_{s,t}$ be the growth in the number of owner-occupied housing units between s and t. A similar approach we explored with CE data computes

$$P_{PTUV} = \frac{X_{s,t}}{N_{s,t}}. \tag{5}$$

where we use the number of owner-occupier consumer units to proxy for the number of owner-occupied housing units.[12] Equation (4) is equal to equation (5) divided by $(V_{s,t}/N_{s,t})/H_{s,t}$ which is the growth in average home values deflated by the constant-quality home price index. We interpret this ratio as a measure of change in dwelling quality which is relevant under the assumption that the total housing market valuations $V_{s,t}$ and the house price indexes $H_{s,t}$ approximate changes in value and price as would be measured by tax assessors. We found that the long-term trends of Eq. (4) and (5) were very similar. As in Canada and the U.K., we do not attempt to control for potential differences in quality of municipal services.

Our preliminary efforts use annual property tax aggregates from the CE, as the survey asks about annual tax obligations rather than monthly payments. The monthly expenditure microdata include these figures divided by 12. We find that that using Equations (4) and (5) on this average monthly data leads to substantial short-term sampling variation. For this reason, we compute the property tax index at an annual frequency and interpolate monthly values

[12] In the CE, consumer units are equivalent to households in the vast majority of cases but are defined by joint economic decision making rather than residence or familiar relationships.

using a spline function. Statistics Canada and the Office for National Statistics, for instance, update their property tax indexes once per year. The CE is not the ideal source for property tax and housing value data, as data for a calendar year are released about nine months after that year ends. For this reason, this paper's analysis only covers through the end of 2021. Finding timelier and larger samples using alternative data is an objective for future research.

3.B. Upper-level Aggregation

As in the CPI, we use CE data to derive upper-level aggregation weights, with some important differences. As shown in

Table 1, the set of eligible elementary item strata now includes property taxes and mortgage interest and excludes owner equivalent rent. The property tax and mortgage interest weight are derived from the monthly expenditures on those items as collected by the CE. In addition, we use the full reported values of expenditures on items like maintenance and repair, homeowner's insurance, appliances, and household furnishings. Under the rental equivalence approach, these items are scaled down for owner-occupiers to reflect the likelihood of a renter making the same purchase. Table 2 compares average housing-related relative importance across consumer units in different subpopulations —by housing tenure, an indicator for being a wage earner or clerical worker (as in the CPI-W), and an indicator for being elderly (age greater than or equal to 62, as in the R-CPI-E)[13]—both under the payments approach and rental equivalence. In general, housing payments make up a smaller share of overall spending under the payments approach than under rental equivalence. For the urban population, for instance, housing under the payments approach amounts to 34.3% of the market basket on average, versus 42.9% on average under rental equivalence. Interestingly, patterns of spending across some subpopulations differ by housing approach. For instance, under rental equivalence, the average share going to housing among the elderly is relatively high at 46.8%. Under the payments approach, however, the elderly have a high proportion going to insurance, appliances, maintenance, and repairs ("other housing"), but relatively less going to mortgage interest, resulting in a total housing weight of 34.1%, slightly less than the overall urban population (34.3%).

[13] Consumer units were classified according to their reported demographic in their last interview in the sample.

Table 1: Weights for Select Housing Items for the HCI Subsample in 2019

Code	Description	Payments $ Bil.	Payments % RI*	Rental Equivalence $ Bil.	Rental Equivalence % RI*
HC01	Owner's Equivalent Rent of Primary Residence	NA	NA	1,144.36	22.40
HC09	Unsampled Own. Equiv. Rent of Second. Res.	NA	NA	56.29	0.75
HD01	Tenants' and Household Insurance	38.02	1.01	17.24	0.38
HH01	Floor Coverings	8.29	0.18	2.54	0.05
HK01	Major Appliances	17.05	0.39	2.38	0.06
HK09	Other Appliances	0.08	0.00	0.07	0.00
HM01	Tools, Hardware, and Supplies	17.23	0.43	11.67	0.26
HM09	Unsamp. Tools, Hardw., Outdoor Equip, Supp.	58.44	1.31	9.35	0.20
HP04	Repair of Household Items	46.52	0.83	4.14	0.08
HP09	Unsampled Household Operations	10.69	0.23	4.29	0.07
HR01	Property Tax of Primary Residence	199.70	4.51	NA	NA
HR09	Property Tax of Secondary Residence	8.61	0.16	NA	NA
HS01	Mortgage Interest of Primary Residence	211.64	4.26	NA	NA
HS09	Mortgage Interest of Secondary Residence	4.55	0.08	NA	NA
HT01	Other Owner Payments for Primary Residence	14.10	0.42	NA	NA
HT09	Other Owner Payments for Secondary Res.	1.29	0.02	NA	NA

* Average (equally weighted) relative importance across consumer units.

Table 2: Average Household Relative Importance for Housing by Subpopulation (percent)

Category	Urban	Wage-earner	Elderly	Own. w/ Mortgage	Own. w/o Mortgage	Renter
Payments Approach						
Rent	9.2	13.0	6.3	0.1	0.2	31.8
Property Tax	4.7	4.2	5.7	6.1	7.0	0.2
Mortgage Interest	4.3	5.2	2.7	10.2	0.2	0.1
Other Housing	16.0	14.8	19.4	16.9	22.0	8.8
Total Housing	34.3	37.2	34.1	33.2	29.5	40.9
Rental Equivalence Approach						
Rent	9.2	13.0	6.3	0.1	0.2	31.7
Owner's Equiv. Rent	23.1	20.9	29.4	31.1	33.9	0.8
Other Housing	10.6	10.4	11.1	10.9	12.0	8.7
Total Housing	42.9	44.3	46.8	42.1	46.1	41.2

Note: Cells show average December 2020 relative importance (2019 reference period weights price-updated to December 2020 values) across households meeting the HCI sample requirement. While expenditures cover a year, consumer units are classified according by attribute from their last collection quarter.

Our upper-level aggregation uses the Lowe formula, and same as the CPI (as of January 2023) the quantity weights pertain to annual expenditure reference periods which are updated each year. The household-weighted aggregation starts from the CE Interview sample, as consumer units contribute up to one year of data and the Interview comprises most eligible expenditures. Eligible expenditures from the Diary survey are imputed to the Interview sample using a matching procedure based on Hobijn, et. al. (2009), which is described further later in this section and similar to that used in Martin (2022). The procedure matches eligible Diary consumer units to an Interview consumer unit based on demographic characteristics that are predictive of total expenditure. The second-stage aggregation is then based on the Lowe formula with lagged expenditure weights.

$$P_{HCI} = \sum_{a\in\mathcal{A}} \sum_{i\in\mathcal{I}} \bar{s}_{a,i,v,b} P_{a,i,t,v} \tag{6}$$

$$\bar{s}_{a,i\{v,b\}} = \left(\frac{H_{a,b}}{H_b}\right) H_{a,b}^{-1} \sum_{h\in\mathcal{H}_{a,b}} \omega_h\, s_{i,v,b,h} \tag{7}$$

$$H_a = \sum_{h\in\mathcal{H}_{a,b}} \omega_h\,, \qquad H_b = \sum_{a\in\mathcal{A}} \sum_{h\in\mathcal{H}_{a,b}} \omega_h, \tag{8}$$

where a indexes the geographic area, i the item stratum, v the index pivot month, b the weight reference period, and h the consumer unit. The set of areas is $\mathcal{A}$, the set of items $\mathcal{I}$, and the set of consumer units in area a during period b is $\mathcal{H}_{a,b}$. The elementary index between pivot month v and period t for item i in area a is given by $P_{a,i,t,v}$. The associated household-weighted expenditure shares are $\bar{s}_{a,i,v,b}$. These are equally (with respect to the population) weighted averages of individual consumer unit annual expenditure shares $s_{i,v,b,h}$, with $\omega_h$being household h's sampling weight. The weight reference period b is the calendar year two years prior to the calendar year containing month t, and the expenditure shares $s_{i,v,b,h}$ are price-updated to represent period v values using the ratio of the elementary index in month v to its average over period b.

Consumer units participate in the CE for up to four collection quarters, providing up to twelve months of expenditures. Because participation is on a rolling basis and there is unit nonresponse and occasional attrition, the number of observations exactly lining up with a single calendar year is relatively small, often only a few hundred. Therefore, for the HCI, we define a "reference year" sample differently than does either the CE or CPI. We assign a consumer unit to a reference year b if its last month of expenditure occurred during year b. So that each h's expenditure basket reflects a whole year, we include only observations which completed all four quarterly interviews, even if some of their expenditures occurred in the prior calendar year. For the 2019 reference year, for instance, (used for indexes in 2021), we include consumer units with at least one month occurring in 2019, meaning we include some observations whose sample tenure started as early February 2018. With the four-quarter requirement, this amounts to a sample of 3,063 unique consumer units (12,252 collection quarters) representing our 2019 reference year. In comparison, 11,740 unique consumer units (comprising 22,957 collection quarters) in the CE have expenditures recorded for the calendar year 2019.[14] For index subgroup definitions, we use consumer unit characteristics from their final collection quarter.

[14] These sample sizes were calculated by counting the number of unique FAMID (or the consumer-unit specific portion of the FAMID) for a given expenditure reference period.

As discussed in Martin (2022), including observations with periods less than one year can distort household-weighted indexes due to greater variability in total expenditures and lower average expenditure shares for less frequently purchased items. However, there is a potential trade-off with the four-quarter requirement due to representativity. Table 3 shows differences in the relative frequencies of a few consumer unit demographics. For the 2019 reference year, the HCI subsample has a greater proportion of owners and elderly than the full sample of urban consumer units. At the same time, Table 2 shows there are differences in the average expenditure shares on housing-related payments across these groups, suggesting potential consequences for price indexes. For instance, the elderly spend relatively more on property taxes than on mortgage interest, reflecting that they are disproportionately owners without mortgages.

Table 3: Frequency of Consumer Unit Characteristics by Sample in 2019 (percent)

	All Urban	HCI Subsample
Owner with mortgage	37.3	41.4
Owner without mortgage	23.6	29.1
Renter	39.2	29.6
Wage earner	27.0	25.3
Elderly	30.8	37.7

Nevertheless, we find little evidence of a sample selection bias stemming from our HCI eligibility criteria, at least over during sample period. Table 4 shows (comparing columns 2 and 3) the impact of using the CE subsample on major group-level weights is small relative to the effect of using the payments approach or household aggregation. Additionally, we find (Appendix C) that the sample selection impact on an expenditure-weighted version of the HCI-U (corresponding to column 4 of Table 4) is minimal, about 0.01 percentage points per year.

Furthermore, our results show a CPI-like index calculated from these subsamples (with Diary expenditures imputed as described in the next subsection), corresponding to column 3 of Table 4 closely matches the published CPI-U. These together imply our results are driven by the payments approach and household-weighted aggregation, and not the reference period or CE subsample. Our current method makes no adjustments to the CE sampling weights, which we leave to future research. Such adjustments may be more important with more recent data than our sample period, particularly with recent surges in mortgage interest rates.

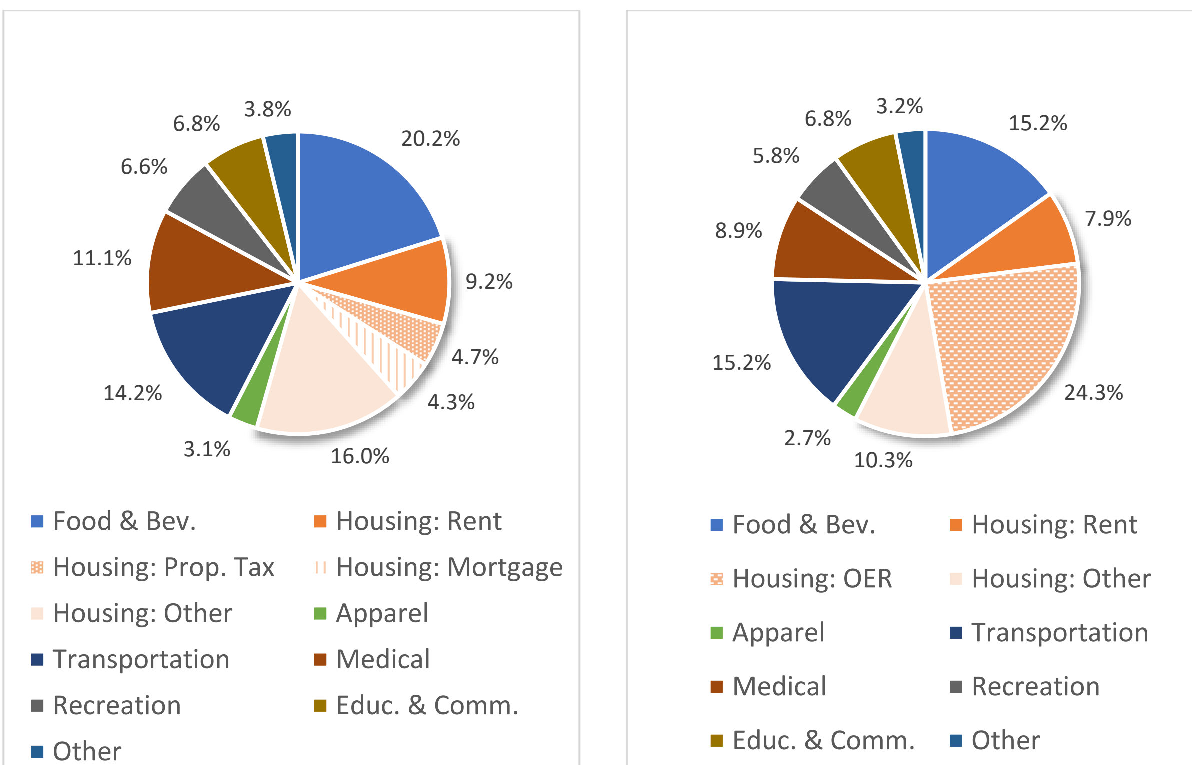
There are a few other differences between our research indexes and official CPI methods. Since the HCI is based on consumer unit-specific shares, which must be weakly positive, we censor negative annual expenditures at zero.[15] We also make some small item-structure changes to simplify calculations using historical data. Finally, we omit weight-smoothing procedures used in the CPI, including composite estimation for the item-area weights, which are designed to lower their sampling variance across geographic areas. Our all items, all areas CPI-U replications closely match the published indexes even without these procedures, and our prototype procedure only estimates property tax and mortgage interest at the national level. We leave it to future research to extend weight-smoothing procedures to the HCIs.

Figure 1 below shows the December 2020 relative importance by major expenditure group and select housing categories and compares them with the published shares for the CPI-U. The HCI shares correspond to the 2019 weight reference year, while for the CPI they

[15] This affects items RC01 “Sports Vehicles, Including Bicycles”, TA02 “Used Cars and Trucks”, and TA09 “Unsampled New and Used Motor Vehicles.” The CPI counts returns or sales as negative expenditures.

correspond to the 2017-18 reference period. Table 4 tracks the change in relative importance by major group as different HCI elements are activated. The effects of the payments approach and household-weighted aggregation on the relative weights are significant, but sometimes have offsetting effects. For instance, the overall housing weight in the HCI is smaller than the CPI, as property tax, mortgage interest, and the increase in other housing outlays amounts to less than the decrease due to the exclusion of OER. By itself, this decrease in housing weight increases the weight allocated to other categories, like medical and recreation. At the same time, however, household-weighted aggregation shifts weight toward households with lower total expenditures, further increasing the relative importance of rent and food while decreasing that of transportation.

Figure 1: December 2020 Relative Importance for HCI-U and CPI-U



Panel a: HCI-U (2019 weights)

Panel b: CPI-U (2017-18 weights)

Table 4: December 2020 Relative Importance for Different Index Types (percent)

Major Group	CPI-U	(2)	(3)	(4)	HCI-U
Food and Beverages	15.16	15.68	15.60	17.96	20.16
Housing	42.39	41.84	42.13	33.34	34.26
Apparel	2.66	2.70	2.67	3.07	3.15
Transportation	15.16	15.43	14.60	16.80	14.23
Medical	8.87	8.79	9.18	10.58	11.09
Recreation	5.80	5.80	6.16	7.08	6.59
Education and Comm.	6.81	6.72	6.57	7.61	6.76
Other	3.16	3.04	3.09	3.56	3.76
*Methods**					
Reference Period	2017-18	2018-19	2019**	2019**	2019**
CE Sample	Full	Full	4-quarter	4-quarter	4-quarter
Aggregation	Expenditure	Expenditure	Expenditure	Expenditure	Household
Owner Occ. Housing	REQ***	REQ***	REQ***	Payments	Payments

* Columns 2-5 also reflect other methodology changes and simplifications described in text.
** Under our sample eligibility criteria, this includes spending back to February 2018.
*** REQ = Rental Equivalence

3.B.1. Interview-Diary Matching Procedure

As mentioned, the basis of our household average expenditure weights is the CE Interview sample, which covers about three-quarters of the expenditure basket as traditionally sourced by the CPI. We implement a statistical matching procedure based on Hobijn et al. (2009) to impute the remaining proportion which CPI sources from the Diary.[16] Similar observations from the Diary sample provide the remaining expenditure data for each Interview consumer unit, according to a model of expenditures as a function of demographic characteristics. The dependent variable is expenditures on items which HCI (and the CPI) sources from the Diary, but for which the Interview either collects the same item or has more

[16] Garner, et. al. (2022) and Martin (2022) also use matching processes based on Hobijn, et. al. (2009).

aggregate data.[17] The model is a convenient way of combining many characteristics according to which linear combination most strongly predicts expenditures. We then use the predicted values to form measures of distance between an Interview recipient and its potential Diary donors. For our main results, the only attribute guaranteed to match between donor and recipient is quintile group membership based on the distribution of annual before-tax income.[18] For our results on housing tenure subpopulations, we also guarantee this attribute matches. The matching procedure is many-to-one, as we draw four donor Diaries for each Interview in each month with replacement. The procedure is implemented separately by month so that weekly Diary donors are evenly distributed temporally over the recipient Interview's sample tenure. Due to the sample selection criteria outlined earlier, for reference year 2019, for example, that means we are running monthly regressions from February 2018 to December 2019. The stratification and model estimation are done on the full Interview sample, not just the four-quarter subsample.

First, we stratify both Interview and Diary consumer unit samples for the reference period by the sample quintiles of annual before-tax income. For each month t and quintile grouping q, we use the Interview sample to estimate the regression

$$y_{ht} = \boldsymbol{x}_{ht}\boldsymbol{\beta}_{qt} + u_{ht}, \tag{9}$$

[17] From Martin (2022), Table A2, these amount to about 80% of Diary-sourced expenditures in 2019. Alternatively, it might seem attractive to use the Diary sample to estimate Diary expenditures as a function of demographic characteristics, as we intend to impute these expenditures for the Interview sample. However, we find that characteristics explain relatively little variation in Diary expenditures, perhaps due to the short (week-long) recall period.

[18] The Diary samples are small enough that conditioning on multiple characteristics quickly leads to empty cells. See Hobijn, et al. (2009) for more discussion.

where y_{ht} is logged expenditure of consumer unit h. The term u_{ht} is an error term, and $\boldsymbol{x}_{ht}$ include Census region, urban/rural, age, race, sex, and education of the reference person, consumer unit size, the log of annual before-tax income (if positive), and an indicator for whether income was negative.[19] We use the least squares estimator weighted by the CE sampling weight, finlwt21. Over the sample period, R-squared values for the quintile and month-specific regressions averaged 0.17, while income quintile itself explained about 0.31 of the variation in the dependent variable.

Let $\widehat{\boldsymbol{\beta}}_{qt}$ be the slope estimate for quintile q in month t. As household characteristics are available and comparably defined in both surveys, we calculate predicted values $\hat{y}_{ht} = \boldsymbol{x}_{ht}\widehat{\boldsymbol{\beta}}_{qt}$ for each Diary and Interview observation. For a given Interview observation h and Diary observation k, the distance metric is defined as

$$\delta_t(h, k) = |\hat{y}_{ht} - \hat{y}_{kt}|. \tag{10}$$

Within each month and income quintile, we calculate $\delta_t(h, k)$ for all $\{h, k\}$ pairs. Then for each Interview observation h, we randomly select (with replacement) four k from the twenty smallest $\delta_t(h, k)$ out of all the Diary observations from the same month and income quintile. The random component is intended to ensure a more even distribution of matches across Diary observations. The detailed set of expenditures of the donor Diary is then assigned to the recipient Interview. As one donor Diary is intended to represent one quarter of one month of expenditure, but Diaries correspond to a one-week recall period, the donor Diary expenditures

[19] These demographic variables technically pertain to the collection quarter or some other reference period, so we implicitly assume they represent the associated reference months. For the matching regressions, we allow a consumer unit's attributes to vary by collection quarter.

are scaled by 13/12. This process is repeated for each Interview observation, for each month it is in the sample.[20] Since the Interview sample is much larger than the Diary on a per-month basis, each Diary is matched with several Interviews. Further analysis of the matching procedure is in Appendix B.

4. Results

We find the HCI-U follows similar patterns of acceleration and deceleration as the CPI-U, but it has significantly lower average rates of growth during our sample period. The average 12-month change in the HCI-U averages 1.51% versus 1.86% for the CPI-U, as shown in

Table 5.

[20] In the CPI, diary expenditures are multiplied by 13 to account for the difference in recall periods between weekly diaries and quarterly interviews. The scaling in our procedure is analogous in that an interview is matched with a total of 12 diaries each quarter, and with the scaling these also represent 13 weeks.

Figure 2 plots the index levels, showing markedly different trends between the CPI-U and HCI-U from 2012-2020. The two indexes increased at a similar rate in 2021, averaging 4.6-4.7% year-over-year growth throughout the year.

Table 5 includes an index (U-EW-REQ) which uses expenditure weighting and the rental equivalence approach but uses our CE subsample and processing methods. It also includes a comparable series (U-EW-PAY) which instead uses the payments approach but uses expenditure weighting as in the CPI. Comparisons of these indexes and the HCI-U show the difference in trends and average growth reflects primarily the impact of the payments approach. U-EW-PAY averages about 0.39 percentage points per year less than U-EW-REQ, and in a single year (2016) averages 0.74 percentage points lower. In 2021, the impact of the payments approach is to add 0.15 percentage points to the average 12-month percent change, reflecting increasing home prices and interest rates. In 2022, we also expect this effect to be positive and much larger in magnitude due to the large increase in mortgage interest rates. In contrast, comparing HCI-U to U-EW-PAY shows the household-weighted aggregation adding only slight amount to the overall average 12-month percent change (0.05%), but yearly average differences are as high as 0.16 percentage points in 2017. In 2021, household-weighted aggregation lowers HCI-U by 0.1 percentage points on average.

Figure 2: HCI-U and CPI-U Index Levels

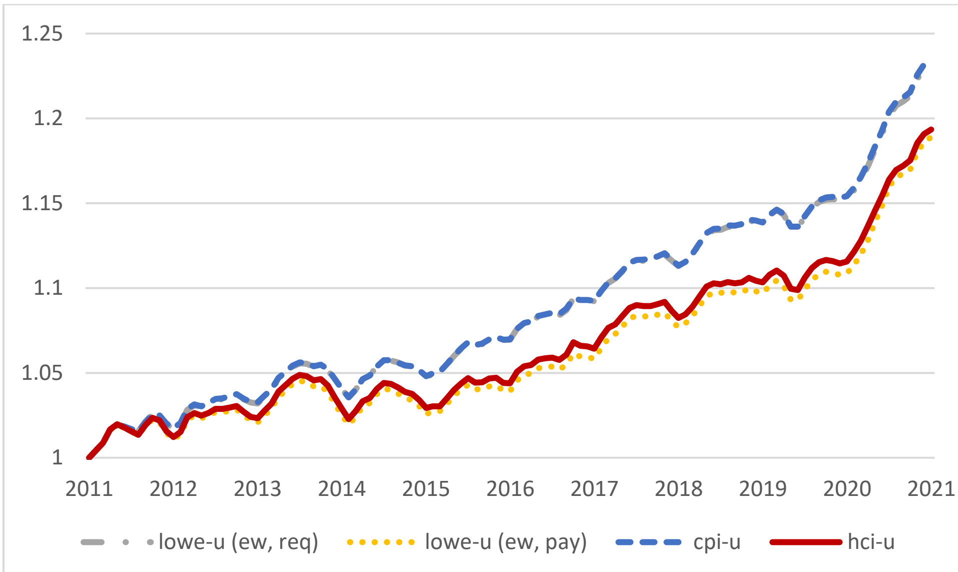


Table 5: Average 12-month Percent Changes by Year, HCI and CPI

Year	HCI-U	CPI-U	U-EW-REQ	U-EW-PAY	HCI-OM	HCI-ONM	HCI-RNT
2013	0.99%	1.47%	1.43%	0.86%	0.52%	1.22%	1.57%
2014	1.41%	1.62%	1.63%	1.27%	1.02%	1.65%	1.77%
2015	-0.44%	0.12%	0.15%	-0.44%	-0.88%	-0.52%	0.27%
2016	0.56%	1.26%	1.24%	0.51%	0.10%	0.55%	1.19%
2017	1.76%	2.13%	2.13%	1.60%	1.41%	1.79%	2.24%
2018	2.36%	2.44%	2.42%	2.33%	2.32%	2.23%	2.52%
2019	1.39%	1.81%	1.81%	1.43%	1.30%	1.02%	1.80%
2020	0.93%	1.24%	1.21%	0.84%	0.65%	0.89%	1.31%
2021	4.62%	4.69%	4.58%	4.73%	4.54%	4.95%	4.44%
Average	1.51%	1.86%	1.84%	1.46%	1.22%	1.53%	1.90%

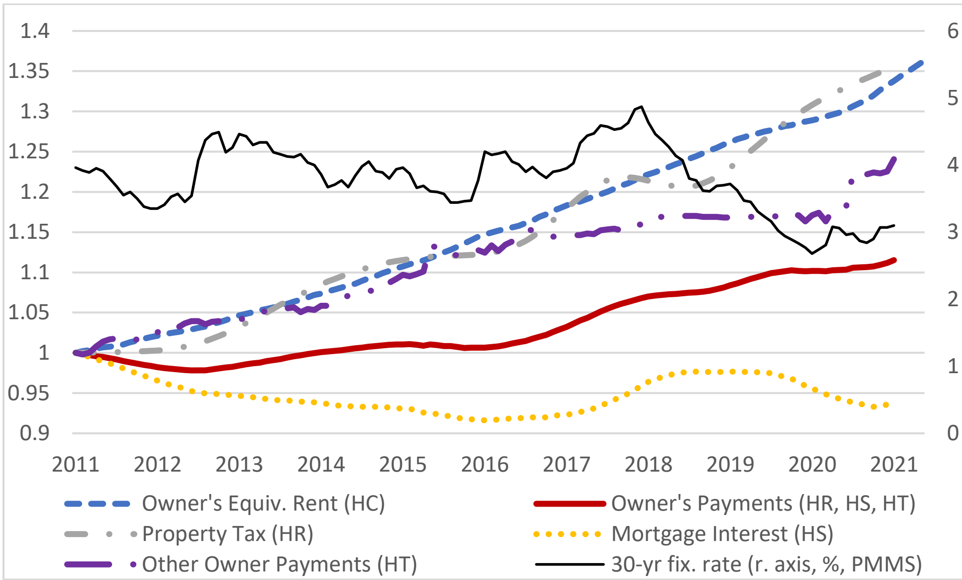
Notes: U signifies urban population. U-EW-REQ is a CPI-like replication using the HCI sample and simplified expenditure processing methods, but expenditure-weighting and rental equivalence. Similarly, U-EW-PAY uses expenditure-weighting, but the payments approach. "OM" is owners with a mortgage, "ONM" is owners without a mortgage, and "RNT" is renters.

Figure 3 describes further how the actual outlays for owner-occupiers are associated with lower inflation than would be implied by rental equivalence. Over the sample period, the official index for owner's equivalent rent increases 33.8% cumulatively, while our sub-aggregate for owner's payments (combining property tax, mortgage interest, and other owner payments) increased only 11.5%. Within owner's payments, the two major components, the trend in the property tax index is similar to owner's equivalent rent for most of the sample period. However, the mortgage interest index trends flat, not yet picking up the sharp increases in interest rates occurring in 2022 after our sample period ends.[21] We also note that evolution of the mortgage interest index is smoother than current average mortgage interest rates (from

[21] Our analysis is constrained by sourcing property tax payments from the CE, which as of June 2023 are only available through the first half of 2022. The average 12-month change for the mortgage interest index is 8.2% in 2022. Using the first half of 2022 property tax burden (X/V) as a crude forecast, we find an average change in the owner's payments index of 10.0% in 2022 (versus 5.7% for owner's equivalent rent), and an average change in the HCI-U of 8.7% (versus 8% for the CPI-U).

the Freddie Mac PMMS), because the index is averaging over 30 years of past mortgage rates in order to reflect current payments.

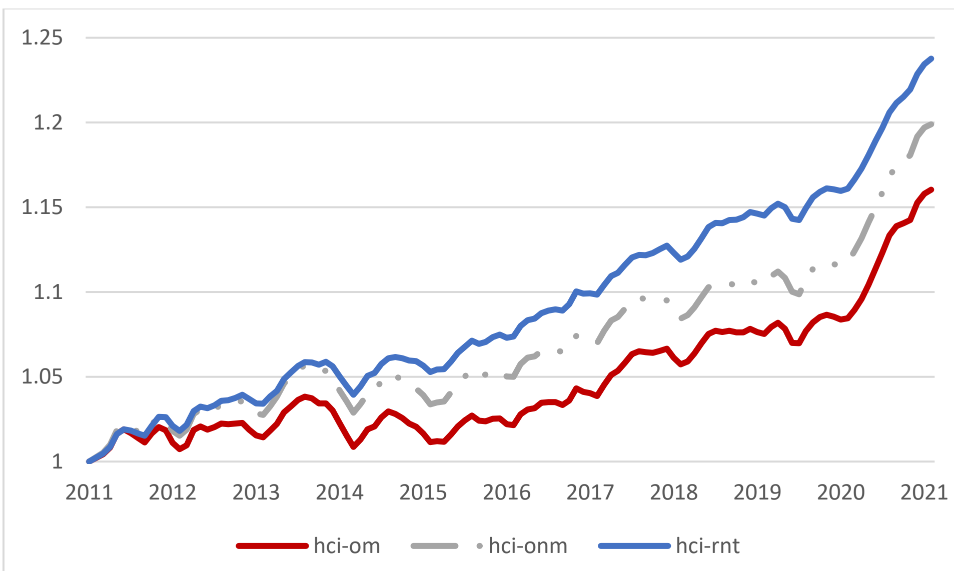
Figure 3: Owner's Equivalent Rent vs. Owner's Payments



Finally, we further illustrate the treatment of owned housing outlays by estimating HCI's for three subpopulations, owners with a mortgage (OM), owners without a mortgage (ONM), and renters (RNT). We define these using the housing tenure value reported by the consumer unit in their final interview. The final three columns of

Table 5 show the average 12-month percent changes, while Figure 4 plots the index levels. HCI-RNT has average inflation of 1.9% and is closest to the CPI-U. While there may be overall weight differences between the urban population and the subpopulation of renters, the evolution of owner's equivalent rent is close enough to the evolution of actual rent that this result is not surprising. In contrast, the HCI inflation for owners is significantly lower, averaging 1.53% per year for those without a mortgage and 1.22% per year for those with a mortgage. As with the urban indexes, the relative rankings are not the same year to year. For instance, owners without mortgages had the highest average inflation in 2021, 4.95%, versus 4.54% for owners with a mortgage and 4.44% for renters.

Figure 4: HCIs for Housing Tenure Subpopulations



4.A. Alternative Treatments of Owner Payments for Housing

As discussed in Section 3.A, we follow international practice in excluding mortgage principal and basing mortgage interest and property tax index changes on two sources: a change in a rate (the interest rate or the effective property tax rate), and the change in a monetary base (the debt level and the housing value). The appendix, including Figure 5 and Figure 6, explore the sensitivity of the indexes to these decisions. Including mortgage principal would raise the owner's payments subindex (combining mortgage interest, property tax, and other payments as in Figure 3) by 0.8 percentage points per year. Combined with the associated weight increase to mortgages, this would result in an all-items HCI-U that is higher by 0.10 percentage points per year. The effect of home prices would be more substantial, lowering the owner's payments index by 4.0 percentage points per year and the all-items HCI-U by 0.38 percentage points per year.

5. Conclusions and Future Research

Our results show the HCI differs substantially from the CPI because it uses the payments approach for owner occupied housing, and slightly because it weights households equally in its upper-level aggregation. The payments approach tracks the actual outlays of homeowners, which over our sample period of 2012 to 2021 have escalated at a lower trend than (imputed) owner's equivalent rent, resulting in lower inflation as measured by the HCI than as measured by the CPI. We do not argue that the payments approach is superior from the standpoint of measuring the cost-of-living as an economic theoretic concept or for use in monetary policy. Rather, by reflecting the explicit outlays of owners, we show the HCI offers a measurement of the household inflation experience which is empirically different than the CPI.

Future research could focus on many areas. Our measures of price change for mortgage and property tax payments use only national-level data. A natural next step would be to extend these to subnational geographic areas, if relevant and feasible. Further down the road, exploring mortgage microdata of the sort described by Bhutta, et. al. (2020) could be informative on different experiences of subpopulations, to the extent that long enough histories can be obtained to account for the long lives of mortgage loans. More timely and granular property tax data would also improve the HCI. In addition, in principle, the payments approach could be extended to any durable good where payment occurs over a long timeframe, with automobiles in particular being a high priority. Martin (2022) suggests treating automobiles under an approach consistent with the target of the index (payments, in our case) is critical if higher-frequency household weights are to be taken seriously, such as for a monthly weighted superlative like the C-CPI-U. Custom sampling weights should also be created to account for demographic differences for the four-quarter sample of consumer units used for the HCIs, but further analysis may also be warranted related to weight frequency and subsample selection. With the payments approach weighting of automobiles, for instance, perhaps infrequent purchase issue discussed in Martin (2022) is less salient. Finally, the impact household-weighted aggregation on the all-items index's sampling variation or the potential of weight-smoothing techniques have yet to be explored.

References

Astin, J., & Leyland, J. (2015). *Towards a Household Inflation Index: Compiling a consumer price index with public credibility.* Royal Statistical Society. Retrieved November 20, 2020, from https://rss.org.uk/RSS/media/News-and-publications/Publications/Reports%20and%20guides/Astin-Leyland-HII-paper-Apr-2015.pdf

Bhutta, N., Fuster, A., & Hizmo, A. (2020). *Paying Too Much? Price Dispersion in the US Mortgage Market.* Washington, DC: Board of Governors of the Federal Reserve System. doi:https://doi.org/10.17016/FEDS.2020.062

Bureau of Labor Statistics. (2020). The Consumer Price Index. In *Handbook of Methods.* Washington, DC. Retrieved from https://www.bls.gov/opub/hom/cpi/home.htm

Central Statistics Office. (2016). *Consumer Price Index: Introduction of Updated Series (Base: December 2016=100).* Cork: Central Statistics Office. Retrieved from https://www.cso.ie/en/media/csoie/methods/consumerpriceindex/CPI_-_introduction_to_series_2016.pdf

Diewert, W. E. (1976). Exact and Superlative Index Numbers. *Journal of Econometrics, 4*(2), 115-145. doi:10.1016/0304-4076(76)90009-9

Diewert, W. E., & Nakamura, A. O. (2009). *Accounting for Housing in a CPI.* Philadelphia: Federal Reserve Bank of Philadelphia. Retrieved from https://www.philadelphiafed.org/-/media/frbp/assets/working-papers/2009/wp09-4.pdf

Diewert, W. E., & Shimizu, C. (2021). Chapter 10: The Treatment of Durable Goods and Housing. In *Consumer Price Index: Theory (Draft).* Washington, D.C.: International Monetary Fund. Retrieved from https://www.imf.org/en/Data/Statistics/cpi-manual#companion

Federal Housing Finance Agency. (2021). *House Price Index Datasets*. Retrieved from https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx

Freddie Mac. (2022). *Primary Mortgage Market Survey - About*. Retrieved April 29, 2022, from Primary Mortgage Market Survey: https://www.freddiemac.com/pmms/about-pmms

Freddie Mac. (2023). *Primary Mortgage Market Survey - Archive*. Retrieved March 17, 2023, from Primary Mortgage Market Survey: https://www.freddiemac.com/pmms/pmms_archives

Garner, T. I., & Verbrugge, R. (2009). Reconciling user costs and rental equivalence: Evidence from the US consumer expenditure survey. *Journal of Housing Economics, 18*(3), 172-192. doi:10.1016/j.jhe.2009.07.001

Gillingham, R., & Lane, W. (1982). Changing the treatment of shelter costs for homeowners in the CPI. *Monthly Labor Review*, 9-14. Retrieved from https://www.bls.gov/opub/mlr/1982/06/art2full.pdf

Goodhart, C. (2001). What Weight Should be Given to Asset Prices in the Measurement of Inflation? *The Economic Journal*, F335-F356. doi:10.1111/1468-0297.00634

International Labor Organization. (2004). *Consumer Price Index Manual: Theory and Practice.* (P. Hill, Ed.) Geneva: International Labor Organization. Retrieved from https://www.ilo.org/wcmsp5/groups/public/---dgreports/---stat/documents/presentation/wcms_331153.pdf

International Labour Organization. (2003). Resolution concerning consumer price indices. *Resolution of the Seventeenth International Conference of Labor Statisticians.* Geneva. Retrieved from http://ilo.org/wcmsp5/groups/public/---dgreports/---stat/documents/normativeinstrument/wcms_087521.pdf

Office for National Statistics. (2017). *Household Costs Indices: Methodology.* Office for National Statistics. Retrieved from https://www.ons.gov.uk/economy/inflationandpriceindices/methodologies/householdcostsindicesmethodology

Office for National Statistics. (2019). *Consumer Prices Indices Technical Manual.* Office for National Statistics. Retrieved from https://www.ons.gov.uk/economy/inflationandpriceindices/methodologies/consumerpricesindicestechnicalmanual2019

Poole, R., Ptacek, F., & Verbrugge, R. (2005). *Treatment of Owner-Occupied Housing in the CPI.* Washington, DC: Bureau of Labor Statistics. Retrieved from https://www.bls.gov/advisory/fesacp1120905.pdf

Prais, S. J. (1959). Whose cost of living? *The Review of Economic Studies*, 126-134. doi:10.2307/2296170

Statistics Canada. (2019). *The Canadian Consumer Price Index Reference Paper.* Statistics Canada. Retrieved from https://www150.statcan.gc.ca/n1/pub/62-553-x/62-553-x2019001-eng.htm

Statistics New Zealand. (2020). *Household living-costs price indexes (HLPIs) data dictionary (Version 33).* Wellington: Statistics New Zealand. Retrieved November 23, 2022, from https://datainfoplus.stats.govt.nz/Item/nz.govt.stats/a46a6353-947a-4062-89e7-c6faef4fece1/?_ga=2.96280540.1570432553.1669226241-1704970333.1669226240

Appendix

A. Alternative Mortgage Interest and Property Tax Indexes

The mortgage payments index which includes mortgage principal replaces the interest rate component, Eq. (3), with the following representing change in full mortgage payments between months s and t:

$$P_f = \frac{\prod_{j=0}^{\theta-1}\left[f(r_{t-j}, \theta - j)\right]^{\varphi_{bj}}}{\prod_{j=0}^{\theta-1}\left[r_{s-j}, \theta - j)\right]^{\varphi_{bj}}}. \tag{11}$$

where $f(r, \omega) = rR^{\omega}/(R^{\omega} - 1)$, $\omega > 1$, where $R = 1 + r$. The function f represents the fixed mortgage payment as a proportion of the current debt amount. In this expression, the interest rate r is the annualized rate divided by 12 so that it corresponds to one month. Note, when estimated using aggregate data, even if r_{t-j} equals an average interest rate across households with loans of age j, the amount $f(r_{t-j}, \theta - j)$ cannot be interpreted as an average mortgage payment ratio across households due to Jensen's inequality. The relationship between $f(r_{t-j}, \theta - j)$ and a true household average is unknown (at least to the authors) but using such an average in a price index would require microdata tracking individual mortgagors across loan changes including refinances (which we can observe in the CE) and new loans (which we often do not observe due to address-based sampling). The mortgage payment indexes without home prices remove the debt index component, Eq. (2), while the property tax index without home prices is just the effective tax rate component, $X_{s,t}/V_{s,t}$ from Eq. (4).

Figure 5 plots the different Owner's Payment subindexes (combining mortgage interest, property taxes, etc., as in Figure 3) and compares them again against owner's equivalent rent. Adding mortgage principal increases the owner's payments index by about 0.8 percentage points per year when home prices are included, and about 1 percentage point per year when home prices are excluded. Given the strong upward trend of home prices over the past several decades, removing their lowers the payments index by 4.0 percentage points per year when mortgage principal is excluded and by 6.6 percentage points per year when mortgage principal is included, resulting in downward trends. Figure 6 tracks these payments indexes changes on the all-items HCI-U, accounting for changes in both the elementary indexes and the aggregation weights. The overall effect of mortgage principal is modest, adding 0.10 or 0.03 percentage points per year depending on whether house prices are included. Home prices themselves have a larger impact on the all-items index, decreasing it by either 0.38 or 0.45 percentage points per year depending on whether mortgage principal is included.

Figure 5: Alternative Versions of Owner's Payments

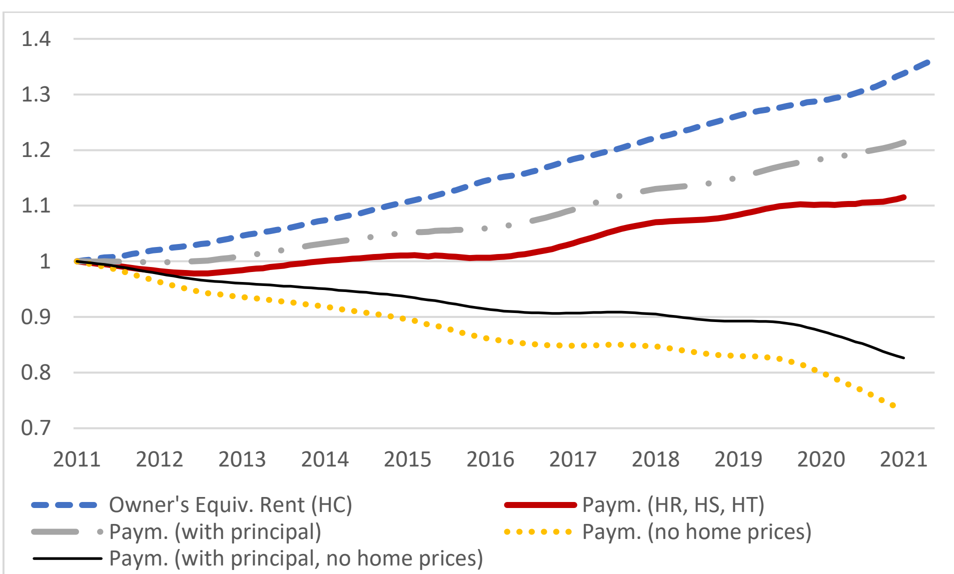
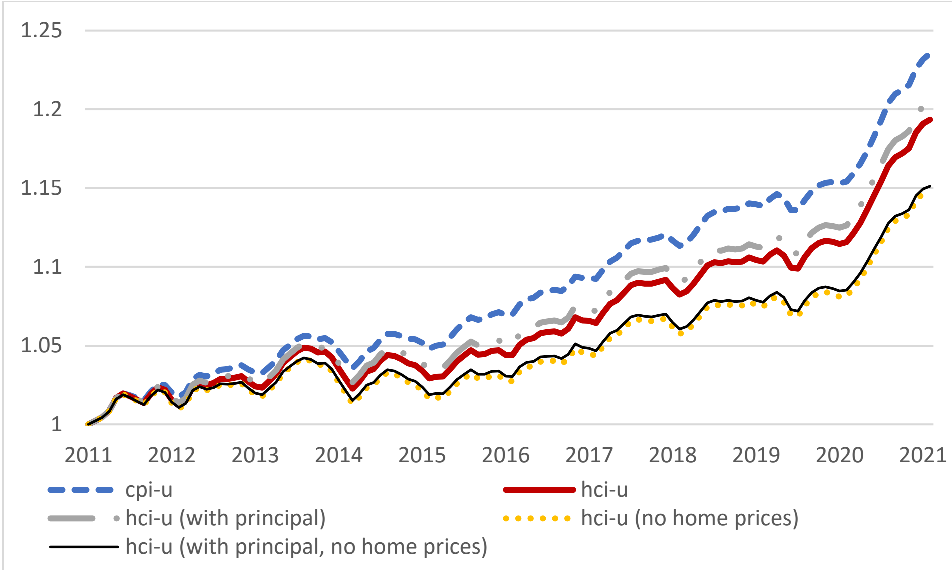


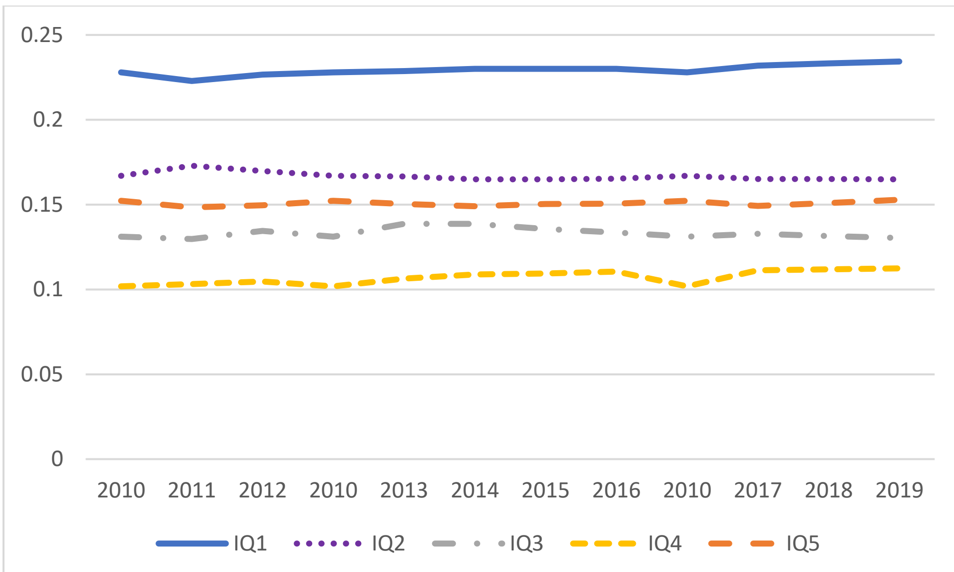
Figure 6: HCI-U Under Alternative Versions of Owner's Payments



B. Interview-Diary Matching Details

We base our household-averaged weights on the CE Interview sample but use a statistical matching procedure to assign sets of weekly Diary expenditures to each Interview consumer unit. Our procedure is similar in spirit to that of Hobijn, et. al. (2009), though that paper models expenditure change (implied by a consumer-unit specific price index) rather than expenditure levels. Modeling expenditure changes is attractive given the ultimate use of the matched dataset for price indexes, but Martin (2022) finds demographics explain much less of the variation in expenditure changes. We limit the dependent variable to categories collected in both the Interview and the Diary to ensure that the correlations picked up by the model are relevant to the expenditures we ultimately wish to impute. Over the sample period, R-squared values for the quintile and month-specific regressions averaged 0.17, while income quintile itself explained about 0.31 of the variation in the dependent variable. Figure 7 below plots the average regression R-squared for each quintile, where the averaging is over the 23 months used for each reference period. The figure shows that average R-squared for the income quintiles are fairly stable over time, averaging about 0.23 for the 1st quintile, 0.17 for the second quintile, 0.13 for the third quintile, 0.11 for the fourth quintile, and 0.15 for the fifth quintile. The fits (conditional on income quintile) are not particularly strong, which motivates matching an actual diary's expenditure set to an interview consumer unit rather than using regression fitted values.

Figure 7: Average R-Squared by Reference Period and Income Quintile



The rest of this section presents figures comparing the imputed weekly diary expenditures to the actual. Figure 8 shows average imputed weekly expenditures for the reference period track the actual averages well over time, always falling within 1% of the true averages. Figure 9 compares average weekly Diary expenditures over time by major group. For food and beverages, which is by far the largest category sourced from the Diary, the imputed averages fall within 1% of the actual averages, and they fall within 10% for all other categories. Figure 10 compares the deciles of weekly imputed Diary expenditures to those of the actual

Diary expenditures for the 2019 reference period (results are similar for other periods). The two marginal distributions line up well—the imputed deciles are within a few dollars of the actual deciles.

Figure 8: Actual and Imputed Average Weekly Diary Expenditures by Reference Period

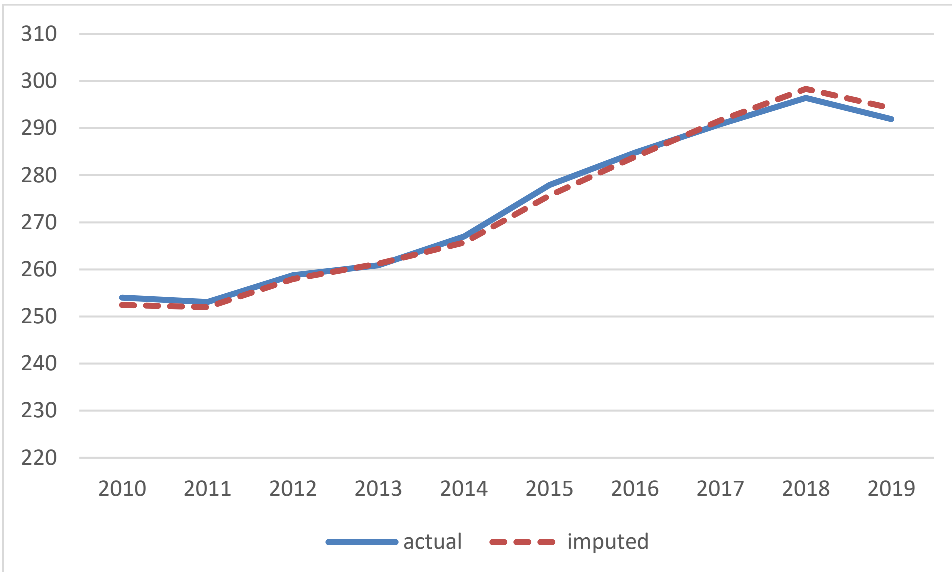
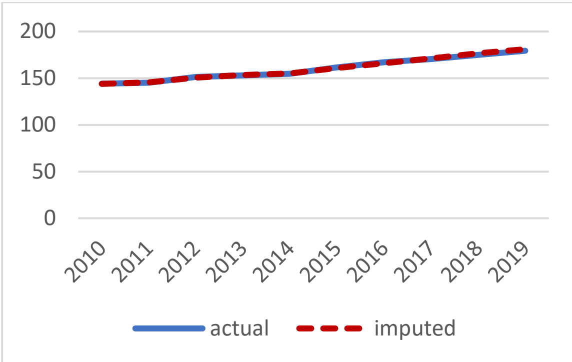
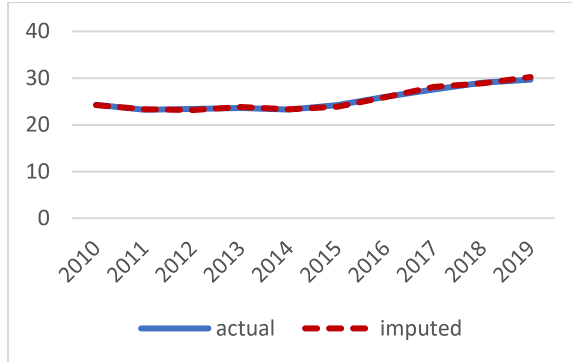


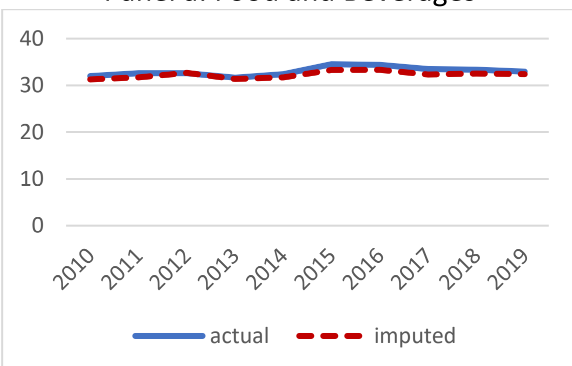
Figure 9: Average Weekly Diary Expenditures by Reference Period and Major Group



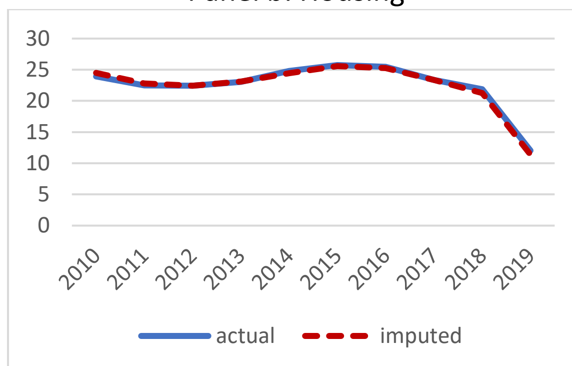
Panel a: Food and Beverages



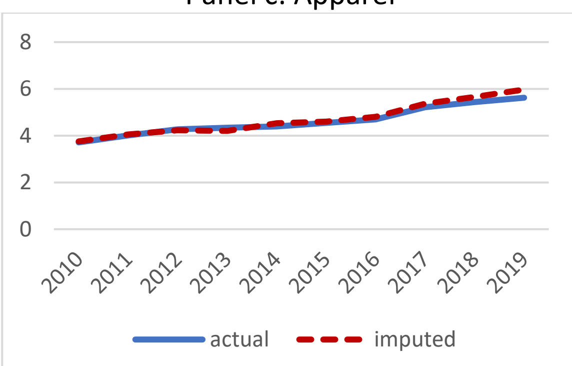
Panel b: Housing



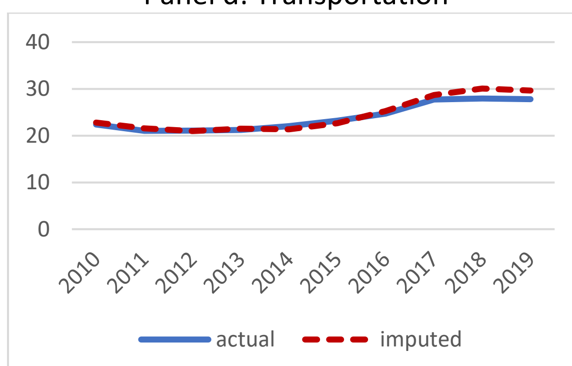
Panel c: Apparel



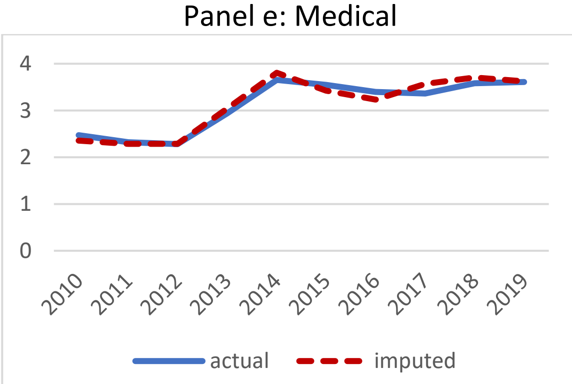
Panel d: Transportation



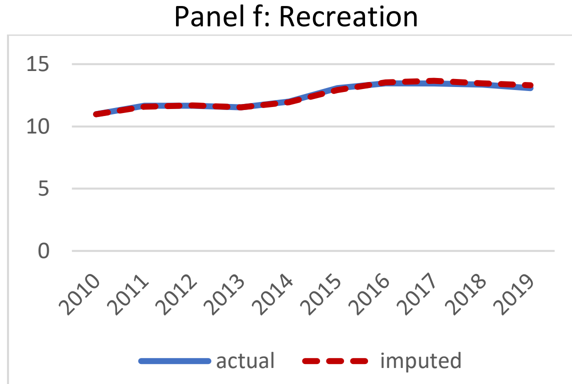
Panel e: Medical



Panel f: Recreation

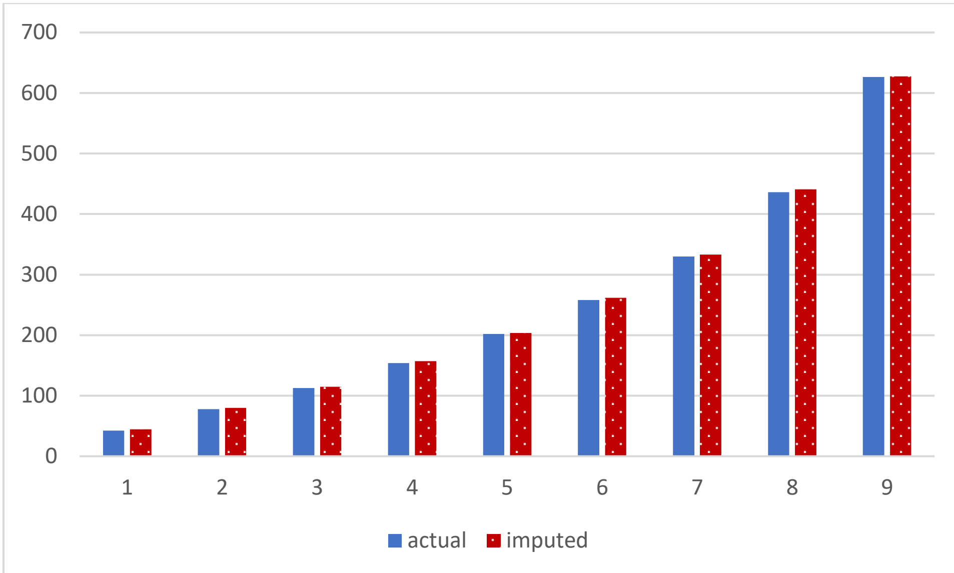


Panel g: Education and Communication



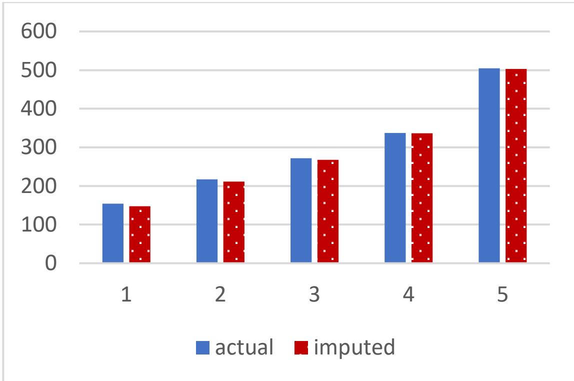
Panel h: Other

Figure 10: Deciles of Actual and Imputed Weekly Diary Expenditures for 2019 Reference Year

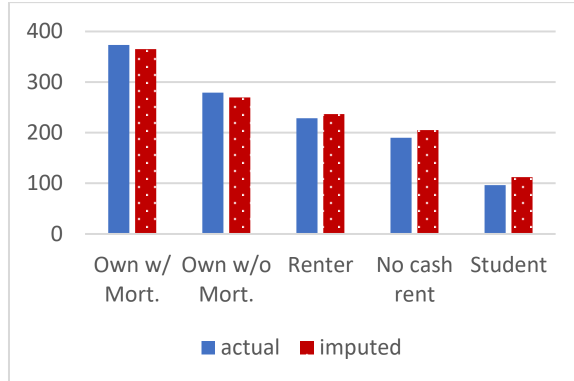


In terms of joint distributions, the matching procedure also does a good job at replicating average diary expenditures by several demographic characteristics, as shown in Figure 11 for 2019. Not surprisingly, because income quintile is conditioned on, the procedure replicates average expenditures by income quintile quite well. The procedure also does well replicating average differences by housing tenure, age categories, Census region, presence of children, and education categories, even though these characteristics are not explicitly conditioned on in the matching process. In these cases, the match quality is being driven by the correlation between these characteristics and income, as well as the extent to which similarity in these characteristics across surveys is predictive of expenditures, and so leading to lower distance between similarly attributed observations.

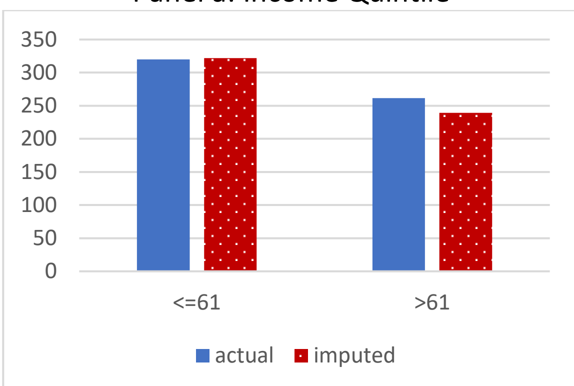
Figure 11: Average Weekly Diary Expenditures by Attribute, 2019 Reference Period



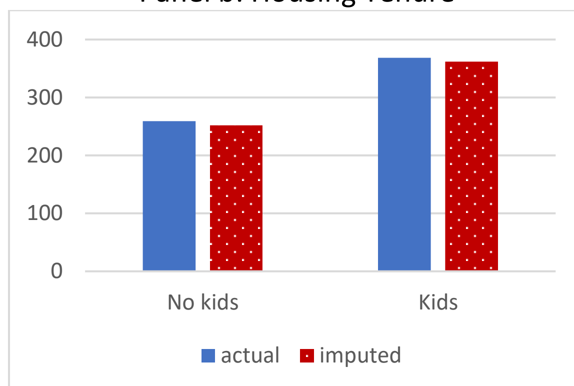
Panel a: Income Quintile



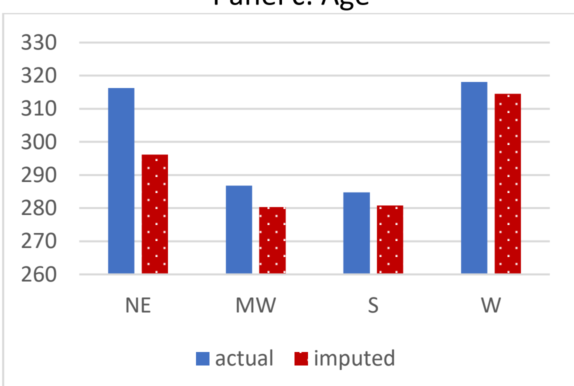
Panel b: Housing Tenure



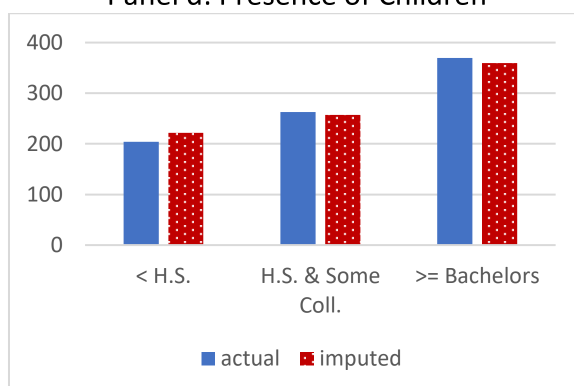
Panel c: Age



Panel d: Presence of Children



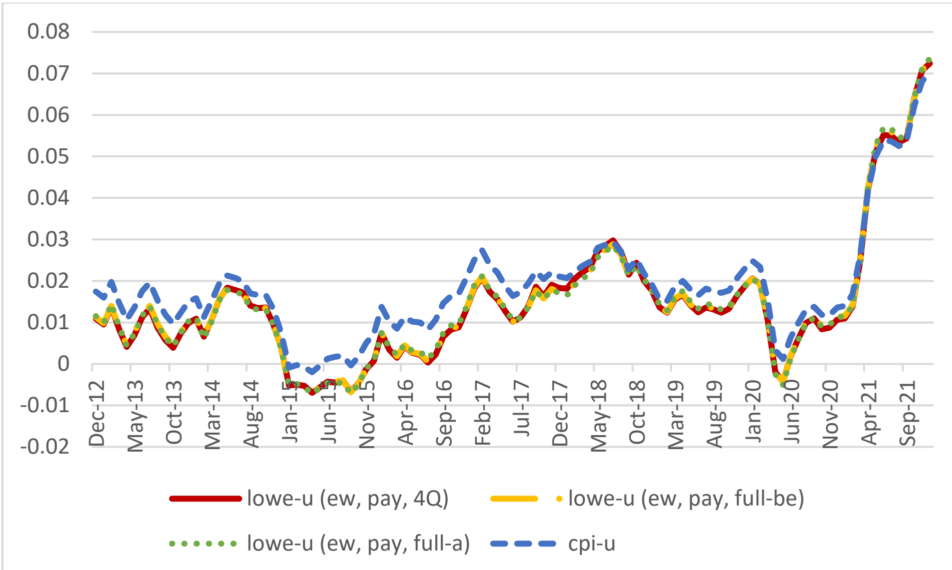
Panel e: Census Region



Panel f: Education

C. All-items Indexes Using Different CE subsamples

Figure 12: Twelve-month inflation of CPI and indexes using payments approach by subsample



As a check of our sample requirement that consumer units contributing to the HCI have four quarters of data in the CE survey, we compare all-items indexes (all using the payments approach) with this eligibility requirement against all-items indexes without. For this comparison, we examine expenditure-weighted aggregates across households, as equally weighted aggregates can be sensitive to weight frequency and overall dispersion in total expenditures (Ley, 2005; Martin, 2022). We consider both the full CE sample for the reference year, as well as for the full CE sample for the biennial period ending in the reference year, as our HCI subsample also includes four-quarter households who entered the CE in the year prior to the reference year. Figure 12 plots the twelve-month percent changes of these indexes as well as the CPI-U for reference. Over this period, average inflation of the CPI-U is 1.86% per year. The payments approach index using the four-quarter sample averaged 1.46%, while the indexes using the full annual and biennial samples averaged 1.47% and 1.46%, respectively.

Figure 13: Twelve-month inflation of HCI and indexes using payments approach by subsample

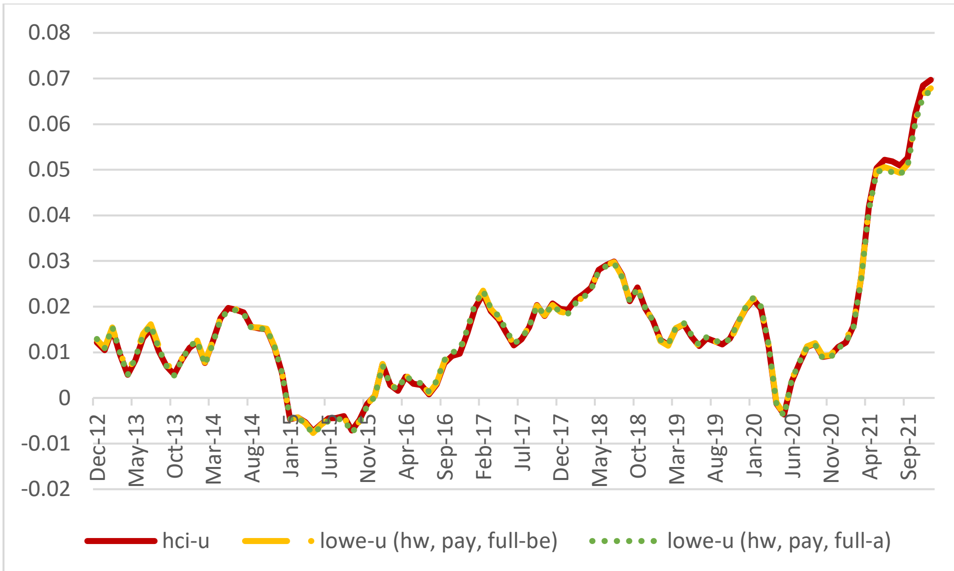


Figure 13 repeats the analysis in Figure 12, but compares the HCI-U and comparable household-weighted indexes using the full annual or biennial CE samples. The HCI-U averaged 1.51% year-over-year, while the index using the full annual and full biennial samples averaged 1.50% and 1.51%, respectively, though larger differences occurred in 2021. Here, index differences could reflect sample selection effects, but also likely reflect the mixed frequencies of household weights underlying the full-sample indexes, as some consumer units have only a few months or quarters of expenditure due to normal sample rotations and unit nonresponse. Higher frequency expenditure shares tend to give less weight to less frequently purchased items and more weight to more frequently purchased items (Martin, 2022). We do not want to capture this latter effect because, in the case of the HCI's, it is an artifact of using CPI weights for automobiles, which are measured by full purchase price at the time of acquisition, rather than ongoing monthly payments. In 2021, when HCI-U (over the four-quarter sample) has slightly higher inflation than the two full sample indexes. In 2021, vehicle price inflation was high relative to the average inflation across all items, and the comparison in the figure is consistent with the full-sample indexes giving too little weight to vehicles. A payments approach for vehicles should mitigate this effect in the full samples.