New Evidence on Consumption and Income Dynamics from a Consumer Payment Diary

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Abstract

This paper extends and refines the finding (Schuh, 2018) that daily transaction-level consumer *payments* in the 2012 Diary of Consumer Payment Choice (DCPC) cover a high percentage of U.S. personal *consumption* expenditures through 2020 with improved measurement. The DCPC now includes household and respondent income, which also cover high percentages of U.S. personal disposable income. Novel estimates of a benchmark PIH model with *daily* DCPC data are consistent with the literature but provide new insights about consumption and expected income dynamics. Results suggest that potential selection effects may arise in convenience samples of transaction data sources. Relative to "big" transactions data, the DCPC has four advantages: 1) more representative of U.S. consumers; 2) publicly available; 3) continuous improvements in measurement; and 4) flexible real-time opportunities for implementation.

JEL Codes: E21, D12, D14

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1 Introduction

Data on individual expenditure and financial transactions that are tremendously valuable for understanding microeconomic consumption and income dynamics have become widely available (Baker and Kueng, 2022). Transactions data include broad ranges of consumers and millions of observations (or more), but typically are proprietary with limited access and convenience samples potentially susceptible to selection effects. A lesser known, essentially equivalent, source of transactions is representative consumer diaries that track daily *expenditures* authorized by account-specific *payment* instruments. Although originally not intended to produce micro data equivalent to transactions sources, payments diary data unexpectedly yield high-quality measures of consumption. Bagnall et al. (2016) reported that aggregate payments are roughly similar to consumption in advanced economies, and Schuh (2018) showed the 2012 (first) U.S. Diary of Consumer Payment Choice (DCPC) generates relatively accurate real-time estimates of U.S. personal consumption expenditures (PCE) and implied disposable personal income (DPI). Relative to other transactions data, the DCPC has many fewer observations but four key advantages: 1) representative of U.S. consumers; 2) publicly available; 3) endogenous continuous measurement improvement; and 4) flexible real-time implementation opportunities.

Although the 2012 DCPC data were intriguing, the analysis (Schuh, 2018) begs three important questions about them in 2015 and beyond. First, was the DCPC's relatively accurate match of PCE in 2012 a fluke, or would it consistently do so even after implementation of better identification and measurement of consumption? Second, would the DCPC's new direct collection of daily *respondent* income be as successful in matching aggregate U.S. DPI as its consumption was in matching aggregate PCE? Moreover, would respondent income be consistent with reported annual *household* income given the existence of multi-member households? And third, would the individual-level DCPC consumption and income data yield estimates of benchmark models of consumption that are consistent with the literature? If so, would they also provide feasible opportunities to build and estimate expanded models, taking advantage of daily or even real-time behavior with data that are representative of all consumers?

This paper answers these and related questions using new DCPC data for 2016-2020 to update and expand the analysis in Schuh (2018). The new DCPC data include improvements to the diary survey that measure consumption more accurately and new estimates of daily income of all types reported by respondents. After briefly summarizing the related literature, we validate the new DCPC aggregate data by comparing them with official U.S. estimates of consumption and income, and with other leading data sources. We also update the real-time (daily) forecasts of DCPC consumption *levels* and expand it to forecasts of *growth rates* of PCE to quantify usefulness for macroeconomic analysis. Using these unexpectedly high-quality DCPC data, we estimate benchmark Permanent Income Hypothesis (PIH) consumption models from Jappelli and Pistaferri

(2017) at both the annual frequency for comparison with the literature and daily frequency for the first time (to our knowledge) for a foundation for extensions. Exploiting the representative nature of the DCPC, we estimate our preferred benchmark consumption model in sub-samples for further insights and to identify potential sample-selection effects that may arise in convenience samples of transactions data.[1]

Data for 2016-2020 show that aggregate DCPC consumption and income covered as much or more of official U.S. estimates than the most respected alternatives designed for the task. Although still not (yet) designed to measure consumption, the revised DCPC survey instrument better distinguishes consumption from non-consumption expenditures, especially in bill payments. This improved measurement led to more payments being excluded from consumption expenditures, so aggregate DCPC consumption in 2016-2020 was lower relative to PCE than in 2012, but it still accounted for 83% of comparable PCE categories and was 20% higher than aggregate CES estimates. To supplement *reported* annual household income, the DCPC survey instrument began *recording* daily respondents' income receipts by type (employment, retirement, investment, etc.) and frequency (weekly, biweekly, monthly, etc.). Aggregate DCPC respondent income accounted for 76% of aggregate DPI and was about the same (2% higher) as aggregate IRS income estimates.

Daily DCPC consumption data for October in 2016-2020 continued to provide accurate real-time forecasts of the *level* of DCPC consumption but may be too volatile to forecast *growth* in October PCE precisely enough for real-time macroeconomic analysis. As in 2012, *daily* projections of aggregate DCPC consumption converge to the *monthly* (October) estimate as the month proceeds. In all years, the daily projection is within standard error bands of the final estimate by mid-October, sometimes within 10 days (or less). Early and reliable estimates of October DCPC consumption may have potential value in forecasting macroeconomic developments because they are available a month before official PCE estimates. Because DCPC consumption underestimates the level of PCE, we use daily projections of 12-month growth in DCPC consumption to forecast PCE growth. Daily DCPC growth projections also converge to October growth in PCE (adjusted for comparability with DCPC), but not until the second half of the month and with economically significant imprecision. In 2016-2020, DCPC consumption growth rates are up to 5 percentage points different (in absolute value) from PCE growth.

The updated analysis of 2016-2020 DCPC data confirm that the 2012 results were *not* a fluke. Aggregate DCPC consumption and income data cover relatively high percentages of official U.S. estimates, making them at least as valuable as traditional data sources used in the literature. Real-time collection of DCPC data and the qualitative success in projecting aggregate data faster than official U.S. data are encouraging indicators that additional investment in expanding and designing the DCPC could produce an even more valuable data resource. Before taking that step, however, it

[1] Brown et al. (2023) conduct similar econometric exercises using Swiss payments diary data to quantify the effects of cashless payments on discretionary consumer spending.

is important to analyze the performance of the DCPC data in estimation of benchmark consumption models and evaluate its consistency (or not) with less representative transactions data.

Novel estimates of a benchmark PIH model with daily DCPC data for 2016-2020 are generally consistent with prior results in the literature, but also provide new insights about consumption and expected income dynamics. Limited data availability requires a synthetic panel structure for annual (October to October) and daily (October 1-31) econometric models of changes in consumption and income that marginally satisfy best practices (Deaton (1985)). Model estimates with the most data-consistent income process (AR(1) with time and age fixed effects) generally reject the PIH as usual. Marginal propensities to consume (MPC) are 0.26 from expected *household* income (annual) and 0.36 from expected *respondent* income (daily) and statistically significant.[2] The MPC from unexpected income are insignificantly different from zero, suggesting income shocks may be mainly transitory. Further distinction between consumption out of household versus respondent income in multi-member households and frequency of data should yield additional insights. Payday effects on non-bill consumption, which likely reflect deviations from the PIH, are statistically and economically significant in the DCPC data but smaller than in less representative data (Gelman et al., 2014; Olafsson and Pagel, 2018).

The DCPC data offer evidence of liquidity constraints that is more modest than in the literature but also new perspectives on departures from the PIH. Estimation with sub-samples of data split by consumers' liquidity or wealth holdings do not provide a clear distinction between the MPCs of constrained and unconstrained agents. This result mainly reflects statistical imprecision but possibly the measurement of liquidity and wealth at the cohort level, which obscures heterogeneity in constraints at the respondent level. However, when the sample is split by credit card borrowing (revolving versus convenience use) to proxy for differences in unobserved discount factors as demonstrated in Fulford and Schuh (2020), the data show a clear distinction between impatient revolvers (significant MPC of 0.77) and patient convenience users (MPC statistically insignificant from zero) as predicted.

Potential sample selection effects may arise in convenience samples of account-level transactions data from large banks (e.g., JP Morgan Chase, Ganong and Noel (2019)), mobile phone applications (e.g., CheckMe Gelman et al. (2014)), or financial management software (e.g., Baker (2018) or Meniga Olafsson and Pagel (2018)). Customers with these kinds of accounts likely chose them for reasons not fully explained by observable demographics. If so, estimates of consumption models may be biased due to uncorrected selection effects. The 2015-2016 DCPC contained adoption of personal financial management (PFM) software apps, providing a modicum of data to identify sample selection behavior. In 2016, only about 6 percent of U.S. consumers had a PFM app or software compared with about 20 percent using Meniga in Iceland (Olafsson and Pagel, 2018). PFM

[2] Model estimates using other income processes more common in the literature with aggregate time-series and lower-frequency micro panel data are all imprecise and thus unreliable.

adopters in the representative DCPC tend to be younger and have higher education and income than non-adopters. This finding is consistent with the literature based on PFM data sources but those data sources cannot identify behavior of non-PFM adopters. A logit model of PFM adoption shows that the aforementioned demographics and at least two consumer behaviors are significant positive determinants of PFM adoption: those who have set up automatic bill payments and those who voluntarily checked their financial records when completing the SCPC/DCPC (presumably for accuracy). Perhaps surprisingly, none of the obvious indicators of financial distress—an obvious reason for needing a PFM—are significant determinants. While the sample sizes for PFM are impractically small, these results suggest that characteristics of PFM users could be useful in future research on consumption.

To summarize, the results in this paper suggest at least one clear policy implication: public value of supporting additional development and expansion of the DCPC. Already, the DCPC provides superior coverage of official U.S. data on consumption and income in real time that appear capable of yielding reliable and insightful tests of frontier consumption models. Although the DCPC data were not originally designed for the task posed them here, focusing on their shortcomings thus far would overlook a more important potential opportunity for the future. A renewed effort to redevelop the SCPC and DCPC with broader goals than just measuring payment choices and increasing sample sizes and frequency would yield a far superior product with many invaluable features.[3] The Federal Reserve Bank of Atlanta is the current owner of the SCPC and DCPC and has the prerogative and resources to undertake expansion. Alternatively, the payments data program could be adopted and/or integrated into existing data sources like the Consumer Expenditure Survey (CES) at the Bureau of Labor Statistics or Survey of Consumer Finances (SCF) at the Board of Governors of the Federal Reserve; the Census Bureau is an obvious potential contributor as well. Importantly, the cost of the SCPC/DCPC is a small compared to the costs of the CES or SCF, and merging data measurement could yield efficiency gains that further reduce costs of expansion. Finally, expansion of the SCPC/DCPC would leverage two advantageous features mentioned at the beginning but not explored in this paper: continuous improvement in data measurement and real-time implementation of the survey instrument during predictable events like randomized tax rebates (Parker, 2017) and natural disasters (such as hurricanes).

2 Related Literature

This paper is related to several distinct branches of the literature pertaining to the measurement and theory of household consumption and financial management behavior at the individual level. Because the literature is too vast for a comprehensive review, this section briefly describes the key

[3] Beyond the discussion in this paper, there also is the potential to address even broader measurement needs, such as the lack of fully integrated coverage of all household financial statements, as advocated by Samphantharak et al. (2018)) and Schuh and Townsend (2020).

citations in each branch that are most relevant and their related to the paper.

2.1 Transactions Data

The increase in availability and quality of transaction data has been used in an emerging literature to study household and consumer expenditure behavior. Baker and Kueng (2022) offers a comprehensive review of these sources and how the literature has used this new source of data. Transaction data come from numerous sources, including personal financial management software (Gelman (2022), Baker (2018), Olafsson and Pagel (2018), Gelman et al. (2014)), bank account records (Ganong and Noel, 2019), credit card transactions (Gathergood et al., 2021), and retail scanner data (Klee, 2008). In some cases, these data sources are accompanied by detailed balance sheet positions of households as well.

Most often, these "Big Data" have massive sample sizes that offer unusually precise statistical inference. Taken together, these benefits allow for a comprehensive analysis of consumption decisions and behaviors at the individual level. One potentially important limitation of these remarkable transactions data sources, however, is that most are not statistically representative of the entire macroeconomy. Instead, their existence is predicated on a form of sample selection, such as choosing a type of bank, adopting a credit card or financial management software, shopping in a particular store, etc. Thus, even if the data demographics are similar to the entire population, failure to control for sample selection effects can mask non-representative behavior.

It has been recently discovered that a new source of high-frequency data from payment diaries can measure consumption. While the DCPC originally is intended to track the daily payments of respondents, Schuh (2018) finds the 2012 DCPC consumption estimates are 17% higher than comparable consumption categories to the PCE estimates. Due to the structure of payment diaries, the DCPC offers trade-offs in data availability compared to other transaction data sources. The DCPC is implemented by federal reserve banks where respondents are chosen to be representative of U.S. demographics. This feature combined with sampling weights ensures researchers that payment decisions by respondents are representative of national behavior as a whole. Further, the data sets are publicly available to researchers, which allows for replication of results. Finally, because the diaries primarily track payment behavior, the DCPC offers payment information which are often not found in other data sources. As discussed by Baker and Kueng (2022), while these benefits of payment diaries are promising, they are limited in sample size and time span. This study shows that even with a limited number of observations, the diaries are capable of studying consumption and income dynamics, and given the new years of the diary offer a promising opportunity to study consumer behavior.

2.2 Consumption Behavior with Traditional and Transaction Data

The advantages of high-frequency transaction data sources have offered a promising avenue in testing predictions from benchmark consumption theory. A large body of the traditional literature uses monthly, quarterly, or annual data to study inter-temporal consumption decisions through the Permanent Income Hypothesis and Life-Cycle Hypothesis models of consumption; see Jappelli and Pistaferri (2010) for a comprehensive review. These models predict consumption should not change to anticipated income (Lusardi, 1996; Hsieh, 2003; Stephens Jr, 2003; Johnson et al., 2006), and there should be little response to unexpected transitory income shocks with larger responses to permanent shocks (Hall and Mishkin, 1980; Blundell et al., 2008; Agarwal and Qian, 2014). A significant amount of this literature finds a rejection of the basic PIH, in that consumption responds to predictable income changes. High-frequency data sources have similar findings for the excess sensitivity of income (Agarwal et al., 2007; Gelman et al., 2014; Kueng, 2018; Olafsson and Pagel, 2018; Gelman, 2021, 2022)[4] and consumption responses to unanticipated income (Baker and Yannelis, 2017; Baker, 2018; Olafsson and Pagel, 2018, 2019; Gelman et al., 2020), with additional benefits achieved through observing high-frequency consumption choices often with more details on consumer financial positions.

Numerous theories have worked to explain deviations in predictions from benchmark consumption models, including liquidity/borrowing constraints (Zeldes, 1989; Deaton, 1991; Carroll, 1997), wealthy hand-to-mouth consumers (Kaplan et al., 2014), and behavioral characteristics of consumers (Shefrin and Thaler, 2004; Laibson, 1997). Studies using transaction data can apply these theories to direct decisions of consumers, such as timing of expenditures to payments (Agarwal et al., 2021; Gilyard, 2023), financial distress relative to income receipts (Baugh and Wang, 2018; Baugh and Correia, 2022), use of PFM services (Carlin et al., 2022; Olafsson and Pagel, 2023), and consumer financing decisions (Hundtofte et al., 2019; Kuchler and Pagel, 2021; Gathergood and Olafsson, 2022) along important theoretical considerations such as liquidity constraints and hyperbolic discounting. This paper analyzes the DCPC as another alternative data set capable of studying consumer behavior with the benefits described above.

3 Consumer Payments Data

An early motivation of data on consumer payment choices emerged from the decline of paper check use in the United States documented in Gerdes and Walton (2002) and analyzed in Schuh and Stavins (2010). With the transformation of payments, researchers in monetary economics, along with payments practitioners and analysts, recognized a need to understand where the transformation would lead. This need was initially blocked by a dearth of data on how consumers—the ultimate end-users of the payment system—made payment choices, especially cash (physical cur-

[4] When estimating the daily consumption response on days in which respondents receive income in Section 8.1, we compare our results to Gelman et al. (2014); Olafsson and Pagel (2018).

rency). Such data are crucial to discovering and providing the types of electronic payment services would maximize consumer utility. One important response was the development by industrial countries of surveys that asked consumer respondents to *recall* their adoption and use of financial accounts and means of payments (instruments). A second response extended recall-based surveys by developing diaries that asked consumer respondents to *record* their payment transactions. The literature on survey methodology documents the superior quality of recording-based measurement instruments, and the optimality of relatively short consumer diaries of one week or less.

3.1 U.S. Survey and Diary Instruments

U.S. efforts to develop public consumer payments data were originated by researchers at the Federal Reserve Bank of Boston in 2003. Motivated by a successful internal trial survey with a convenience sample of employees (Benton et al., 2007), the Boston Fed launched the official Survey of Consumer Payment Choice (SCPC) in 2008. It has been implemented annually ever since; the Federal Reserve Bank of Atlanta took over management in 2018. The SCPC is an approximately 30-minute online questionnaire that asks respondents to recall two main types of information about their payments: 1) adoption of bank accounts, payment instruments, and other payment-related services; and 2) use of payment instruments measured as the number (volume) of payments made in a typical month with each type of payment instrument.[5]

The success and value of the SCPC, particularly in documenting the resilience of consumer use of cash, motivated the addition of the Diary of Consumer Payment Choice (DCPC) in 2012.[6] Initially, the goal of the Diary was to validate the measurement of recall-based survey data on the number of payments by asking respondents to record each payment and cash management activity every day for three consecutive days. Respondents spend approximately 15-30 minutes per day completing an online questionnaire about their daily activity, plus a brief survey the night before their Diary begins. After analyzing the 2012 data for a couple years discovering its value, the DCPC has been implemented annually since 2015. Over time it became clear the Diary had greater value for several reasons. First, it collected the dollar value of each payment (not in the SCPC), which offers additional insights to payment choices but also reflects consumer expenditures in some cases. Second, by also collecting the dollar values of asset balances (cash and checking account holdings) and their management (deposits and withdrawals), the Diary data provide an exact accounting of financial flows. Third, the Diary also collects unique, nearly real-time information about each payment (time and date, payment instrument, merchant or payee type and name), the conditions impacting the consumer's transaction (cash on hand, payment instruments available at the time, etc.), and consumer attitudes about the transaction (actual versus preferred instrument, planned

[5] The SCPC also collects data on consumer attitudes about the characteristics of payment instruments, and a host of other payments-related information.

[6] For more details about the SCPC and DCPC, see Greene et al. (2018), Schuh (2018), (Greene and Stavins (2021)), and the Federal Reserve of Atlanta's website.

versus unplanned expenditure, etc.).

The SCPC and DCPC are implemented jointly in a manner analogous to the Consumer Expenditure (CE) survey and diary. In September, the selected respondents complete the SCPC and indicate their willingness to participate in the subsequent DCPC. Between 84-91% of Survey respondents agree to participate in the Diary during a randomly selected three-day period between September 29 and November 2. The night before their Diary period begins, respondents complete a brief online survey to update information they provided in their Survey that year, which may have occurred up to nearly two months before the Diary. Respondents in the SCPC and DCPC can be linked by their unique identifiers so that all data from both instruments can be used to analyze each respondent.

3.2 Sampling Frames

The consumer payment Survey and Diary are implemented with random sampling frames populated by ongoing participants in a longitudinal internet survey panel. From 2015-present, the primary sampling frame has been the Understanding America Study (UAS) panel.[7] The UAS was designed to produce a sampling frame that reflects cutting-edge panelist recruitment techniques for modern survey panels. Thus, random samples of consumers from UAS are expected to be as representative of U.S. consumers as is possible for survey conducted without the benefit of government administrative records for the entire population. The UAS also includes day-of-the-week, daily, annual and individual post-stratification weights that use the Current Population Survey (CPS) to match any discrepancies arising from the variation of annual recruitment differences.[8]

3.3 Sample Selection and Design

Upon completion of the SCPC, the respondents who agree to participate in the DCPC are randomly assigned to a consecutive three-day period starting on September 29. Each day thereafter, a new three-day wave of respondents is assigned until October 31. The last wave ends November 2. This process of randomly assigning diarists over the month of October ensures that there are representative transactions being recorded each day of October during the diary. Each day contains overlapping days with an approximately equal share of respondents on each diary day (1, 2, and 3); September 29-30 and Nov 1-2 are not representative. While respondents begin

[7] From 2008-2015, the primary sampling frame was RAND's American Life Panel (ALP). Adjustment costs occurred due to the transition from the ALP to the UAS that affected the size and quality of the 2015 samples. The UAS began its first panel in 2015 so it had recruited only a relatively small sample that was not at an optimal composition for representing all U.S. consumers. As a result, the SCPC and DCPC were implemented in separate samples drawn from the ALP and UAS in 2015 only. Unfortunately, the 2015 UAS sample is less than half the size of 2016, which limits its use in the subsequent analysis. For more details about the challenges of the 2015 sampling frame, see Angrisani et al. (2018).

[8] Actual sampling weights for Diary are available for two frequencies, $\tilde{d} = \{d, \overline{d}\}$, corresponding to daily and average day-of-the-week, respectively. The latter are used because they have lower variance given the relatively small samples.$\{d, \overline{d}\}$ are available for only the October dates. Individual weights are not time dependent, and are available for each respondent in the SCPC and DCPC.

keeping track of transaction on the first diary day, there is an initial diary day (diary day 0) in which respondents complete an online survey, updating their information from the SCPC and recording account balances and income payments. On these initial diary days, no transaction data is recorded from respondents and thus cannot be used when calculating consumption and income measurements.[9]

While transactions for a given respondent are limited to three days, the categorization of respondents into waves allows for an analysis of expenditures throughout the entire month of October. Each of these 33 waves are staggered sequentially throughout the, as visualized by Figure A1. Total expenditures and recorded income on any given day is the sum of each respondent's transaction who are a part of the three waves completing the diary on that day. Therefore, one can analyze daily and monthly consumption behavior through the wave structure of the diaries. Furthermore, the five years of the diaries allows for a panel analysis of consumption and income.

3.4 Innovations since 2012

Since the 2012 diary, six more years have been included in the DCPC (2015 - 2020). The DCPC has undergone multiple changes during this time as summarized by Table A10 of Appendix A. At its core the DCPC remains the same by tracking consumer transactions over three consecutive diary days randomly assigned in the month of October.

In recent years, merchant categories have been improved to allow for increased identification of recipients and purposes of payments made by respondents. In the 2012 diary, there were 45 merchant categories used to identify the merchant type for which the payment was received. In 2015 forward, additional categories were added to track the purpose of the payment. These categories changed each year from 2015 to 2018, but since 2018 have remained the same. Categorization of each merchant category and purpose category can be found in Appendix A, Table A8. The inclusion of these additional categories have reflected more detailed tracking of consumer payments. These detailed categories have led to better identification of loan repayments by respondents. This includes credit card repayments and student loans as examples. Therefore, the 2015 through 2020 diaries can exclude non-consumption expenditures more accurately than possible in 2012.

One of the most significant changes since the 2012 DCPC is the inclusion of recording income receipts. First, on the initial diary day where no transactions are recorded and their SCPC information is updated (diary day 0), respondents are asked the types of income from Table A1 found in Appendix A that they generally receive. Throughout the three diary days, respondents record if they received income on the diary days, the amount of income received, the income type, and how it was deposited. This detailed income information allows for identifying certain types of income

[9] Unlike payments, income receipts are recorded for respondents on the initial diary day 0. This allows for the possibility of recorded in September and November. In the estimation of the income results, aggregate income is calculated using day-of-week weights, and therefore any income not received during the three diary days are excluded.

payments and their amounts, as well as when they will be paid again. Furthermore, the DCPC tracks all money coming into the respondents possession. In the public data, this is treated as income. However, some of these cash inflows may be conceptually different from income defined by the IRS and BEA, such as money from a family member. While these income types have missing categories, we are able to see the source and location if the transaction is a checking deposit or cash withdrawal. A significant portion of checking deposit sources are direct deposit from employer. Therefore, we categorize these income receipts as *unidentified* income receipts, while income with non-missing income type as *identified* income receipts. Any other income receipt with a missing income type which is not a direct deposit from employer are excluded from income. When calculating aggregate income, this unidentified income is reported separately from the identified income types.

4 Data Construction

This section describes the DCPC data used to measure consumption and income. It defines the respondent-level variables obtained from the diary survey instrument and how consumption and income are derived from them, as well as setting the detailed notation needed for two further analyses. One analysis is the construction of aggregate data using sampling weights to match U.S. estimates. Another analysis is construction of unbalanced and balanced longitudinal panels for constructing growth rates and regression analysis.

4.1 Consumption Data

4.1.1 Identification

Measuring consumption from a payment diary requires identifying the subset of all payment expenditures that are defined as consumer expenditures in official government data. All payments, X, are dollar-value transfers involving a payment instrument, or "derivative media" of money (see Tobin (2008)), that is exchanged (e.g., currency) used to authorize by instruction (e.g., check or debit card). Importantly, payment instruments serve as the link between line items of the balance sheet, which fund transfers, and the income statement, which records expenditures, through cash-flow relationships.[10] For this reason, payments include both official consumption expenditures, C, and numerous expenditures:

$$X = [C + C^u] + [I^c + (-\Delta D^-) + P2P^-] + A2A$$

where C^u are unclassified consumer expenditures (e.g., underground economy or illegal activity, which can appear in payment diaries), I^c is investment purchases of consumer durable goods or

[10] For more details about the role of payments in financial statements, see Samphantharak and Townsend (2010) and Samphantharak et al. (2018).

other assets (e.g., art) excluded from official consumption, ΔD^{-} is debt-reduction payments (e.g, mortgage or credit card), $A2A$ are asset-to-asset transfers, and $P2P$ are person-to-person transfers (e.g., gifts or bequests to others; $P2P^{+}$ is income). Broadly speaking, the first term in braces represents comprehensive consumption and the second term in braces represents changes to net worth (i.e., part of saving).

Identification of consumption occurs by separating C from non-consumption payments $X - C$ using the structure of the diary survey. Each payment expenditure includes information about the payee, or "merchant," who received the payment from the consumer. The merchant is identified not specifically, like Whole Foods in Boston MA, but rather by an industry category, like Grocery Stores. The industry categories were constructed based loosely on several input criteria: NAICS codes, official consumer expenditure categories (PCE and Consumer Expenditure Survey), and the goals and needs of payments research. Merchant industry categories are further refined using variables with information about the reason and purpose for the payment. These purpose variables identify narrower categories as to the type of payment made to the merchant when merchant categories are board (such as loan repayments to financial service providers). Consumption expenditures are defined by this information to match theoretical concepts and classified into consumption categories $j = \{1, \ldots, J_t^c\}$ for comparison with PCE and CES estimates. Time variation in J_t^c reflects the fact that the consumption classification scheme varied over time as improvements were made to increase precision of consumption identification. A crucial improvement to the 2012 Diary was the ability to identify and separate portions of ΔD^{-} in later years that had to be included in C by Schuh (2018). For more (gory) details about this meticulous process, see Appendix A and Tables A3-A9

The rich and unique structure of the DCPC requires unavoidably detailed notation and derivations. Let C_{ijdmt} denote consumption expenditures for respondent (consumer) $i = \{1, \ldots, N_t\}$ in consumption category j. Discrete time periods are represented by day of the month, $d = \{1, \ldots, D_m\}$, month of the year (September and October), $m = \{9, 10\}$, and year, $t = \{2012, \ldots, 2020\}$.[11]

4.1.2 Aggregation

The DCPC's sampling design for representation of U.S. consumers introduces additional details in notation and derivation. Aggregation of consumption *within* respondents can occur without sampling weights. Thus, daily consumption for individual i is simply

$$C_{idmt} = \sum_{j=1}^{J} C_{ijdmt}.$$

[11] This classification is a parsimonious version of even more complexity. Consumption expenditures also vary by other features such as location (e.g., in-person or online), type (e.g., bills or non-bills), and payment instrument (hence, source of funding). We exclude these for simplicity here and focus only on consumption categories, but refer to the other features as needed later.

Unweighted total consumption for individual i is

$$C_{imt} = \sum_{d=d_{i,1}}^{d_{i,3}} C_{idmt},$$

the sum of each individual's daily consumption during the idiosyncratic three-day diary wave in the month.

However, any aggregation across respondents or days requires the inclusion of representative sampling weights. Let the representative sampling weights for individual data be denoted w_{it}^S for the Survey and w_{idt}^D for the Diary. The daily Diary sampling weights aggregate to the number of respondents included in the Diary, N_{mt} for the whole month as follows:

$$N_t = \sum_{i=1}^{I_{dt}} w_{idt}^D$$

where I_{dt} is the number of individual respondents on each day. See Angrisani et al. (2018) for more technical details about sampling weights.

The DCPC enables estimation of aggregate consumption for each day in October and for the entire month. Consumption estimates first must be converted to per capita because the number and composition of respondents in a Diary wave varies each day of the month. Thus, daily aggregate consumption per capita (denoted by overline) is

$$\overline{C}_{dmt} = \frac{\sum_{i=1}^{I_{dt}} w_{idt}^D \cdot C_{idmt}}{\sum_{i=1}^{I_{dt}} w_{idt}^D},$$

and average daily consumption per capita for October ($D_{10} = 31$) is:

$$\overline{C}_{mt} = \frac{1}{D_m} \sum_{d=1}^{D_m} \overline{C}_{dmt}.$$

Finally, nationally representative estimates of consumption per capita can be used to estimate monthly and annual *levels* of consumption (no overline) for the entire United States. Let P_t denote the DCPC annual targeted population for the DCPC from the Current Population Survey (U.S. non-institutional population ages 18 and older). Then monthly aggregate U.S. consumption for October is

$$C_{10,t} = \overline{C}_{10,t} \cdot P_t \cdot D_{10}.$$

Annual aggregate U.S. consumption is estimated as

$$C_t = \overline{C}_{10,t} \cdot P_t \cdot 365.25$$

as there are 365.25 days in a year.[12] Analogous procedures are used to estimate aggregate U.S. income and other DCPC data.[13]

4.2 Income, Asset, and Liability Data

Measuring income from a payment diary depends on the idiosyncratic structure of the data instruments, and the U.S. payments data include two different measures of income. The SCPC includes reported annual gross income for the respondent's entire household, Y^H. This measure of income can be easier and more accurate to recall or report for at least some households and respondents, but concerns have been raised elsewhere about the accuracy of such measures (e.g. Moore et al. (2000), Meyer et al. (2015)). Y^H also does not provide any useful understanding of the higher frequency dynamics of income receipts and expectations that are central to understanding consumption. Furthermore, Y^H does not necessary reflect the income earned and received (or controlled) by individual respondents (consumers) living in the household, except for single-member households where the consumer and household are the same. However, the SCPC also asks where the respondent's (consumer's) individual income ranks within the household, qualitatively from most to least.

In addition, the DCPC *records* all types of income received each day by the respondent (individual consumer), Y_{ijdmt}, and the frequency at which income payments are received. Here, subscript $j = \{1, \ldots, J_t^y\}$ denotes *income* categories. Time variation in J_t^y likewise reflects the fact that categories of actual received income varied over time as improvements were made to diary survey. The main improvement was the inclusion of received income Y^R, which was not available in the analysis of the 2012 DCPC by Schuh (2018). Income categories are found in Table A1; employment income is the most common. As discussed in section 3.4, some recorded income types are unidentifiable due to some recorded income having having no recorded type. Like most other transactions-level data sets, income payments are discrete and thus less frequent than consumption, which is essentially continuous (daily). As a result, a significant number of respondents do not receive any income on a given day. Appendix Table A2 shows that 23% of respondents are recorded receiving income over the 5 years, while 21.1% of the income payments are unidentified in type.

The DCPC is unique in that it tracks income receipts of respondents as well as asking the respondent's household income. Recorded income can shed light on the exact periodic income payment value the respondent receives. The diary asks respondents if they received any of the 10 income types listed in Table A1 and the after-tax amount as well as the frequency in which they receive this income. However, a respondent does not necessarily receive income during their diary period, and

[12] October also may have a seasonal component that is not factored into the calculation. However, the Fed chose October in part because it is a month with relatively minor seasonal factors in most U.S. economic data.

[13] Household income is aggregated in a similar manner, except is averaged over all respondents within a diary year as household income does not vary by day within respondents. Individual weights are used when calculating household income estimates.

furthermore does not reflect the other income earned by the household. Household income takes into account not only the respondent's income, but all other income within the household within the last 12 months. However, we are not able to see the source of household income reported by the respondent. Therefore, each income measurement has its benefits and limitations. Like other survey data, income is prone to measurement error.[14]

In addition to recording expenditure and income information, the DCPC also records ending day and stored cash balances by the respondent. Since 2012, the diary has also kept track of primary checking account balances, and in 2019 includes savings balances. To measure liquidity, we include the total amount of checking account balances, ending cash balances, and stored cash balance per day.[15] The SCPC collects broad information from respondents on both assets and liabilities. Respondents are asked their home value, as well as the outstanding debt on their home. In addition, respondents are asked the value of any remaining assets and remaining liabilities.[16] To measure net worth, we subtract the sum of the two liability categories from the sum of the asset categories. All liquidity and net worth values are in 2012 USD.

4.3 Longitudinal Panels

In principle, the DCPC data can be merged into a longitudinal panel. However, unique frequency and sampling pose challenges for construction of a panel that enables proper analysis of the joint consumption and income dynamics. Two main design factors are important. First, the time series of the Diary is discontinuous. The daily DCPC is administered only in seven of the nine years from 2012-2020, and only in one of 12 months. Second, the time series of individual respondents also is discontinuous in that it only includes three of 31 days of the month.

4.3.1 Structure

For these reasons, the DCPC longitudinal panel is unbalanced within months and across years. The problem is less severe within one month because respondents rotate randomly according to the sampling design, few exit and none enter during a wave, and all respondents in the public data completed each of the three diary days. This makes the DCPC longitudinal panel for one month (diary year) less susceptible to selection effects that might bias estimated coefficients. However,

[14] Angel et al. (2019) shows that survey can be misreported based on how the respondent compares to the mean wage (biased towards the mean, therefore mean reverting), certain demographics over report income, and longer time-spans between the reference period and interview increases the likelihood of misreporting.

[15] Stored cash balance is only tracked the night before and the last diary day. For consumers without a checking account, we replace missing checking account values to 0. If the consumer has a missing value in only checking or cash accounts, the non-missing value is used. In 2016 and 2017, checking account balances were only reported on the night before the diary and the last day of the diary. We use linear interpolation to fill in the days in between.

[16] If respondents report not owning a home, home value and home debt is recoded as $0. Respondents who have both missing categories of assets are excluded, as well as respondents who have both missing categories of liabilities. Note that given the structure of the question on other assets and debt, it is possible that other assets include liquid assets as defined previously, dependent on if the consumer views their checking accounts and cash as an asset. For this reason, we do not add in liquid assets to the net worth category as to not potentially double count.

using DCPC data for only one month (year) significantly reduces the number of observations relative to a panel that pools multiple diary years. Pooling across years is more problematic due to unexplained entry and exit of respondents. The Diary sampling design strives to recruit the same respondents every year but only some respondents return each year, so selection effects can be significant across years.[17]

Two other choices are important features for the construction of a longitudinal panel. One choice is the data frequency, or time aggregation: daily, diary wave (3-day periods), or monthly. The other choice is the consumer unit of observation: individual, synthetic cohort, or aggregate (representative agent). Lower frequencies and higher levels of aggregation across individuals both reduce the number of observations available for regression analyses. However, despite reducing the number of cross-section observations, synthetic cohorts produce balanced panels of data with continuous time-series data for all 31 days in October. These synthetic cohorts are utilized when measuring consumption and income dynamics in sections 7 and 8.

All factors considered, the DCPC offers multiple feasible possibilities for constructing a longitudinal panel with which to estimate joint consumption and income dynamics, each with trade-offs between advantages and disadvantages of key features. The unbalanced daily panel of individual consumers is imperfect but maximizes the number of observations. Unfortunately, the DCPC does not contain sufficient information about respondent entry and exit across years to make proper econometric adjustments for the imbalance, as recommended by Hsiao (2022). On the other hand, balanced panels for 2016-2020 have much lower numbers of observations, especially when 2020 is included because it had considerably fewer respondents. Consequently, we report estimates of the joint consumption and income dynamics for multiple panel specifications and show they can approximately replicate conventional results in the literature.

4.3.2 Changes and Growth

To estimate the marginal propensity to consume and consumption elasticities with respect to income in sections 7 and 8, it is necessary to transform the data to changes and growth rates (log changes). Given the discontinuities of the DCPC longitudinal panels, the calculation of changes and growth rates is non-standard and requires additional choices in specification. We use two definitions of changes for any variable Z_{idmt} based on data frequency. The daily change is based on daily data and defined as

$$\Delta_d^\tau = Z_{idmt} - Z_{i,d-\tau,mt} \;\; \forall \;\; d > \tau$$

[17] See Figure A2 of the Appendix for a visual representation of the respondent's decision to stay in the dairy.

where τ denotes the length of difference over periods in the frequency. The annual change is based on monthly data and defined as

$$\Delta_m^\tau = Z_{imt} - Z_{im,t-1}$$

where $\tau = 12$. This annual change represents the difference between data for October in year t and data for October in year $t-1$.

4.4 Data Cleaning and Robustness

The analysis of DCPC consumption and income uses the raw observations from the data made available to the public on the Atlanta Fed's website. However, the Fed cleans the observations when calculating DCPC reports published on their website. The consumption and income results in Section 5 used the raw observations as to not exclude important consumption expenditures and these are the data available publicly to researchers. To test the sensitivity of the aggregate results to outliers, cleaning scripts were obtained from the Fed. Appendix D compares the results without Fed cleaning (WOFC) and with Fed cleaning (WFC) for robustness. Comparable consumption and adjusted income are approximately 8% and 7% lower when cleaning observations. Thus, we conclude that the core results remain the same when using cleaned or raw data. In sections 6, 7, and 8 observations are cleaned using the Fed cleaning scripts.

5 Aggregate U.S. Consumption and Income Statistics

This section extends the comparison in Schuh (2018) of 2012 aggregate consumption in the DCPC with U.S. personal consumption expenditures (PCE) from the Bureau of Economic Analysis (BEA) and the Consumer Expenditure (CES) survey and diary from the Bureau of Labor Statistics (BLS). It also adds a comparison of new DCPC aggregate recorded income income payments to BEA personal income and IRS aggregate income. Both analyses are for 2016-2020 and compared with the 2012 DCPC. Appendix A provides more detailed information about the classification of consumption and income categories.

5.1 Consumption Expenditures

As explained in Schuh (2018) and Appendix A, PCE data include many data sources and are a more comprehensive estimate (broader coverage) of consumption expenditures than either the DCPC or CES data. Furthermore, the three consumption sources have somewhat different classification schemes for expenditures. For these reasons, the comparison includes two smaller aggregate measures of consumption. One measure is *Adjusted Consumption*, which excludes consumer expenditure categories not included in all three data sources.[18] A second measure is *Mostly Comparable*

[18] Most items are related to housing, non-profits goods and services, and consumer loan servicing. Imputed rent and non-profit goods and services are in PCE but not DCPC, and vice versa for mortgage payments and expenses

Consumption, which limits the analysis to expenditure categories that are most similar among the three data sources and generally follows the official BLS correspondence between CES and PCE.[19] Mostly Comparable categories The DCPC consumer expenditures are matched as best as possible to the PCE and CES categories using merchant categories (see Tables A8 and A9).

Aggregate DCPC consumer expenditures are somewhat lower in 2016-2020 than 2012 due to better identification in the questionnaires, but the DCPC expenditures continue to match PCE better than do CES data, as shown in Figure 1.[20] Before any adjustments, the DCPC matched 97 percent of PCE total expenditures from 2016-2020, while the CES only matched 58 percent of PCE consumption. Adjusted DCPC consumption is only 72 percent of PCE, down from 92 percent in 2012, but still higher than CES (52 percent). In Mostly Comparable categories, the DCPC and CES both match more of PCE on average (83 and 63 percent, respectively), but the DCPC continues to be notably closer than CE. Year-to-year estimates of DCPC and CES aggregate consumption fluctuate as shares of PCE non-trivially, as shown in Appendix B1.

Figure 1: 5-year Consumption Averages

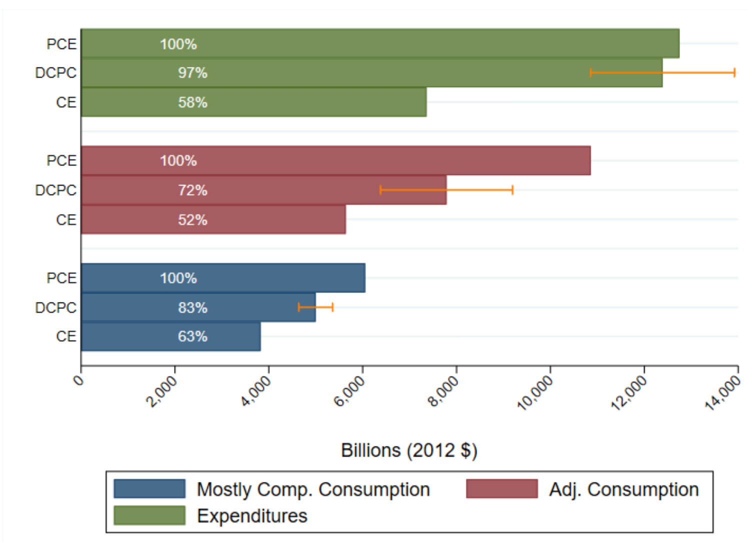


Figure 1 shows the five-year consumption averages for the DCPC, PCE, and CE corresponding to table B1. The y-axis are different categories of expenditures, while the x-axis is dollar values. Percentages reported are all indexed to PCE values of each consumption category and therefore PCE is always 100%. Orange range plots are the 95% confidence intervals for DCPC estimates. All estimates are reported in billions 2012 USD.

for owned dwellings. Additional unique categories removed from the DCPC include taxes, payments to person, non-classifiable payments, and loan repayments.

[19] See the BLS correspondence between CES and PCE. Non-comparable categories mainly are related to medical payments, insurance payments, vehicle related purchases, tuition payments, professional services, and other miscellaneous categories which are difficult to directly compare. For details on the exact categorization, see Table A8.

[20] Data in the figure are in constant 2012 USD. The bars show five-year averages of PCE, DCPC, and CES consumption estimates corresponding to Table B1 of the Appendix, which reports a detailed comparison of consumption categories j defined in section 4.1. The percentage values are indexed to PCE as the benchmark (100%).

5.2 Recorded Income

BEA personal income is the most comprehensive income measure, as it encompasses current income received by individuals from all sources. IRS income only includes sources of taxable income, and therefore excludes some income types found in BEA personal income.[21] DCPC recorded income also has some categories different from BEA and IRS income. For these reasons, we construct a smaller *Adjusted Income* aggregate category, which converts all measures to after-tax (disposable) and excludes a few categories that are not in all three income sources.[22] We also include the DCPC household income estimates for comparison. However, since we cannot identify the components of household income, we compare it to total BEA and IRS income only and do not make any adjustments.

Figure 2: Income Averages

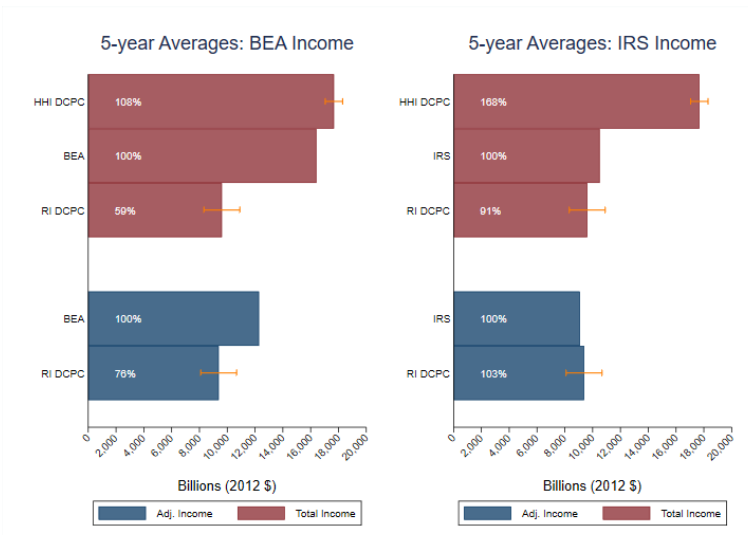


Figure 2 shows the four and five year income averages of the DCPC compared to BEA and IRS income, corresponding to tables B2 and B3. The y-axis are different categories of income, while the x-axis is dollar values. Percentages reported are all indexed to either BEA or IRS category values. Orange range plots are the 95% confidence intervals for DCPC estimates. All estimates are reported in billions 2012 USD. "RI DCPC" is for income measured by recorded income, while "HHI DCPC" is the DCPC measure of household income.

Aggregate DCPC recorded income also matches a significant portion of BEA and IRS income, as shown in Figure 2.[23] Before adjustments for comparability, DCPC aggregate total income matches about three-fifths of BEA income (59 percent). However, DCPC income matches over three-quarters of Adjusted BEA disposable income (76 percent). Compared to IRS income, DCPC matches a large

[21] The gap between IRS and Personal Income estimates is described in Ledbetter (2004).

[22] In addition to taxes, the categories include employee retirement contributions and supplements to wages and salaries (in BEA but not DCPC), and alimony and child support (in DCPC but not BEA or IRS).

[23] Data in the figure are in constant 2012 USD. The bars show five-year averages for the BEA and IRS income comparison to the diaries. The percentage values are indexed to either BEA or IRS income as benchmarks (100%). See Appendix Table B2 and Table B3 for comparisons of the detailed income categories, including *Mostly Comparable* and non-comparable.

portion of total income (91 percent). After making the two income sources comparable, the DCPC income covers essentially almost all of IRS income (103 percent). Year-to-year estimates of DCPC aggregate income fluctuate as shares of BEA and IRS non-trivially, as shown in in Figure B2 of the Appendix. DCPC household income closely matches BEA income, while is significantly higher than IRS income. This is likely for the same reasons BEA income is higher than IRS income (as discussed in Ledbetter (2004)). As we are not able to determine the components of household income in the DCPC, there are likely income types that aren't as comparable between data sets for DCPC household income.

6 Real-Time Data and Forecasting

The DCPC data are essentially real-time because respondents complete their questionnaires every diary night and recorded activity includes the exact time of each expenditure, cash management, and related activities. At present, only their producers (Atlanta Fed and CESR) can take advantage of the real-time nature because the data are proprietary for about a year or so before the Fed releases them to the public. However, the relative success in matching official U.S. aggregate data documented in Section 5 motivates *ex post* investigation of potential advantages of leveraging the real-time nature of the DCPC data. In particular, the potential availability of daily DCPC consumption and income data suggests they may have value in macroeconomic forecasting.[24] This section reports the results of two preliminary investigations of the real-time aggregate forecasting potential of the DCPC data.

6.1 Forecasting DCPC Aggregate Consumption

The first task is to assess how well daily DCPC consumption levels forecast the final estimate of the level of DCPC consumption in October, denoted as $\widehat{\overline{C}}_{10,t}$, using the methodology in Schuh (2018). Let $\bar{C}$ denote adjusted consumption per capita (consumer). Then the daily projection (denoted by a caret) of monthly consumption per capita is

$$\widehat{\overline{C}}_{mt,d} = \sum_{s=1}^{d} \left(\frac{31}{d}\right) \overline{C}_{smt} \ . \qquad (1)$$

This simplistic and naive projection is inefficient because it does not take into account any prior information about DCPC consumption, most notably $\widehat{\overline{C}}_{9,t}$, but is necessary because the data are collected only one month per year. Implementing the DCPC every month might enable significantly better forecasts.

Figure 3 plots the daily real-time projections of the October levels of DCPC consumption in 2012

[24] Exercises in this section are simple but analogous to the Atlanta Fed's GDPNow estimates of daily real GDP growth. GDPNow stems from Faust and Wright (2009) which compared the Fed's Greenbook projections with forecasts of the FOMC's four projection variables based on large-scale real-time data sets. See GDPNow.

and 2016-2020.[25] Dashed lines are 95 percent confidence intervals. As reported in Schuh (2018), the daily projection of October DCPC consumption in 2012 converges quickly to the final estimate on October 31, falling within the standard error band by October 10. In 2016-2020, the DCPC data continued to quickly converge to their final October estimates well before the end of the month with statistical confidence.[26] Encouragingly, from 2016-2020 the daily estimates start closer to their final means and converge statistically to their final means faster than in 2012. In fact, the 2016-2017 estimate within their confidence intervals every day of the month, and the 2018 estimate arrives there after only a week. In 2019-2020, the confidence intervals are wider due to smaller sample sizes, but the point estimates still approach the monthly mean in 9-17 days.

These updated projections also confirm that the 2012 DCPC were not a fluke. Given the evidence from 2016-2020, we can conclude more confidently that the DCPC data have reliable real-time forecasting power for the final DCPC estimate well before the end of the month. For comparison, note that official U.S. PCE data for October are not made available to the public until late November or early December, plus they are subject to revisions. Thus, the DCPC data may provide potentially valuable information about aggregate U.S. consumption approximately 1-1/2 months (45 days) before the official U.S. PCE data are released.[27] Recall from Section 5, however, that although the DCPC data have relative high coverage they understate official U.S. PCE significantly. Thus, there is a time-varying gap between the level of the final DCPC estimate and actual PCE (not shown in Figure 3), which limits its usefulness in real-time forecasting.

6.2 Forecasting PCE Growth Rates

A second task is to assess how well 12-month growth rates of DCPC consumption forecast 12-month rates of U.S. PCE growth. Although the levels of DCPC consumption data are downward biased by 28 percentage points due to omission of some expenditures categories, hard-to-reach sub-samples (e.g., very wealthy), etc., it's possible that growth in the relatively representative DCPC data might be better predictor of more representative PCE growth than the levels data. This subsection extends the preceding analysis of consumption level to quantify how well daily DCPC consumption *growth* matches the annual growth rate in the PCE.

Constructing the growth rate of DCPC consumption involves additional challenges stemming from limited data availability. Let C^*_{mt} denote adjusted PCE data, which is the best unbiased estimate of U.S. consumption but only available publicly at the monthly frequency. To project the monthly growth rate of October PCE, $G^*_{10,t} = (C^*_{10,t} - C^*_{9,t})/C^*_{9,t}$, we would need construct the monthly growth rate of October DCPC adjusted consumption, $G_{10,t} = (C_{10,t} - C_{9,t})/C_{9,t}$. However, $C_{9,t}$

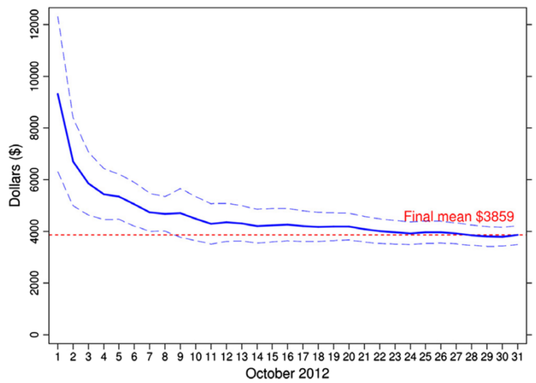
[25] This figure uses the Fed scripts for cleaning DCPC data outliers.

[26] Note that 2012 data included payments in consumption expenditures that were identified improperly, as discussed earlier, so the final 2012 estimate is significantly higher than 2016-2020.

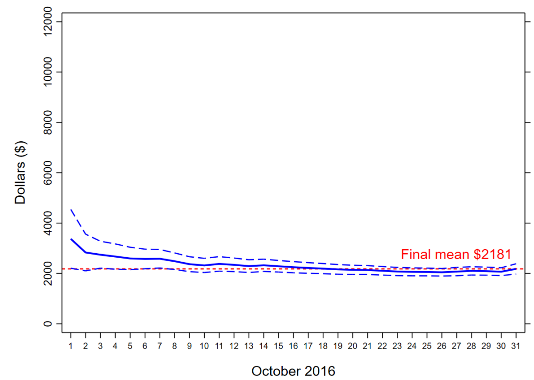
[27] The initial BEA estimate of October 2022 PCE was released on December 1, 2022, one month after October 31 and more than seven weeks after October 10. See October 2022 PCE.

Figure 3: Daily Estimate of Monthly Payments per U.S. Consumer

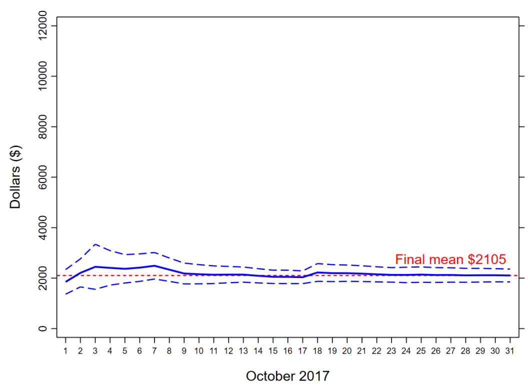
(a) 2012



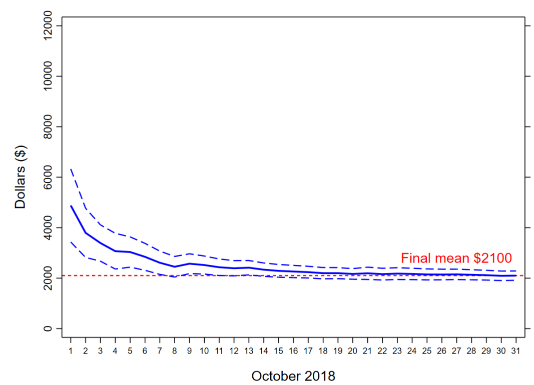
(b) 2016



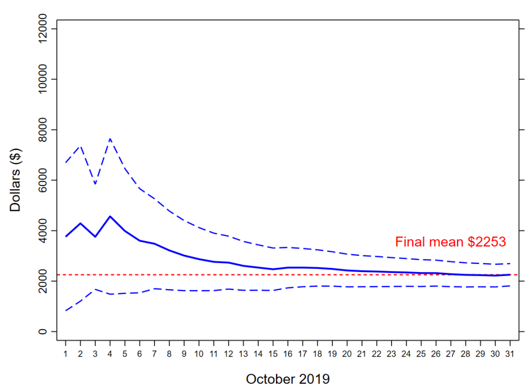
(c) 2017



(d) 2018



(e) 2019



(f) 2020

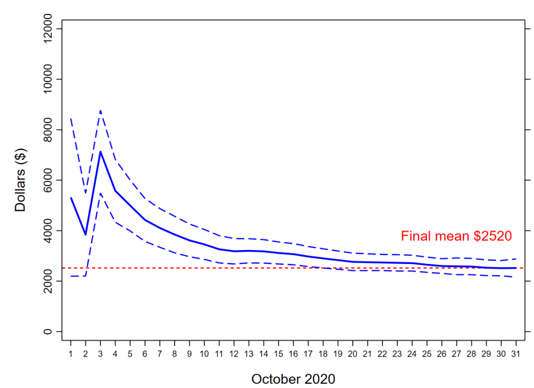


Figure 3 reports the results of the daily estimates of monthly payments per consumer, as discussed in section 6.1. Dashed lines indicate 95% confidence intervals, and dotted red lines are the final mean. Subfigure 3a is taken directly from Schuh (2018), while subfigures 3b - 3f are calculated from the data. The daily estimate of monthly payments equals the 31-day projection of average daily consumption derived from the cumulative sum of payments since October 1, divided by the number of days (see equation 1). The estimation procedure from Schuh (2018) is used for calculating standard errors.

does not exist because the Diary is implemented only one month per year in October. Limited DCPC data are available for September 29-30 each year from the phase in of Diary wave, so in principle $G_{1,mt}$ could be constructed but the short, noisy, and non-representative two-day September DCPC sample makes the exercise unacceptably imprecise.

Instead, we construct a daily projection of the 12-month growth rate of DCPC consumption (G) from October in year $t-1$ to October in year t as follows:

$$G_{d,10,t} = \left[\frac{\sum_{s=1}^{d} \overline{C}_{s,10,t}}{\overline{C}_{10,t-1}} \right]^{\frac{D_t}{d}} \tag{2}$$

and then compare these daily projections to the actual 12-month growth rate of PCE:

$$G^*_{10,t} = \left[\frac{C^*_{10,t}}{C^*_{10,,t-1}} \right] \tag{3}$$

which is known with certainty *ex post* for this exercise but not in real time.

Figure 4 plots the daily projections of $G_{d,10,t}$ for 2017-2020 (one less year due to the growth rate calculation) to demonstrate how well the daily DCPC data can forecast the future (end of October) value of PCE. Scatter points denote values that lie outside of the reported range and are truncated for display purposes. The solid blue lines are the DCPC estimates of $G_{d,10,t}$ and the dashed blue lines are standard error bands. The red line are the (fixed) PCE estimates of G^*_{mt}. Like the projections of DCPC consumption levels, G_{dmt} converges to its end of month growth rate, which is close to the PCE growth. However, convergence is slower for the growth rates and generally takes at least half or more before the estimate is reasonably close; though relatively quick in 2017, convergence takes longer in later years. Even an accurate estimate of PCE growth at the end of October would provide one month of valuable advance notice of the real-time state of the economy. However, the standard error bands are too large to provide confidence in the projected growth rates, especially in 2020.

The figure legends report the quantitative estimates of the end-of-month growth rates for the DCPC projections and actual PCE. The average difference between DCPC and PCE growth rates ($G^*_{mt} - G_{mt}$) is smaller: $-.028$ for four years and .012 excluding the 2020 outlier. However, the gap between DCPC projections and PCE is sometimes as large as 5 percentage points in absolute value. The magnitudes of these differences are too large for the DCPC project to be useful for real-time forecasting and policy analysis for macroeconomics yet. More development of the Diary and expansion of the sample size are needed to produce a more useful forecast of PCE in real-time.

Figure 4: Forecasting Annual DCPC Growth

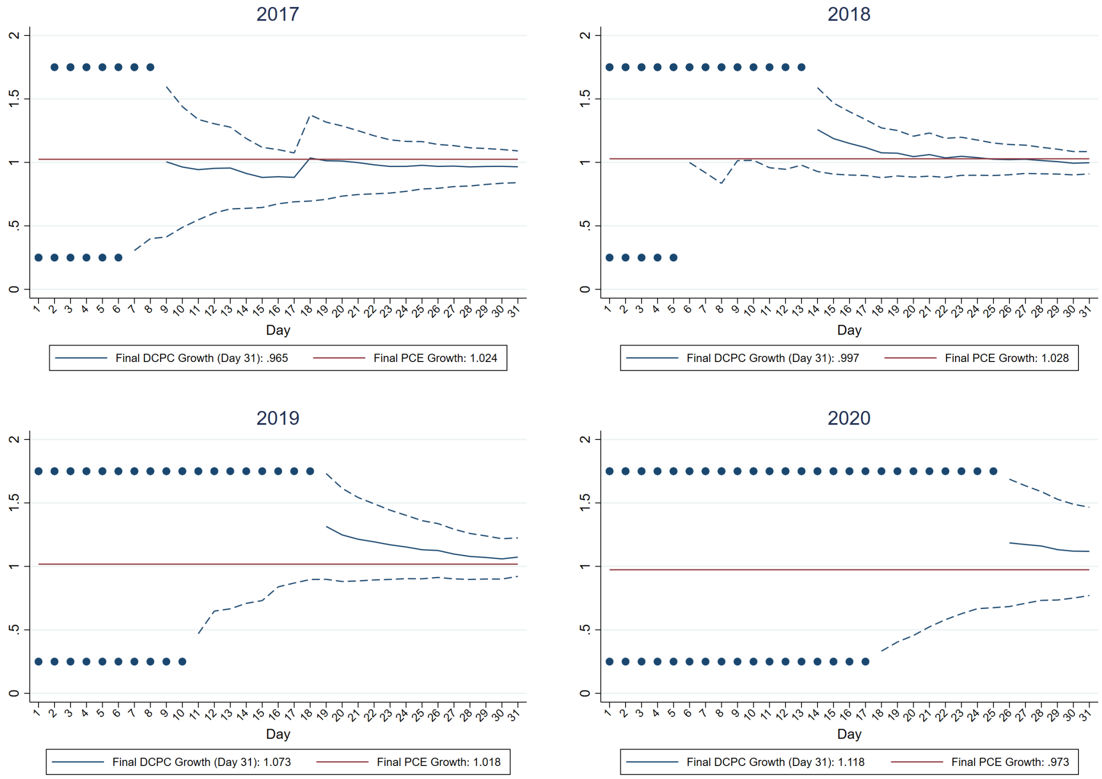


Figure 4 reports the daily estimates of annual DCPC growth. The solid blue line reports G_{dmt} for each day of the diary. The red line reports PCE growth G^*_{mt}. The legend reports end-of-month growth estimates for DCPC and the PCE growth rate. Scatter points cap estimates above 1.25 and below .25 for display purposes.

7 Consumption Models: Annual

Given the ability of DCPC data to match official aggregate U.S. consumption and income reasonably well, it is logical to ask how well a benchmark model of consumption fits these high-frequency micro data. In principle, the DCPC micro data offer the opportunity to estimate consumption models at the highest-frequency ever (daily) for individual consumption choices.[28] In practice, however, two limitations (one theoretical, one due to sample selection) make such estimation extremely challenging. So, as a natural first step, we estimate a basic inter-temporal consumption model using a balanced panel of synthetic cohorts. We aggregate daily expenditures to a monthly frequency and compare annual changes in consumption and income. We assess whether the annual relationship between consumption and income in the DCPC data is consistent with standard theoretical models, and compare the results to analogous ones in the literature.

[28] The DCPC even supports estimation of models at the transaction-level within days, which is extremely rare, but see Briglevics and Schuh (2014) for an exception.

7.1 Benchmark PIH Model

The econometric model is derived from the benchmark Permanent Income Hypothesis (PIH) model with stochastic income and certainty equivalence. To introduce our model, we follow Jappelli and Pistaferri (2017) for notation and setup. A representative agent maximizes the expected present value of utility,

$$\mathbb{E}_t \sum_{t=0}^{\infty} (1+\delta)^{-t} U(C_t) \tag{4}$$

where $\mathbb{E}$ is the expectations operator, δ is the rate of time preference, and $U(\cdot)$ is the utility function. Given a standard inter-temporal budget constraint with assets A_t, income Y_t, and a time-invariant interest rate r, the standard Euler equation is

$$U'(C_t) = \mathbb{E}_t U'(C_{t+1})$$

when $r = \delta$. Assuming certainty equivalence and linear marginal utility yields:

$$C_{t+1} = C_t + e_t \tag{5}$$

which is the standard martingale process of Hall (1978). See Appendix C for details. Thus far, the model is entirely standard.

However, the benchmark model poses two significant challenges. First, it implicitly assumes that consumption is equal to expenditures. This assumption is clearly violated at high-frequencies where many goods are durable in the short-run.[29] Consumption may be continuous and smooth while expenditures on goods and services are lumpy, which is further complicated when income is discrete (weekly, bi-monthly, etc.). Thus, the application to the data requires modification to match the predictions of the theoretical model. A second challenge is that the DCPC respondents report data for only three consecutive days in a month. The advantageous sampling methodology, which produces representative data for each day (and low respondent burden), yields an unbalanced panel of consumers with limited time-series horizons at the individual level.

7.2 Daily to Monthly Data: Synthetic Cohorts

To circumvent the challenges of using daily data in studying the benchmark model, we make two adjustments to the DCPC data. First, we time-aggregate the DCPC to monthly by summing data across all days, denoted by subscript $d = \{1, 2, \ldots, 31\}$, in October and treating the month, denoted by subscript $m = \{1, 2, \ldots, 12\}$, as a once-per-year observation. Thus, the difference between October in years t and $t+1$ is a 12-month change measure of annual data, denoted $\Delta_m^{12} Z_{mt} = Z_{mt} - Z_{m,t-1}$ for any variable Z.

[29] Aguiar and Hurst (2005); Baker et al. (2024)

The second adjustment is converting to a balanced panel with continuous time series observations by constructing synthetic cohorts of consumers, denoted by subscript $i = \{1, 2, \ldots, N\}$. Synthetic cohorts have been used to study life-cycle behavior within the literature, especially with repeated cross-sections (Blundell et al., 1994). Each cohort is defined by exogenous respondent characteristics that are fixed across time and denoted by subscript $k = \{1, 2, \ldots, K\}$. It is unnecessary to carry both i and k subscripts because each individual is uniquely assigned to a demographic cohort, so only the relevant identifier is included. In this section, we use demographics and set $K = 14$ as determined by seven age categories and two biological genders; other cohort definitions are used and described later. Thus, cohort-level consumption is

$$\overline{C}_{kdmt} = \frac{\sum_{i=1}^{I_{kdt}} w_{idt}^{D} \cdot C_{idmt}}{\sum_{i=1}^{I_{kdt}} w_{idt}^{D}}$$

which is than aggregated to annual levels. Cohort is an admittedly arbitrary empirical specification, chosen judgmentally to maximize K (heterogeneity) given the sample size and limited years. These cohorts are also chosen as they are exogenous to the respondent but allow for a sufficient number of observations needed for analysis. Because the cohorts aggregate over multiple individual consumers, we are able to measure the annual changes in monthly cohort consumption and annual income. Deaton (1985); Verbeek (1996) describe that using cohort means result in cohort fixed-effects which correspond to individual fixed-effects if these individual effects are additive. Age fixed-effects are important to control for in the model to control for life-cycle stages of income. When the number of cohort members and time periods are sufficiently large, this cohort method results in consistent estimators. From simulated data, Verbeek and Nijman (1993) find that 100 individuals per cohort obtain minimal bias from small samples. Given the limited number of years and respondents on any given day of the diary, in our specification the median number of respondents in a cohort cell is 16. Therefore, while synthetic cohorts allow us to study the PIH in the DCPC, the lack of individuals per sample may suffer from small sample bias. The estimators on variables of interest can be adjusted to produce more consistent estimates (Deaton, 1985; Verbeek, 1996), which we will be pursuing in future drafts.

The DCPC also offers a choice between two income types. Annual household income, denoted Y_{it}^{H} and reported in the SCPC during September, is the gross total income earned by all members of the respondent's household for the entire calendar year. Respondent income, denoted Y_{idmt}^{R} and recorded daily in the DCPC, is any income received only by the respondent on each day. The type (wages and salaries, retirement, interest, etc.) and implied frequency (last received, next received) of each recorded income payment are reported as well. Given that C_{idmt} is consumption only for respondent i and the DCPC typically does not include consumption for other members of a multi-member household, it is not immediately clear which income measure is better.

Choosing between Y_{it}^{H} and Y_{idmt}^{R} is complicated by conceptual and empirical discrepancies absent from the benchmark PIH model. Implicitly, the model assumes Y_t is total consumer income, which aligns more closely with Y_{it}^H, except for two details. First, individual consumers (respondents) may have multiple types of income, denoted by subscript $j = \{1, 2, \ldots, J\}$, so total monthly consumer income is $Y_{imt}^R = \sum_j \sum_d Y_{ijdmt}^R$. However, the DCPC limits this calculation to three diary days for each respondent, during which many do not report any income, so it is impossible to forecast consumer income for all 31 days in October with any precision. Second, a household may contain more than one consumer, in which case $Y_{it}^H/12 \geq Y_{imt}^R$, with equality for single-consumer households, and $Y_{imt}^H = Y_{it}^H/12 \ \forall \ m$ is the same for all months, which may not be correct for October.

Taken together, data limitations induce a conundrum over whether individual C_{idmt} is best determined primarily by expectations of a time-invariant average monthly household income ($Y_{it}^H/12$) or an incomplete measure of time-varying daily respondent income (Y_{imt}^R). Taking all factors into account, we use Y^H in our benchmark PIH model for two reasons. First, C_{idmt} is likely influenced by income shared from other household members—spouses and partners being the obvious example. Second, three days of respondent income likely omits a large portion of actual Y_{imt}^R. However, we explore modeling of cohort-level respondent income (Y_{kdmt}^R) later in the paper as a first step toward future analysis.

To derive an econometric specification of the benchmark PIH model for estimation with the DCPC data, we first write down the monthly version and convert it annual changes. From the martingale process, it follows that monthly cohort-level consumption is

$$
\begin{aligned}
C_{k,10,t} &= C_{k,9,t} + e_{k,10,t} \\
C_{k,9,t} &= C_{k,8,t} + e_{k,9,t} \\
&\vdots \\
C_{k,11,t-1} &= C_{k,10,t} + e_{k,11,t-1} \ ,
\end{aligned}
$$

but DCPC data are available only for $m = 10$ each year $t = 2016 - 2020$. Therefore, substituting recursively gives:

$$
\begin{aligned}
C_{k,10,t} &= e_{k,10,t} + e_{k,9,t} + e_{k,8,t} + \ldots + e_{k,11,t-1} + C_{k,m-12,t} \\
C_{k,10,t} &= \sum_{\mu=0}^{9} e_{k,10-\mu,t} + \sum_{\mu=0}^{1} e_{k,12-\mu,t-1} + C_{k,10,t-1} \\
\Delta_m^{12} C_{kmt} &= \sum_{\mu=0}^{9} e_{k,10-\mu,t} + \sum_{\mu=0}^{1} e_{k,12-\mu,t-1}
\end{aligned}
\tag{6}
$$

where $\Delta C_m^{12} = C_{k,10,t} - C_{k,10,t-1}$ denotes the annual change in October consumption. Using the inter-temporal budget constraint, Appendix C derives the following equation:

$$
\begin{aligned}
\Delta_m^{12} C_{kmt} &= \sum_{\mu=0}^{9} e_{k,10-\mu,t} + \sum_{\mu=0}^{1} e_{k,12-\mu,t-1} \\
&= \frac{r}{1+r} \left\{ \sum_{j=0}^{8} \left[\frac{(\mathbb{E}_{k,10-j,t} - \mathbb{E}_{k,9-j,t}) Y_{k,10,t}^H}{(1+r)^j} \right] + \frac{(\mathbb{E}_{k,1,t} - \mathbb{E}_{k,12,t-1}) Y_{k,10,t}^H}{(1+r)^9} \right. \\
&\left. + \sum_{j=0}^{1} \left[\frac{(\mathbb{E}_{k,12-j,t-1} - \mathbb{E}_{k,11-j,t-1}) Y_{k,10,t}^H}{(1+r)^{10+j}} \right] + \xi_{10,t} \right\}
\end{aligned} \tag{7}
$$

which shows the annual (12-month) change in consumption depends on two terms: 1) the cumulative monthly change in expected current income $Y_{k,10,t}^H$ during the 12 months since the last diary; and 2) $\xi_{k,10,t}$, representing a composite term of unexpected income realizations between diaries and any modifications to expectations of all future income. For more details of the derivation of Equation 7 and the exact definition of $\xi_{k,10,t}$, see Appendix C. The model predicts that $\Delta_m^{12} C_{kmt} = 0$ when realized income is expected by the cohort and expectations remain constant, while $\Delta_m^{12} C_{kmt} \neq 0$ otherwise.

7.3 Regression Equations

The previous subsection and Equation 7 motivate use of the following simple regression equation to test the benchmark PIH model:

$$
\Delta_m^{12} C_{kmt} = \beta_0 + \beta_1 \widehat{\Delta_m^{12} Y_{k,10,t}^H} + \beta_2 u_{k,10,t} + \varepsilon_{k,10,t} \tag{8}
$$

where actual income change, $\Delta_m^{12} Y_{k,10,t}^H = \left[\widehat{\Delta_m^{12} Y_{k,10,t}^H} + u_{k,10,t} \right]$, is the sum of predicted (term with a caret) and unexpected ($u_{k,10,t}$) components. The PIH implies $\beta_1 = 0$.[30] Jappelli and Pistaferri (2010) conclude the evidence in the literature rejects this hypothesis and shows consumption is excessively sensitive to predicted income increases, thus liquidity constraints may play an important role. With $K = 14$ cohorts and $T = 5$ years, the DCPC data offer 70 observations for estimation. To conserve the modest degrees of freedom, we estimate two restricted versions of Equation 8: 1) $\beta_2 = 0$ and $H_0 : \beta_1 = 0$; and 2) $\beta_1 = 0$ and $H_0 : \beta_2 > 0$.

Estimation of Equation 8 requires identifying the unobserved components of $\Delta_m^{12} Y_{k,10,t}^H$. Two strategies are common. One is to model the income process explicitly, which may be susceptible to misspecification errors.[31] Another is using observed changes to income that can be plausibly identified as anticipated or unexpected, which avoids misspecification but offers less structure for interpreta-

[30] Hall (1978) first tested the martingale hypothesis. Flavin (1981) decomposed income into predictable and unpredictable components and rejected the PIH. Zeldes (1989) found that liquidity constraints can explain excess sensitivity of consumption to predicted income. Since then, numerous studies have found similar results.

[31] Notable examples include Hall and Mishkin (1980) and Blundell et al. (2008).

tion.[32] There are no data or events in the DCPC that would support the latter approach and the use of cohorts precludes identification of consumer-specific events, so we adopt the former and use multiple models to assess potential misspecification.

Following various branches of the literature, we use three different models to predict income and its changes. The first model is a unit root with drift (stochastic trend):

$$\Delta_m^{12} Y_{k,10,t}^{H} = \alpha + u_{k,10,t}^{M1} \tag{M1}$$

which is very common in the macro literature and has advantages of simplicity and parsimony.[33] The second model is a two-stage IV regression:

$$\Delta_m^{12} Y_{k,10,t}^{H} = \alpha + \gamma \Delta_m^{12} Y_{k,10,t-2}^{H} + u_{k,10,t}^{M2} \tag{M2}$$

where the instrument $\Delta_m^{12} Y_{k,10,t-2}^{H}$ is popular in the applied micro literature (Jappelli and Pistaferri, 2017; Deaton et al., 1992). While this specification may be optimal with more observations, it only allows a paltry 28 observations in this analysis. The third model is a practical reduced-form AR(1) specification in levels with fixed-effects:

$$\Delta_m^{12} Y_{k,10,t}^{H} = \alpha + (\rho - 1) Y_{k,10,t-1}^{H} + \lambda_t + \eta_{AGE} + \lambda_t \cdot \eta_{AGE} + u_{k,10,t}^{M3} \tag{M3}$$

where λ and η are standard (macro) time and (life-cycle) age effects plus their interaction. M3 is motivated by Appendix Figure C1, which plots the time-series graphs of income by age. Although the time-period is short and samples sizes small, incomes exhibit heterogeneous trends that roughly conform with standard life-cycle expectations. That is, income trends upward more for younger ages, stagnates for the middle ages, and is flat or slightly decreasing for older age cohorts. M3 is equivalent to an AR(1) in levels where $Y_{k,10,t-1}^{H}$ is subtracted from both sides so the first stage dependent variable is in differences as in M1 and M2 to follow the PIH model. In all models M1 - M3, $\beta_1 = 0$ if the PIH holds regardless of the income process.

Consumption models with each income process are estimated using OLS in two stages. M1 - M3 are estimated in the first stage, and using their predicted values in the second stage (equation 8). We correct the standard errors in the second stage for the fact we are using predicted values, robust to heteroscedasticity.[34] We estimate the models with two data units: 1) dollar values (C, Y), which

[32] Perhaps the closest to our study is Baker (2018). Other notable examples include Parker (1999), Souleles (1999), Souleles (2002), Hsieh (2003), Stephens Jr (2008) for income increases, and Aguiar and Hurst (2005) and Aguila et al. (2011) for income decreases.

[33] Note that for M1, we run equation 8 without the constant term β_0 given M1 is regressed only on the constant α. CITATIONS TBD.

[34] When including the error term from the first stages, standard errors are estimated through bootstrapping with

yields a measure of the MPC; and 2) logs (c, y), which converts changes to growth rates and thus yields a measure of *elasticity* (the specification that emerges from a PIH model with isolelastic utility). Although we cannot identify unexpected income changes directly, we use the estimated residuals from the first-stage income regressions, $\widehat{u_{kmt}}$, as a proxy for unexpected income changes.

7.4 Estimation Results

Table 1 reports the estimation results for equation 8 and each income model, M1 - M3, with dollar values (Panel A) and logs (Panel B). The consumption and income data have been converted to real 2012 dollars. Each column contains results for a separate regression grouped by sample: "All" denotes the full DCPC sample; "Low/High Share" denotes samples split according to the consumers' level of liquid assets (described in detail below). In each Panel, the first row reports β_1 coefficients (MPC in Panel A, elasticity in Panel B) and the second row β_2 coefficients.

Table 1: Annual Consumption Estimates

	M1			M2			M3		
	(1) All	(2) Low Share	(3) High Share	(4) All	(5) Low Share	(6) High Share	(7) All	(8) Low Share	(9) High Share
Panel A: $\Delta C_{k,10,t}$									
$\widehat{\Delta^{12}_m Y}^H_{k,10,t}$	0.038	-0.078	0.242	0.022	-0.128	1.274	0.255*	0.244	0.186
	(0.534)	(0.758)	(0.711)	(0.340)	(0.386)	(0.931)	(0.141)	(0.151)	(0.263)
$\widehat{u}_{k,10,t}$	0.149			0.134			-0.227		
	(0.115)			(0.136)			(0.295)		
Panel B: $\Delta c_{k,10,t}$									
$\widehat{\Delta^{12}_m y}^H_{k,10,t}$	0.121	-0.078	0.421	0.627	0.413	2.907	0.660*	0.718*	0.315
	(1.247)	(1.799)	(1.712)	(0.998)	(1.280)	(2.316)	(0.347)	(0.379)	(0.645)
$\widehat{u}_{k,10,t}$	0.392			0.380			-0.478		
	(0.291)			(0.352)			(0.720)		

[1] Table 1 reports the second stage regression results for consumption changes to predicted income. Panel A is change in 2012 USD values, while Panel B is change in logs. Columns (1) - (3) reports the results for Model 1, which imposes a unit root in the change in income. Columns (4) - (6) reports the results for Model 2, which predicts the current change in income with the change in income at time $t-2$. Columns (7) - (9) models the annual difference income as an AR(1) process, where the time trend is allowed to differ by age cohort. The first columns in each model group (columns 1, 4, 7) report the results over all cohorts. The rest of the columns split the sample into low shares and high shares of liquidity constrained respondents. High Share denotes cohorts with the highest tercile of liquidity constrained respondents, and Low Share are the remaining terciles. Liquidity constraints proxied by respondents in bottom quartile of liquidity. Lower case letters denote natural log transformations. The results of including the first stage residuals are included at the bottom of each panel, labelled $\hat{u}_{kmt}$. Standard errors are corrected for in second stage and are robust to heteroscedasticity, and standard errors for the residuals are bootstrapped.

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Annual N: 70 (5 years, 14 cohorts). Average number of respondents per cohort per day: 16. Cohorts: Age (7), gender (2).

The full-sample results in Table 1 offer very modest but imprecise support for the PIH model. Estimated MPCs and elasticities are not statistically significantly different from zero, consistent with the PIH. Estimated MPCs for income models M1 and M2 are close to zero, and 0.26 for M3, but estimated elasticities are considerably larger $(0.12 - 0.66)$. Models M1 and M2 report standard which are uncomfortably large, reducing confidence in model inference. However in M3 thee standard errors are marginally lower suggesting a rejection of the PIH as found within the literature. Estimates of β_2 also are not statistically significantly different from zero. If income shocks

1000 replications.

are entirely transitory, this result lends additional support for the PIH model. But it's unlikely the DCPC would not capture any permanent income shocks over five years. Indeed, β_2 estimates are positive, economically significant, and much closer to statistically significant for income models M1 and M2. This result suggests more DCPC data might offer better model inference and possible support of the PIH model. Negative estimates of β_2 with income model M3 may be reflecting misspecification problems.

As discussed in Jappelli and Pistaferri (2017), liquidity constraints can lead to higher estimates of MPC (and elasticity) when agents are unable to borrow and smooth consumption. Thus, relatively high full-sample estimates in Table 1 may reflect liquidity constrained consumers in the DCPC. To test this hypothesis more directly, we follow the seminal paper of Zeldes (1989), who split the sample on a threshold of wealth. The DCPC does not contain daily data on wealth but it does have liquidity, which may serve as a useful measure for daily spending. We define liquidity as the real 2012 dollar value of respondents currency (cash on hand and at home) plus checking account balances on the night *before* their diary starts (i.e., Day 0, which is predetermined in the model). Other liquid assets (savings accounts, money-market funds, and short-term government bonds) may be relevant liquidity but are not in the DCPC. Before cohorts are created, respondents are classified into constrained (lowest quartile of liquidity *ex ante*) and unconstrained categories (all others). When constructing cohorts, we create the share of respondents within the cohort who are constrained each diary day and split cohorts shares into terciles of liquidity constrained respondents.[35]

Consistent with the literature, the split-sample results in Table 1 offer evidence that liquidity constraints may be important for some consumers. Columns labeled "High Share" denotes the sample with the top tercile of cohorts (*"Constrained"*), and "Low Share" denotes the sample with the bottom two terciles of cohorts (*"Unconstrained"*).[36] For income models M1 - M2, the MPC and elasticity point estimates for are economically significantly larger for constrained consumers (High Share), as expected. In contrast, the analogous estimates for unconstrained consumers (Low Share) are relatively close to zero and statistically insignificant. For income model M3, the coefficients are surprisingly larger for the unconstrained consumers than the constrained. While the difference between constrained and unconstrained are statistically insignificant for M3, the result suggests the AR(1) classification of income for constrained consumers may be weaker for subsample analysis. Point estimates for income model M2 are abnormally large and imprecise, perhaps reflecting misspecification.

[35] Alternatively, we could use average liquidity of each cohort to measure liquidity constrained agents. However, results are unclear with this measure, perhaps because cohorts comprise a mix high- and low- liquidity agents. Using the share of respondents in each cohort with low liquidity gives a more accurate measure of cohorts with liquidity-constrained consumers. Lower-liquidity agents are more likely to be constrained, but agents with high amounts of liquidity could still be liquidity constrained. Therefore, this proxy may underestimate the true number of liquidity constrained agents within the diaries.

[36] As a robustness check, we also estimated the models with the High Share and Low Share indicators interacted with income. The (unreported) results are quantitatively similar results but have higher standard errors.

7.5 Analytical MPC from Unexpected Income

The full-sample results in Table 1 provide modest evidence in favor of the PIH with mainly transitory income shocks. To test this conclusion further, we specify the income process as an AR(1) model and solve analytically for the implied response to an income shock following the methodology in Jappelli and Pistaferri (2017). As shown in Appendix C, with an AR(1) model of income the annual change in consumption after an income shock:

$$\Delta_t^1 C_{kt} = \left(\frac{r}{1+r}\right)\left(\frac{1+r}{1+r-\rho}\right) \cdot u_{kt} = \Omega \cdot u_{kt} \tag{9}$$

where ρ is the AR(1) lag coefficient that determines persistence of the income shock and r is the real interest rate.[37] Respondents may not form income expectations with an AR(1) model, but it's a simple approximation that makes the analytical calculation and interpretation straightforward. Note that ρ can be viewed as a proxy for permanent vs. transitory shocks, as explained by Jappelli and Pistaferri (2017). When $\rho = 1$, $\Omega = 1$ and income innovations are fully realized as changes in consumption, suggesting a permanent income shock. When $\rho = 0$, $\Omega = \frac{r}{1+r}$, which is small for low values of real interest rates. Although this model does not necessarily capture all the nuances of a fully specified income process, it gives a simple benchmark with which to evaluate econometric tests of the PIH.

Table 2: Implied Consumption Response to Unanticipated Income

	(1) ρ	(2) r=.01	(3) r=.02	(4) r=.05
Panel A: MPC				
$\Omega = \frac{r}{1+r-\rho}$	.754***	0.04**	0.08**	0.17***
	(0.10)	(0.02)	(0.03)	(0.06)
Panel B: Elasticity				
$\Omega = \frac{r}{1+r-\rho}$	.805***	0.05**	0.09**	0.20**
	(0.09)	(0.02)	(0.04)	(0.08)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table 2 reports the implied coefficient from equation. r are the different interest rates.

Table 2 reports estimates of ρ from income model M3 and Ω for calibrated annual real interest rates of 1 to 5 percent. Again, Panel A contains estimates with real 2012 dollar values (MPC) and Panel B with logs (elasticity). Estimated persistence of annual income is relatively high $(0.75 - 0.81)$, as might be expected for annual income, albeit far from a unit root. The estimates of Ω are generally smaller than those in Table 1 for all interest rates except perhaps 5 percent. From 2016-2020,

[37] Equation 9 refers to annual data but the derivation is analogous for a 12-month change in consumption (October-to-October) and annual change in income, as are available in the DCPC. A similar process holds for monthly data.

the actual real 10-year interest rate fluctuated between 0 and 1.3 percent.[38] Therefore, analytical estimates of the MPC (or elasticity) from unexpected income in a PIH model with a data-consistent real rate (1 percent) and income process (persistence of 0.8) are relatively small. This finding implies that the small, insignificant estimates of β_2 in Table 1 are likely due to the DCPC data containing a relatively higher proportion of transitory rather than permanent income shocks.

7.6 Summary of Section Results

Section 7 has analyzed the diaries' capacity for studying a simple yet fundamental consumption model. While the advantage of the DCPC lies in studying daily decisions of consumers, measuring its capability in measuring standard consumption and income dynamics is essential for understanding how the diaries compare to other data sets. Broadly speaking, estimation of the benchmark PIH model and explicit specification of income processes using DCPC data yields results consistent with the literature. The full-sample estimates are perhaps slightly more supportive of the PIH model than the literature, but the relatively small sample size and imprecision limits the drawing of firm conclusions. Similar to the literature, the split-sample estimates provide mixed support for the existence of liquidity constrained consumers who deviate from the PIH and unconstrained consumers who do not. Although coefficient estimates on unexpected income changes are insignificant, their relatively low point estimates are roughly consistent with an AR(1) model of income that implies that income shocks in the DCPC data are primarily transitory in nature.

8 Consumption Models: Daily

The previous section shows that DCPC data yield estimates of a benchmark PIH model for individual consumers at an *annual* frequency that are broadly similar to results in the literature with other data. This section extends the analysis to the *daily* frequency, for which there are no comparable results. It begins by replicating evidence in the literature of payday effects on consumption, then presents estimates of the benchmark PIH models with daily cohort-level DCPC data. It also tests for sample-selection effects in consumption behavior that may arise in non-representative transactions data sources.

8.1 Payday Effects on Consumption

Prior studies using daily individual-level transaction data have documented an economically significant payday effect in which average consumption expenditures are greater on days when anticipated income is received (see especially Gelman et al., 2014; Olafsson and Pagel, 2018), testing the predictions of the Life-Cycle and Permanent Income Hypotheses. To test for a similar payday effect

[38] See variable *REAINTRATREARAT10Y* in the St. Louis Fed's FRED data base.

in the DCPC data, we estimate an equation similar to the literature:

$$\frac{C_{idmt}}{\bar{C}_i} = \sum_{s=-7}^{7} \beta_s I_i(Paid_{d+s,mt}) + \eta_i + \lambda_t + \lambda_{DOW} + \lambda_{WEEK} + \varepsilon_{idmt} \tag{10}$$

where $C_{idmt}/\bar{C}_i$ is the ratio of consumption spending by consumer i on day d in year t to the individual's average daily spending; $I_i(Paid_{d+s,mt})$ is an indicator variable equal to 1 if consumer i received income on day $d+s$; η_i is a consumer fixed effect; and λ are time fixed effects for the year (λ_t), day-of-the-week (λ_{DOW}), and week of month (λ_{WEEK}). Coefficient β_s measures the fraction by which individual consumption deviates from average daily spending on each day of the two weeks surrounding income paydays ($s = 0$). Despite an unbalanced panel with only three consecutive days of respondent data on consumption and income values, the DCPC has sufficient data on paydays to estimate equation 10 at the consumer level and daily frequency.[39]

Table 3: Consumption Response to Income Payments

	(1) All Consumption	(2) Bill Consumption	(3) Non-bill Consumption	(4) Food Consumption
Payday	0.597***	1.088***	0.233***	0.100
	(0.083)	(0.150)	(0.076)	(0.108)
Gelman et al. (2014)	≈ .70		≈ .40	< .10
Olafsson and Pagel (2018)			.56	.33

Table 3 reports the regression results from equation 10. Dependent variable denoted by columns. The dependent variable is the ratio of spending within the consumption category to the average daily spending on the payday. Includes dummy variables for date of income payments, and days for leading to and following income days. Controls for day of week effects and week of month effects. Errors are clustered by respondent. The last two rows shows comparable estimates to Gelman et al. (2014) and Olafsson and Pagel (2018). Gelman et al. (2014) results are approximate reported in paper, while results are compared to Olafsson and Pagel (2018) Table 2 columns (1) and (4) respectively, averaged across salary quartiles. * p<0.1, ** p<0.05, and *** p<0.01.

For comparison with the literature, we estimate equation 10) with data on total (all) consumption and three subcategories of spending. The literature focuses on non-recurring spending, which *excludes* regular bill payments (non-bill) that are due on or by a certain date. Bill payments are often regarded as commitment expenditures (Chetty and Szeidl, 2007; Baugh and Wang, 2018; Vellekoop, 2018) that are different from a payday effect on more discretionary spending. Fast food and restaurant (food) spending is included to measure discretionary, non-durable consumption and payday effects perhaps most clearly. However, bill payments are interesting in their own right and thus included as an extension. Consumers may choose the timing and magnitudes of bills endogenously with their receipts of income. Gilyard (2023) explores this and other bill behavior in the DCPC and finds an analogous spending effect on days bills are paid (whether due or not).

Estimated payday effects (β_0 from equation 10) in the representative DCPC data are positive and statistically significant but economically different from the literature, as shown in Table 3.

[39] Respondents report dollar values of income received during their three-day diary period, plus the dates of their last income was received before the diary period and their next income expected afterward. These data allow for the construction of all 15 indicator variables $I_i(Paid_{d+s,mt})\ \forall\ s = [-7, 7]$ for all respondents, even those who did not receive income during the diary.

Total consumption spending in the DCPC increases about 60% on paydays relative to average expenditures. This estimate is qualitatively similar but smaller than the payday effect of about 70% reported in Gelman et al. (2014). As expected, the payday effect for discretionary non-bill consumption is much smaller: 23% in the DCPC and 40-56% in Gelman et al. (2014) and Olafsson and Pagel (2018), respectively. In the DCPC, the payday effect on food consumption is insignificant with a point estimate of 10%, similar to Gelman et al. (2014) in magnitude.[40] For bill payments, the payday effects more than double (109%). Unfortunately, we cannot assess the statistical significance of differences between estimates from the DCPC and literature without the other data or standard errors. However, the representativeness of the DCPC, especially relative to selected sample in Gelman et al. (2014), suggests there may be economically non-trivial quantitative selection effects (but not qualitative).

Figure 5 plots the estimated β_s coefficients of around paydays for all spending categories. Consistent with the literature, estimates of $\beta_s \neq 0$ for non-bill and food spending are essentially zero, indicating the observed effect on discretionary spending is unique to paydays themselves. In contrast, the spending effect continues to be statistically and economically significantly positive for three days after paydays for bill payments and even all consumption, as shown by Figure 5, albeit steadily declining. The magnitude and persistence of payday effects on bill consumption suggests consumers may intentionally align their bill payments with income payments.

8.2 Econometric Models and Estimation

Next, we apply the PIH model from section 7.1 to daily data. The applied macro literature often uses lower frequency data, as theoretical models are often built under this assumption. Studies using high-frequency will also aggregate transaction data to monthly or lower frequencies to test benchmark models, such as Ganong and Noel (2019) and Gelman (2021). Applying the model to daily frequencies allow for a much higher amount of observations to be utilized for further precision, and to test if the PIH holds even at the highest frequencies.

There are important factors to consider when estimating the model at high frequencies. At the daily level, many goods are likely to be more durable and thus consumption may not be equal to expenditures. Income is paid at specific frequencies, and it is not clear how consumers form expectations on income. As an initial test, we apply models M1 - M3 to the daily data using seven age and two gender cohorts which extends the number of time periods for analysis.[41] At the daily level we estimate the following:

$$\Delta_d^1 C_{kd,10,t} = \beta_0 + \beta_1 \widehat{\Delta_d^1 Y_{kd,10,t}^R} + \beta_2 u_{kd,10,t} + \varepsilon_{kd,10,t} \tag{11}$$

[40] Gelman et al. (2014) finds a modest increase in food spending a number of days after the payday.
[41] With 14 cohorts, the daily panel of cohorts allows for 2,170 observations.

Figure 5: Consumption Response to Income Payments

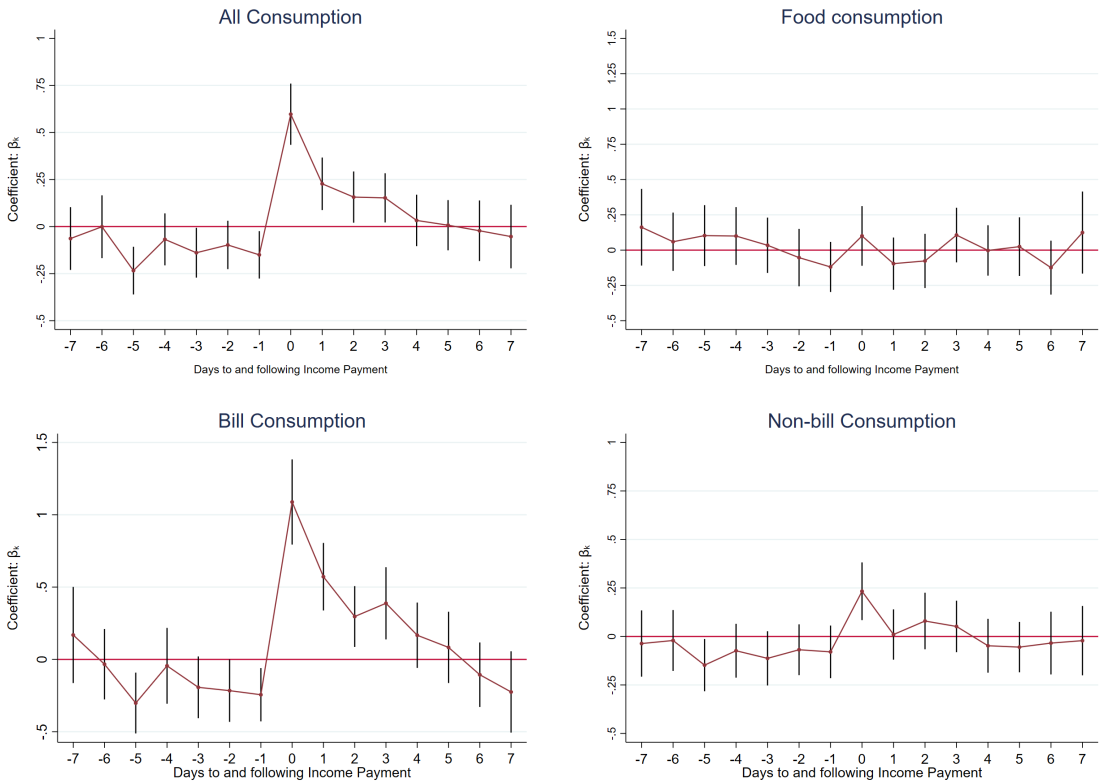


Figure 5 reports the β_s coefficients from equation 10 over the four consumption categories. Negative days denote days before income payment (-7 through -1), while positive days denote days after income payment (1 through 7). Day 0 corresponds to estimates reported in Table 3. Black lines denote 95% confidence intervals.

Where consumption and income are differenced daily. Similar to the annual specification, we model predicted income based on a unit root (M1) and a second lag of income (M2):

$$\Delta_d^1 Y_{kd,10,t}^R = \alpha + u_{dk,10,t}^{M1^d} \tag{M1$^{\mathrm{d}}$}$$

$$\Delta_d^1 Y_{dk,10,t}^R = \alpha + \gamma \Delta_d^1 Y_{k,10,t-2}^R + u_{dk,10,t}^{M2^d} \tag{M2$^{\mathrm{d}}$}$$

Models M1$^{\mathrm{d}}$-M2$^{\mathrm{d}}$ are identical to the daily counterparts to the annual specifications. Here we also use respondent income Y^R, as any changes in household income are due to variations within the cross-section of respondents within cohorts. We extend M3 as follows:

$$\begin{aligned} \Delta_d^1 Y_{kd,10,t}^R = \alpha &+ (\rho - 1) Y_{k,d-1,10,t}^R + \lambda_t + \lambda_{DOW} + Share_{kdmt}^{Payday} \\ &+ \lambda_{EoM} + \lambda_{MoM} + \lambda_{BoM} + \eta_{AGE} + \lambda_t \cdot \eta_{AGE} + u_{k,10,t}^{M3^d} \end{aligned} \tag{M3$^{\mathrm{d}}$}$$

Where the AR(1) process is daily, we we control for day-of-week λ_{DOW}, end-of-month λ_{EoM}, middle-of-month λ_{MoM}, and beginning-of-month λ_{BoM} time fixed-effects.[42] We include the share of cohort members who are receiving income payments on day d as an proxy for income expectations. This assume respondents are likely expecting the arrival of these income payments, which is likely true for the majority of income types in the diaries.

Table 4: Daily Consumption Estimates

	M1$^{\mathrm{d}}$			M2$^{\mathrm{d}}$			M3$^{\mathrm{d}}$		
	(1) All	(2) Low Share	(3) High Share	(4) All	(5) Low Share	(6) High Share	(7) All	(8) Low Share	(9) High Share
Panel A: ΔC_{kdmt}									
$\widehat{\Delta_d^1 Y}^R_{kdmt}$	-3.124	-14.814	1.641	2.562	1.462	10.650	0.358**	0.331*	0.526
	(13.679)	(93.318)	(6.274)	(2.855)	(2.760)	(13.683)	(0.181)	(0.192)	(0.453)
$\widehat{u}_{kdmt}$	0.260*			0.287**			0.073		
	(0.136)			(0.140)			(0.216)		
Panel B: Δc_{kdmt}									
$\widehat{\Delta_d^1 y}^R_{kdmt}$	-0.376	0.710	-0.094	0.008	-0.032	0.087	0.017***	0.022***	0.006
	(1.270)	(5.028)	(0.237)	(0.036)	(0.045)	(0.077)	(0.005)	(0.006)	(0.009)
$\widehat{u}_{kdmt}$	0.020***			0.021***			0.011*		
	(0.003)			(0.003)			(0.006)		

[1] Table 4 reports the second stage regression results for consumption changes to predicted income. Panel A is change in 2012 USD values, while Panel B is change in logs. Columns (1) - (3) reports the results for Model 1, which imposes a unit root in the change in income. Columns (4) - (6) reports the results for Model 2, which predicts the current change in income with the change in income at time $d-$. Columns (7) - (9) models the level of income as an AR(1) process, where the time trend is allowed to differ by age cohort. The first columns in each model group (columns 1, 4, 7) report the results over all cohorts. The rest of the columns split the sample into low shares and high shares of liquidity constrained respondents. High Share denotes cohorts with the highest tercile of liquidity constrained respondents, and Low Share are the remaining terciles. Liquidity constraints proxied by respondents in bottom quartile of liquidity. Lower case letters denote natural log transformations. The results of including the first stage residuals are included at the bottom of each panel, labelled $\hat{u}_{kdmt}$. Standard errors are corrected for in second stage and are robust to heteroscedasticity, and standard errors for the residuals are bootstrapped.
[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Cohorts: Age (7), gender (2).

We use the fitted values $\widehat{\Delta_d^1 Y^R_{kd,10,t}}$ in equation 11, which can be found in Table 4. Similar to the annual estimates of Table 1, the daily estimates in Table 4 report coefficients of predicted income in equation 11 for income specifications M1$^{\mathrm{d}}$-M3$^{\mathrm{d}}$ across samples of constrained cohorts, and report the measurement of unexpected income $\widehat{u}_{kdmt}$. For both MPC and elasticity estimates in Panels A and B respectively, models M1$^{\mathrm{d}}$ and M2$^{\mathrm{d}}$ report large, imprecise estimates for the daily analysis suggesting these models do not fit the daily model well. However, income specification M3$^{\mathrm{d}}$ reports surprisingly precise estimates.[43] For both MPC and the elasticity, we reject the null hypothesis $\beta_1 = 0$. For MPC, the unconstrained sample has more precise estimates but constrained consumers have imprecise higher estimates. The elasticity estimates are more precise, though unconstrained cohorts have greater excess sensitivity. The MPC estimates are quite large for a daily measurement while the elasticities are much smaller.

The daily estimates of MPC and elasticities suggest that out of the three specifications, M3$^{\mathrm{d}}$ models income surprisingly well. For the reasons discussed, daily applications of the PIH should be

[42] λ_{EoM}: October 31. λ_{MoM}: October 14, 15, 16. λ_{EoM}: October 2nd (we do not use the September DCPC in this analysis).
[43] The R^2 for models M1$^{\mathrm{d}}$ and M2$^{\mathrm{d}}$ for the first stage are near zero for both level and log changes in income, but .65 and .95 for level and log income respectively.

interpreted with caution, though this initial application suggests that representative cohorts may behave as predicted by the PIH in terms of unexpected income ($\beta_2 > 0$), and are spending in excess of expected income ($\beta_1 > 0$).

8.3 Sub-sample Estimation

Given its relative strength in representing U.S. consumers, the DCPC data offer a unique opportunity to compare and contrast differences in convenience samples from the representative population. Although much larger in terms of observations and time periods, some proprietary transactions-level data sets are convenience samples that are less representative whereas the SCPC and DCPC can identify potential sample selection effects in a statistically robust manner. We perform a similar analysis as in Section 8.2 across net worth and credit behavior subsamples. This section leverages the advantage and unique focus of the SCPC and DCPC data to help guide researchers in potential sample selection influences when analyzing consumption and income dynamics using these convenience sample.

Given the diaries are intended to primarily track payments, the SCPC can be combined with the DCPC to examine differences across heterogeneous samples not widely available in many data applications. Given the evidence that the diaries are capable of measuring consumption and income dynamics from section 7.3 and 8.2, we now demonstrate the ability of the DCPC and SCPC in quantifying selection effects in consumption behavior across convenience samples.

In order to quantify sample selection effects, we repeat our analysis from Section 8.2 with some necessary modifications. The previous consumption and income analysis utilized synthetic cohorts, with 7 age and 2 gender cohorts (K = 14). In this cohort specification, each diary day had respondents from every cohort. Adding additional cohorts to this specification adds additional stress to the data: incorporating another cohort with only 2 possible categories would still require K = 28 total cohorts. This becomes a challenging constraint as many convenience samples are not necessarily represented each day of the diary through each of the 14 age and gender cohorts. One potential solution would be to only use two cohorts, a cohort which follows the convenience sample definition and another which is not a part of the sample. However, when K = 2 there would be 10 observations available for the annual analysis. As an alternative, we reduce the number of age and gender cohorts to allow for including an additional cohort each diary day.

For the analysis, we choose two additional cohorts to quantify selection effects. The cohorts chosen have both a theoretical implication which can be tested empirically, as well as necessity of maintaining the cohort specification discussed above. The first cohort is determined by those who are below the median net worth ($NW^{\leq M}$) and those above the median net worth ($NW^{>M}$). If net worth proxies for liquidity constraints, than we would expect a stronger rejection of the PIH for the cohort below the median net worth. We choose to define the cohort at the median net worth to maximize the number of respondents in that cohort each diary day.[44] The second cohort is chosen based on credit choice behavior: those who revolve their credit card debt each month and those who us credit cards as a convenient means of payment, and pay off the balance in full each month.[45] Fulford and Schuh (2020) show that credit card debt revolvers have higher discount rates and a higher average marginal propensity to consume. Therefore, we expect that revolving users would have a higher MPC than convenience users.

Given convenience samples are split into 2 categories based on net worth or credit use, we first collapse the data only by the 3 age cohorts and 2 gender cohorts as a relative benchmark (K = 6). Next, we collapse the data by the age and gender cohorts, as well as the net worth cohorts (K = 12). Finally, we collapse the data into these age and gender cohorts as well as the credit use cohorts (K = 12). We then perform the analysis over these three cohort groups separately. In order to compare the convenience sample with the non-convenience sample, we split the sample based on the convenience sample net worth and credit use respectively. Therefore, at the annual level we have 60 observations in total, with 30 observations per convenience sample. This restricts the analysis for differentiating differences across these convenience samples. Indeed, when we run equation M3 with at the annual level with Y^H, y^H, we find that large standard errors on all cohorts. This may suggest that we cannot reject PIH, similar to 1. However, given the lack of observations, this may be due to a lack of precision as well.

In order to test the PIH along convenience samples in greater detail, we utilize the daily nature of the DCPC as in Section 8.2. With 31 days and 5 years, the 3 age and 2 gender cohorts allows for 930 observations, increasing the degrees of freedom of the analysis. For the daily analysis, each convenience sample split also has 930 observations as well. As in Section 8.2, we use respondent income Y^R_{kdmt} and utilize the AR(1) process from equation M3$^{\mathrm{d}}$ to estimate predicted income and run equation 11 across convenience samples. Results can be found in Table 5. Each group above columns denote how the data was collapsed into difference cohorts, while each column denotes a separate regression. Column (1) reports the results for the age and gender cohorts for a benchmark comparison as how a change in the number of cohorts influences the estimates, and are similar (though larger standard errors) to those in column (7) of Table 4 which has 4 more age cohorts. When including the net worth cohort, we see statistically insignificant differences across these cohorts suggesting little difference in behavior. However, when examining the credit debt cohorts we see a stark difference. For both elasticities and MPC, those who revolve credit card debt exhibit significant consumption responses to predicted changes in income, while those who use credit cards as a means of convenience do not. This corresponds with the findings of Fulford and Schuh (2020) that revolvers exhibit higher discount rates than their convenience counterparts.

[44] Wealthy hand-to-mouth consumers may also be liquidity constrained as shown by Kaplan et al. (2014). Because of this, the results may understate the actual difference in consumption behavior.

[45] Revolvers are defined from the SCPC, and include respondents who have revolved their credit within the last 12 months. Respondents who do not own a credit card are coded as convenience users.

Table 5: Consumption and Income Dynamics Across Convenience Samples

	A(3), G(2) (K=6)	A, G, Net Worth (K=12)		A, G Revolving (K=12)	
	(1) Benchmark	(2) $NW^{>M}$	(3) $NW^{\leq M}$	(4) Convenience	(5) Revolving
$\widehat{\Delta_d^1 Y}^R_{kdmt}$	0.424	0.176	0.426	0.405	0.766***
	(0.310)	(0.215)	(0.359)	(0.321)	(0.276)
$\widehat{\Delta_d^1 y}^R_{kdmt}$	0.019***	0.013*	0.003	0.009	0.019***
	(0.005)	(0.007)	(0.009)	(0.006)	(0.007)

[1] Table 5 reports the consumption response to predicted daily income, where predicted income is estimated from equation M3[d]. Panel A is change in 2012 USD values, while Panel B is change in logs. Groups above columns denote the cohorts. Column (1) includes 3 age cohorts, A(3), and two gender cohorts, G(2). Columns (2) - (3) utilizes the cohorts A(3), G(2), and a net worth cohort. The net worth cohort is determined by respondents above median net worth ($NW^{>M}$) and below net worth ($NW^{\leq M}$). First and second stage regressions are estimated over the sample $NW^{>M}$ and $NW^{\leq M}$. Columns (4) - (5) utilizes the cohorts A(3), G(2), and a cohort of convenience sample credit card respondents and revolving respondents. Respondents without credit cards are included as convenience users. Standard errors robust to heteroscedasticity.
[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The daily results of sections 8.2 and 8.3 some promise in using the cohort analysis for studying daily consumption behavior relative to benchmark consumption models. The findings of conflicting differences in constrained vs. unconstrained cohorts, as well as the net worth sub-sample, suggests that defining liquidity requires further identification for examining its role in spending patterns within the DCPC. Given that Table 5 is finding results consistent with Fulford and Schuh (2020), the partition based on credit card debt seems more convincing.

9 Personal Financial Management (PFM)

One potential manifestation of sample selection is the use of personal financial management (PFM) methods in budgeting and household finance. PFM methods are central to some prominent analyses in the literature (Section 2) and covered by the payment Survey and Diary as well. Payment choices are a key part of PFM, so the unique focus of the SCPC and DCPC also provides additional information not found as often or completely in other data sources. In addition to analyzing PFM characteristics, PFM adoption is one of numerous distinctive payment-related attributes provided by the DCPC.

9.1 PFM Data

In 2015-2016 only, the SCPC asked respondents if they had a PFM service or app for budgeting and monitoring account balances as defined by the Survey. To reply in the affirmative, respondents could choose one or more of the following: Mint.com, You Need a Budget, Moneystream.com, moneyStrands, BudgetSimple, MoneyWiz, GoodBudget, or Other.[46] Although respondents who use any form of PFM other than those listed could have chosen "Other," it is possible some respondents use another method of PFM that might not be triggered by question recall or even recognized by the respondent as being "PFM." For example, a consumer who uses a spreadsheet to develop a budget and actively manages it using online or mobile banking features judiciously could reasonably be defined as "doing PFM." Thus, the SCPC data may understate actual PFM behavior. The 2016 DCPC had a typical number of respondents (2,848). In 2015, the UAS sampling frame was small and less representative, so the 2015 DCPC had less than half as many respondents (1,392) but is still included in the adoption analysis. PFM responses to the SCPC are merged with the DCPC. Because there are proportionately fewer longitudinal matches of respondents between 2015 and 2016, dynamic adoption analyses are not conducted here and 2015 is excluded from dynamic consumption analyses.

In 2016, only 6.1% of respondents had adopted PFM services, although this percentage may have increased since then. Table 6 reports the demographic composition of all 2016 DCPC respondents (first column) and demographics by PFM adoption (columns two and three). The last column reports the percentage-point differences between PFM and non-PFM respondents (*statistical significance forthcoming*). PFM adopters exhibit several economically significant differences. PFM adopters tend to be younger (especially 25-34 year old), better educated (college or higher), and higher income ($100,000 or more). Adoption is monotonically increasing across income categories but drops notably at $200,000, perhaps because the highest income households can afford better to outsource PFM services. Interestingly, white consumers are relatively less likely to adopt PFM whereas non-white consumers relatively more likely. Women are slightly more likely to adopt PFM but the difference is relatively modest.

The results in Table 6 reflect the demographic characteristics of presumably *all* PFM users, so they should not be expected to match the demographics in a transactions-level data set obtained from just one PFM service. For example, the PFM data sets of Gelman et al. (2014) and Baker (2018) show similar compositions in younger individuals. The sample from Baker (2018) shows a younger population than the PFM DCPC sample, while Gelman et al. (2014) sample has slightly lower education attainments. Gelman et al. (2014), Olafsson and Pagel (2018), and Baker (2018) sources show higher shares of male as than the DCPC as well. While these data sets are examined over different years, and for Olafsson and Pagel (2018) the population of Iceland,[47] there seems to be a common trend among of younger households using PFM, while the DCPC sample shows a lower share of males and higher education.

[46] These were the survey options in the 2016 SCPC, but GoodBudget and MoneyWiz were not in 2015.

[47] Olafsson and Pagel (2018) utilize Meniga, a PFM software used by $\sim 20\%$ of the Icelandic population. The PFM is marketed to consumers automatically through their bank, suggesting a relatively representative sample of Iceland.

Table 6: Demographic Comparisons of the 2016 DCPC: PFM

	Full Sample (%)	PFM (%)	Non-PFM (%)	Difference (p.p)
Race				
White	74.5	64.5	75.1	-10.6
Black	12.8	14.2	12.7	1.5
Asian	3.2	8.2	2.9	5.3
Other	9.4	13.1	9.2	3.9
Age				
< 25	5.4	3.5	5.5	-2.0
25-34	23.3	39.5	22.2	17.3
35-44	16.9	21.0	16.6	4.4
45-54	17.6	17.6	17.6	0.0
55-64	17.2	10.5	17.6	-7.1
> 64	19.7	8.0	20.5	-12.5
Male	47.9	45.6	48.1	-2.5
Education				
No high school diploma	7.2	4.6	7.4	-2.8
High school	32.8	8.9	34.3	-25.4
Some College	17.9	14.7	18.1	-3.4
College - Bachelor's Degree	28.0	41.4	27.1	14.3
Post-Graduate Study	14.2	30.4	13.1	17.3
Household Income				
Less than \$25,000	21.2	8.8	22.0	-13.2
\$25,000 - \$49,000	23.7	16.7	24.2	-7.5
\$50,000 - \$74,999	17.6	16.0	17.7	-1.7
\$75,000 - \$99,000	11.8	10.6	11.9	-1.3
\$100,000 - \$124,999	10.9	17.4	10.5	6.9
\$125,000 - \$199,999	11.1	24.0	10.2	13.8
\$200,000 +	3.7	6.4	3.5	2.9

Table 6 presents selected demographics comparisons of the DCPC. The first three columns are percentages. The first column reports demographic compositions for the entire sample. The second column reports the demographic compositions for only PFM users, while the third column reports the compositions for respondents without PFM services. The last column reports the percentage point difference between PFM users and respondents without PFM services.

9.2 Adoption of PFM

This section reports an initial investigation of the determinants of adoption of PFM using limited dependent variable analysis. Let A_{it} denote the binary indicator for adoption ($A = 1$) of PFM. Following the approach in Schuh and Stavins (2010), we estimate a logit equation

$$\text{Prob}(A_{it} = 1) = f(DEMOG_{it}, Z_{it}) + \varepsilon_{it} \tag{12}$$

separately for 2015 and 2016. $DEMOG$ is the vector of basic demographic characteristics motivated by Table 6 and supplemented with additional demographics, and Z_{it} is a vector of explanatory variables that may explain PFM adoption. Lacking a "deep" theory of PFM, we populate Z_{it} with a set of variables available in the SCPC or DCPC with some intuitive logic and possibly predetermined assuming adoption occurred in the year of estimation. Of course, a limit of this static analysis is that adoption measured in year t may not reflect the actual year PFM was first adopted (or perhaps re-adopted after discarding).[48] Unfortunately, neither the SCPC or DCPC collects data on the intensive margin of PFM use, so we cannot estimate a two-step Heckman selection model.

Beyond demographics, we see two core motives for consumer adoption of a PFM service : financial conditions and personal preferences. Some consumers (and households) may need better financial management because they are experiencing financial distress (conditional on income). Distress variables are: credit card revolver, self-reported FICO score; and experienced (during the past 12 months) checking overdraft, payday loan, or a significant event causing "financial distress."[49] Other consumers may want PFM services because they enjoy financial planning or have a comparative advantage in it, and thus have a higher propensity to adopt PFM even if they are not experiencing financial distress. Preference variables are: adoption of automatic bill payment; checked records while completing the (recall-based) SCPC; and the degree of responsibility in shopping, bill payment, saving/investment, or other financial matters. Of course, the distress and preference variables may be correlated.

Table 7 reports the estimated average marginal effects in 2015 and 2016 for the logit regression in equation (12), with estimates of $DEMOG$ listed in the first vertical panel and estimates of Z_{it} continued in the second vertical panel. The simplified versions of demographic variables from Table 6 are statistically significant predictors of PFM adoption: younger, better educated, higher income, and non-white consumers are more likely to be adopters. In fact, even the lowest income consumers within a household are less likely to adopt conditional on household income. In contrast to income, the *lowest* wealth households are more likely to be adopters. Estimates for marital status and household size are mixed, modest, and less precise.

[48] For these reasons, we plan to investigate dynamic adoption behavior between 2015 and 2016 despite fewer observations.

[49] This includes someone within the household losing a job, foreclosure, bankruptcy, credit account closed/frozen.

Table 7: Marginal Effects from PFM Logit

	(1) 2015	(2) 2016		(1) 2015	(2) 2016
Demographics			***Preferences***		
Age	-0.002***	-0.001***	Ever Automatic Bill	0.044***	0.043***
	(0.001)	(0.000)		(0.017)	(0.011)
Non-White	-0.003	0.033**	Checked Records	0.019	0.025**
	(0.020)	(0.015)		(0.020)	(0.012)
Education (Base: Any College)			Most Bill Resp.	0.019	-0.034*
High school or less	-0.058***	-0.045***		(0.027)	(0.019)
	(0.015)	(0.010)	Most Shopping Resp.	0.018	0.014
Higher Education	0.047	0.026		(0.018)	(0.012)
	(0.029)	(0.016)	Most Saving/Invest. Resp.	0.042*	0.004
Married	-0.028	0.021*		(0.025)	(0.014)
	(0.020)	(0.012)	Most Other Financial Resp.	-0.032	0.021
Household Size	0.012*	-0.003		(0.033)	(0.016)
	(0.006)	(0.004)	***Distress***		
H.H Income: $50,000 and up	0.030*	0.024**	Revolver	-0.002	0.011
	(0.016)	(0.012)		(0.017)	(0.010)
Income Rank: Lowest	-0.004	-0.033***	Overdraft	0.012	-0.002
	(0.019)	(0.010)		(0.018)	(0.012)
Net Worth (Base: $ 0 - Median)			FICO score (Base: 750 and up)		
Less than $0	0.032	0.031*	Below 600 - 749	-0.006	-0.015
	(0.025)	(0.017)		(0.021)	(0.011)
Median - 75th Perc.	0.011	-0.009	Unkown to Respondent	-0.050**	0.007
	(0.020)	(0.013)		(0.021)	(0.019)
Above 75th Perc.	0.011	0.006	Payday Loan	0.026	-0.002
	(0.022)	(0.014)		(0.062)	(0.024)
			Experienced Financial Distress	0.002	-0.006
				(0.027)	(0.016)
Obs.	1,216	3,151			

[1] Table 7 presents the marginal effects from the logit regression, where the dependent variable is PFM adoption. All results from the table are from one regression, and are separated by panel columns for space. Columns (1) and (2) denote a separate regression with subsamples of respondents form 2015 and 2016 respectively. Standard error in parentheses. Base next to categorical variables denote omitted variables. Age and household size are continuous, while all other variables are categorical. Median Net Worth: $ 49,000. Revolver, overdraft, payday loan, and financial distress indicators are all within last 12 months. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results generally suggest that consumer preferences help explain PFM adoption somewhat but financial distress does not help at all, surprisingly. Consumers who have have adopted automatic bill payments are significantly more likely to be PFM adopters; those who have most of the saving/investment responsibility or checked their records when filling out the Survey have positive and occasionally significant positive coefficients. In contrast, the coefficients on all variables reflecting financial distress, hence the consumer's need for better PFM, are statistically insignificant. Even revolving credit card debt is not associated with higher PFM adoption. Perhaps these variables are not the right measures of financial distress, or maybe financial distress simply does not causal PFM adoption.

10 Future Opportunities

Although the DCPC continued to provide valuable new representative, publicly available data on individual-level consumption and income in 2016-2020, it still has limitations relative to large, proprietary, transactions data sets—especially data frequency and number of respondents. However, the DCPC has another crucial advantage: it can be expanded and improved. Rather than accepting the "accidental" success of the DCPC as is, the payment diary instrument is a blueprint for the intentional development and implementation of a more sophisticated data construction instrument that moves closer to a fully integrated set of household financial statements.[50] Given the relative success and promise documented here, government policy makers and even private-sector agents may find it profitable to fund future development of the payment diary instrument.

Development of the payment diary would benefit from three improvements to data construction. First, the measurement instruments (survey and diary) need better identification of key theoretical concepts (consumption, income, emergency saving, etc.), expanded coverage of balance sheet items (especially more forms of liquidity and longer term assets and liabilities), and upgraded use of "real-time" transaction interviews each night of data entry. Second, data collection needs more respondents (especially for geographic coverage), greater frequency (at least quarterly for macroeconomic analyses), and perhaps longer diary periods for individual consumers. Switching to a household sampling unit and expanding the sampling frame (especially higher income households) would be major improvements as well. Finally, expanding the professional staff devoted to data production is needed for data: management, design, and delivery; documentation and instructions; user bibliographies; and cleaning and imputation procedures based on economic theory.

Research using the DCPC data for analysis of consumption and income has been limited thus far, but three directions for future research are promising. First, the diary instrument could be implemented around special upcoming topics, such as randomized tax rebates, policy regime shifts, and semi-predictable natural disasters or health pandemics. If combined with incisive real-time

[50] For detailed descriptions of this idea, see Samphantharak and Townsend (2010), Samphantharak et al. (2018) and Schuh and Townsend (2020).

interviews tailored to elicit consumer decision making, these projects could yield important new insights. Second, the DCPC data can be merged with other data in creative ways, such as credit-bureau files (Cole et al., 2018) and private-sector data breaches (Rodriguez and Schuh 2021), or jointly with access to existing transactions data bases, such as financial institution customers. Finally, if the Atlanta Fed made the data available to the public in real-time (rather than with a one-year lag), researchers could use them for forecasting and business cycle analysis.

Expanding the DCPC data and research capabilities requires additional funding and resources, of course. The Federal Reserve would seem to be readily able to provide this support. However, the Fed's original interest in payment diaries was to develop data and knowledge about payments, a much narrower focus than consumption, income, and household financial behavior generally. Therefore, the Fed would need to adopt a broader vision for the DCPC data program. Alternatively, other government agencies, such as the U.S. Bureau of the Census, Bureau of Economic Analysis (BEA), and Bureau of Labor Statistics (BLS), may be better suited to this broader vision and more able to adopt many of the insights gleaned from the research program. Private firms also may find this data program profitable if they can find ways to monetize the data.

11 Conclusion

This study has demonstrated the capability of the DCPC in measuring accurate consumption and income behavior as a high-frequency data set. The proficiency of the payment diaries as a transaction data source was shown through three primary findings. First, extending the work of Schuh (2018) this study displayed the DCPC continues to captures core U.S. consumption and income estimates, comparable to standard aggregate measures such as the PCE consumption and BEA DPI. Second, the accuracy and rapidness of the real-time data analysis showed the diary's representative estimates are realized quickly throughout October, finding the daily dynamics of consumption converging to aggregate monthly statistics with precision and timeliness. Third, we exhibited that the DCPC shows potential in estimating consumption and income behavior by replicating common results found within the consumption literature. Together, these findings highlight the capacity of the DCPC as a high-frequency data source in measuring daily consumption behavior.

From these findings, this study advocates the DCPC as a promising alternative to proprietary transaction data sets. The DCPC offers four unique and substantive benefits : 1) representative of U.S. consumers; 2) publicly available; 3) endogenous continuous measurement improvement; and 4) flexible real-time implementation opportunities. Utilizing these distinguishing qualities, this study analyzed demographic and consumption behavior in convenience samples. The results provide evidence of characteristic differences in convenience samples which data across unique samples.

While the DCPC offers a viable alternative to other transaction data sets, this study proposes that the DCPC should be viewed as a complementary, non-competing data source. Other transaction data may contain information not available in the payment diaries as well as more observations. This allows for calculating consumption estimates with potential greater accuracy, given the limited sample size of the DCPC. Through the advantages of the payment diaries exhibited by this study, the DCPC can be analyzed jointly with other transaction data to gain a comprehensive understanding of daily consumption and income dynamics.

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Technical Appendix

Appendix A Data Construction Details

Appendix A reports the details in constructing consumption and income for the DCPC. Tables A1 - A9 report income and consumption types in the DCPC, and maps them to CE, PCE, BEA, and IRS data sets for Section 5. Table A10 offers a summary of changes to the DCPC. Figures A1 -A3 offers visual representations of the wave structure of the diaries, the panel nature of the diaries, and how merchant categories have evolved over the years, respectively.

Table A1: DCPC Income Identified Categories

1 - Employment income
2 - Employer paid retirement
3 - Self-employment income
4 - Social Security
5 - Interest and dividends
6 - Rental income
7 - Government assistance
8 - Alimony
9 - Child support
10 - IRA, Roth IRA, 401k, or other retirement fund

Table A2: Recorded Income Identifications: 5-year Averages

Respondents with Recorded Income	23.0%
Recorded Income Unidentified	21.1%
Recorded Income Identified	78.9%
Identified Income by Type:	
Employment	54.5%
Employer paid retirement	5.0%
Self-employment income	12.3%
Social Security	11.7%
Interest and dividends	3.3%
Rental income	2.9%
Government assistance	5.3%
Alimony	.2%
Child Support	2.7%
IRA, Roth IRA, 401K or other retirement fund or other retirement fund	1.9%

Table A2 reports the average percentage shares of different recorded income types over 2016 - 2020. The first row reports the percentage of respondents in which report recorded income. Of the recorded income, rows 2 and 3 report the percentage of recorded income which can be identified by income category. The remaining rows show the share of identified income by income categories.

Table A3: Mapping IRS and DCPC Income Categories

Income Categories	IRS	DCPC
Wages and Salaries	Salaries and wages	1 - Employment income
Proprietor's Income	Business net income, Partnership and S corporation net income	3 - Self-employment income
Interest and Dividends	Taxable interest, ordinary dvidends	5 - Interest and dividends
Retirement Income	Pensions, Annuities, IRAs	2 - Employer paid retirement 10 - IRA, Roth IRA, 401k, or other retirement fund
Rental Income	Rental and royalty net income	6 - Rental income
Social Security	Taxable social security income	4 - Social Security
Gov Assistance	Unemployment compensation	7 - Government assistance
Alimony	Alimony income	8 - Alimony
Unidentifiable Income	-	Any cash inflow categorized as income by DCPC, without identified categorization
Other	Tax refunds, Sales of capital assets and property, Estate income, Farm net income, Net operating loss, Debt Cancellation, Taxable health savings distributions, foreign-earned income exclusions, Gambling, Other income, Limitation on business losses, Global intangible low tax income	9 - Child support
Taxes	Total income tax	All types of taxes defined by DCPC

[1] Table A3 maps payment coding to income categories found in the aggregate income results in Table B3. Codes reported correspond to Table A1.

Table A4: Mapping BEA and DCPC Income Categories

Income Categories	**BEA**	**DCPC**
Wages and Salaries	Wages and Salaries	1 - Employment income
Proprietor's Income	Proprietors' income	3 - Self-employment income
Retirement, Interest, and Dividends	Personal interest income, Personal dividend income*	5 - Interest and dividends 2 - Employer paid retirement 10 - IRA, Roth IRA, 401k, or other retirement fund
Rental Income	Rental income of persons	6 - Rental income
Social Security	Social security	4 - Social Security
Gov Assistance	Medicare, Medicaid, Unemployment insurance, Veterans' benefits, other; less contributions for gov. social insurance.	7 - Government assistance
Unidentifiable Income	-	Any cash inflow categorized as income by DCPC, without identified categorization
Other	Other business transfers, Supplements to wages and salaries	8 - Alimony 9 - Child support
Taxes	Personal Current Taxes	All types of taxes defined by DCPC
Employee Contributions to Wages and Salaries	IRS elective retirement contributions*	-

[1] Table A4 maps payment coding to income categories found in the aggregate income results in Table B3. Codes reported correspond to Table A1.

[*] The identifiable income reported in the DCPC is the amount received during the diary day, and thus would exclude any employee contributions to retirement. However, BEA Personal Income would include this under wages. In order to correct for this discrepancy, employee contributions to retirement are taken from Form W-2 for 2016-2018. As of this paper, 2019-2020 W-2 information is not available. Therefore, 2019 and 2020 values are calculated by averaging the ratio of employee contributions to total personal income in 2016-2018, and using this ratio to impute employee contributions in 2019-2020.

Table A5: DCPC Payment Categories: 2016

Merch (M)	Purpose (P)
1 Financial services provider	1 Loan repayment
2 Education provider	2 Insurance payment
3 Medical care provider	3 Travel or transportation
4 Government	4 Utilities
5 Non-profit/charity	5 Government taxes or fines
6 A person	6 Housing (excluding utilities)
7 Retail store or online retailer	7 Miscellaneous goods or services
8 Business that primarily sells services	8 Other purpose
9 Other	-
Submerch (SM)	Subpurpose (SP)
1 Doctor, dentist, other health care professional	1 Credit card
2 Hospital, residential care, other medical institution	2 Mortgage
3 Pharmacy	3 HEL/HELOC
4 Insurance company	4 Auto/car loan
5 Grocery store/supermarket	5 Installment loan
6 Fast food restaurant, food service, food truck	6 Zero-interest or no-money-down loan
7 Coffee shop	7 Payday loan
8 Sit-down restaurant	8 Student loan
9 Bar	9 Marketplace or peer-to-peer loan
10 Gas station	10 Loan from another person
11 Convenience store	11 Health insurance
12 Large retailer (Walmart, etc)	12 Life insurance
13 Home improvement	13 Umbrella insurance
14 Online retailer	14 Vehicle insurance
15 Liquor store	15 Homeowner's or renter's insurance
16 Pet store/pet grooming	16 Other type of insurance
17 Auto rental and leasing stores	17 Parking
18 Auto vehicle and parts dealers and websites	18 Tolls
19 Clothing and accessories stores and websites	19 Public transportation
20 Department and discount stores and websites, wholesale clubs and websites	20 Trash collection
21 Furniture and home goods stores, appliance and electronics stores, hardware and gard estore and websites	21 Electricity/natural gas/water/sewer/heating oil/propane
22 Mail, delivery and storage	22 Landline, cable, internet, mobile phone (possibly bundled)
23 Rental centers	23 Federal taxes
24 Movie theaters	24 State taxes
25 Online shopping	25 Local taxes
26 Online and print news, online games	26 Property taxes
27 Other stores (book, florist, hobby, music, office supply, pet, sporting goods) and websites	27 Car/vehicle taxes
28 Personal care, dry cleaning, pet grooming and sitting, photo processing salons and stores	28 Rent
29 Stores that repair electronics and personal and household goods	29 Building contractor services
30 Tuition, Child care, Elder care, youth and family services, emergency and other relief services	30 Building services
31 Employment services, travel agents, security services, office and administrative services	31 Homeowner's association or condo fees
32 Repair/maintenance services for electronics and personal and household goods	32 Personal gift or allowance
33 Vending machines	33 Alimony/child support
34 Veterinarians	34 Charitable donation
35 Entertainment, recreation, arts, museums	35 Pay a fee
36 Movie theaters	36 Transfer money to another account
37 Legal, accounting, architectural, and other professional services	37 Make an investment
38 Hotels and motels, RV parks, camps	38 Lend money
39 Rent, real estate agents, and brokers	39 Memberships and subscriptions
40 Building contractors (HVAC etc)	40 Used goods
41 Building services	41 Tuition
42 Sporting events	42 Child care
43 Casinos, gambling, lotteries	43 Purchase goods and services
44 Vehicle maintenance	44 Split a check or share expenses

[1] Table A5 reports the different payment categories which respondents could fill out. Merchant categories include broad merchant types, while submerchant categories is a more specific definition of merchant categories. Additionally, respondents could put down the purpose of their payment, and a more detailed definition of their payment in subpurpose. All enteries are separate, so many purchases have a merchant, submerchant, purpose, and purpose entry though any combination of the four categories is possible.
[2] These category numbers correspond to Table A8. Example: SM3 in Table A8 for 2016 corresponds to Pharmacy, submerch 3.

Table A6: DCPC Payment Categories: 2017

Merch (M)	Purpose (P)
1 - Grocery stores, convenience stores without gas stations, pharmacies	1 - Credit card repayment
2 - Gas stations	2 - Mortgage
3 - Sit-down restaurants and bars	3 - HELOC
4 - Fast food restaurants, coffee shops, cafeterias, food trucks	4 - Auto or car loan
5 - General merchandise stores, department stores, other stores, online shopping	5 - Installment loan
6 - General services: hair dressers, auto repair, parking lots, laundry or dry cleaning, etc.	6 - Zero-interest or no-money-down loan
7 - Arts, entertainment, recreation	7 - Payday loan
8 - Utilities not paid to the government: electricity, natural gas, water, sewer, trash, heating oil	8 - Student loan
9 - Taxis, airplanes, delivery	9 - Marketplace or peer-to-peer loan
10 - Telephone, internet, cable or satellite tv, video or music streaming services, movie theaters	10 - Loan from another person
11 - Building contractors, plumbers, electricians, HVAC, etc.	11 - Health insurance
12 - Professional services: legal, accounting, architectural services; veterinarians; photographers or photo processers	12 - Life insurance
	13 - Umbrella insurance
13 - Hotels, motels, RV parks, campsites	14 - Vehicle insurance
14 - Rent for apartments, homes, or other buildings, real estate companies, property managers, etc.	15 - Homeowners or renters insurance
15 - Mortgage companies, credit card companies, banks, insurance companies, stock brokers, IRA funds, mutual funds, credit unions, sending remittances	16 - Other type of insurance
	17 - Parking
16 - Can be a gift or repayment to a family member, friend, or co-worker. Can be a payment to somebody who did a small job for you.	18 - Tolls
	19 - Public transit
17 - Charitable or religious donations	20 - Utilities
18 - Hospital, doctor, dentist, nursing homes, etc.	21 - Federal taxes
19 - Government taxes or fees	22 - State taxes
20 - Schools, colleges, childcare centers	23 - Local taxes
21 - Public transportation and tolls	24 - Property taxes
Payee (PY)	25 - Car or vehicle taxes
1 - Financial services provider	26 - Charitable donation
2 - Education provider	27 - Offering, tithe, collection plate
3 - Hospital, doctor, dentist, etc.	28 - Purchase goods or services
4 - Government	29 - Gift or allowance
5 - Nonprofit, charity, religious	30 - Lend money
6 - A person	31 - Split check or share expenses
7 - Retail store or online retailer	32 - Make a remittance
8 - Business that primarily sells services	33 - Alimony or child support
	34 - Pay a fee
	35 - Transfer money to another owned account
	36 - Make an investment
	37 - Tuition or fees
	38 - Child care
	39 - Pharmacy
	40 - Doctor dentist or other health care professional
	41 - Hospital, residential care, or other medical institution

[1] Table A6 reports the different payment categories which respondents could fill out. In 2017, Payee replaced the 2016 merch category, and merch in 2017 is a reworked category of submerch from 2016. Purpose was also reworked.
[2] These category numbers correspond to Table A8. Example: M2 in table A8 for 2017 corresponds to Gas stations, merch - 2.

Table A7: DCPC Payment Categories: 2018-2020

Merch (M)
- 1 - Grocery stores, convenience stores without gas stations, pharmacies
- 2 - Gas stations
- 3 - Sit-down restaurants and bars
- 4 - Fast food restaurants, coffee shops, cafeterias, food trucks
- 5 - General merchandise stores, department stores, other stores, online shopping
- 6 - General services: hair dressers, auto repair, parking lots, laundry or dry cleaning, etc.
- 7 - Arts, entertainment, recreation
- 8 - Utilities not paid to the government: electricity, natural gas, water, sewer, trash, heating oil
- 9 - Taxis, airplanes, delivery
- 10 - Telephone, internet, cable or satellite tv, video or music streaming services, movie theaters
- 11 - Building contractors, plumbers, electricians, HVAC, etc.
- 12 - Professional services: legal, accounting, architectural services; veterinarians; photographers or photo processers
- 13 - Hotels, motels, RV parks, campsites
- 14 - Rent for apartments, homes, or other buildings, real estate companies, property managers, etc.
- 15 - Mortgage companies, credit card companies, banks, insurance companies, stock brokers, IRA funds, mutual funds, credit unions, sending remittances
- 16 - Can be a gift or repayment to a family member, friend, or co-worker. Can be a payment to somebody who did a small job for you.
- 17 - Charitable or religious donations
- 18 - Hospital, doctor, dentist, nursing homes, etc.
- 19 - Government taxes or fees
- 20 - Schools, colleges, childcare centers
- 21 - Public transportation and tolls

Payee (PY)
- 1 - Financial services provider
- 2 - Education provider
- 3 - Hospital, doctor, dentist, etc.
- 4 - Government
- 5 - Nonprofit, charity, religious
- 6 - A person
- 7 - Retail store or online retailer
- 8 - Business that primarily sells services

Pay010
- 1 - Pay a credit card bill
- 2 - Make a loan payment (Examples: mortgage, student loan, auto, home equity, installment, zero interest, no-money-down)
- 3 - Pay for insurance (Examples: health, auto, homeowners, renters, life, umbrella)
- 4 - Make a remittance to a person in a foreign country
- 5 - Pay a fee (Examples: checking account, foreign ATM, overdraft, late payment, loan origination)
- 6 - Transfer money to another account that you own
- 7 - Make an investment (bought stocks, bonds, mutual funds)
- 8 - Other (specify)

Pay011
- 1 - Mortgage
- 2 - Student loan
- 3 - Auto loan
- 4 - Home equity loan or home equity line of credit
- 5 - Installment loan
- 6 - Zero-interest or no-money-down loan
- 7 - Payday loan
- 8 - Online marketplace or peer-to-peer lender (examples: Lending Club, Prosper)
- 9 - Another type of loan

Pay016
- 1 - Homeowners insurance
- 2 - Renters insurance
- 3 - Health insurance
- 4 - Vehicle insurance
- 5 - Life insurance
- 6 - Umbrella insurance
- 7 - Other types of insurance

Pay020
- 1 - Tuition or fees
- 2 - Repay student loan
- 3 - Childcare
- 4 - Other (specify)

Pay030
- 1 - Doctor, dentist, other health care professional
- 2 - Hospital, residential care, other medical institution
- 3 - Pharmacy
- 4 - Insurance company
- 5 - Other (specify)

Pay040
- 1 - Purchases of goods and services (Examples: local utilities and other services, public transportation, entrance to National Parks, municipal parking.)
- 2 - Taxes (Examples: Federal, state, local taxes, including property and excise taxes.)
- 3 - Fines
- 4 - Other (specify)

Pay041
- 1 - Electricity, water, sewer
- 2 - Tuition
- 3 - Daycare
- 4 - Parking
- 5 - Tolls
- 6 - Trash collection
- 7 - Public transportation
- 8 - Health insurance - out of pocket, including Medicare supplemental insurance
- 9 - Childcare
- 10 - Used goods
- 11 - Other (specify)

Pay042
- 1 - Federal taxes
- 2 - State taxes
- 3 - Local taxes
- 4 - Property taxes
- 5 - Car or vehicle taxes
- 6 - Other kind of payment to the government (Specify

Pay050
- 1 - Make a donation
- 2 - Make an offering, tithe, put money in the collection plate, etc.
- 3 - Purchase goods and services
- 4 - Other (specify)

Pay082
- 1 - To give a gift or allowance
- 2 - To lend money
- 3 - To repay money I borrowed (a loan)
- 4 - To purchase goods or pay for services
- 5 - To split a check or share expenses
- 6 - Other (specify)

[1] Table A7 reports the different payment categories which respondents could fill out. In 2018-2020, purpose was replaced with pay categories, which directly correspond to the questionnaire and are follow up questions dependent on the type of merchant payment made.

[2] These category numbers correspond to Table A8. Example: M2 in table A8 for 2018-2020 corresponds to Gas stations, merch - 2.

Table A8: Mapping DCPC Merchant Codes

Expenditure Category	2016	2017	2018-2020
Mortgage Payments, Expenses for Owned Dwellings, Taxes, Payments to Persons, Loan Repayments	SM40, SM41, SP1-10, SP23:27, SP29, SP30, SP32, SP33, SP36:38, missing	M11, P1:10, P21:25, P29, P30, P32, P33, P35, P36, missing	M11, Pay010-1, Pay010-2, Pay010-4, Pay010-6, Pay010-7, Pay011-1:9, Pay020-2, Pay040-2, Pay042-1:6, Pay082-1:3, missing
Food and Food Services	SM5, SM6, SM7, SM8, SM9, SM11, SM15	M1, M3, M4	M1, M3, M4
General Merchandise	SM12, SM14, SM19, SM20, SM25, SM27, SM28, SM33	M5	M5
Housing and Utilities	SM13, SM21, SM23, SM26, SM29, SM32, SM39, P4, P6, SP20, SP21, SP22, SP28, SP31, SP42	M8, M10, M14, M20, P38	M8, M10, M14, Pay020-3, Pay041-1, Pay041-6, Pay041-9
Transportation	SM10, SM24, SM44, P3, SP17, SP18, SP19	M2, M9, M21, P17-19	M2, M9, M21, Pay041-4, Pay041-5, Pay041-7
Entertainment and Recreation	SM16, SM24, SM25, SM34, SM35, SM36, SM38, SM43	M7, M13	M7, M13
Pharmaceuticals	SM3	P39	Pay030-3
Other	-	M6	M6
Noncomparable	SM1, SM2, SM4, SM17, SM18, SM22, SM30, SM31, SM37, SM42, SP11-SP16, SP33, SP34, SP35, SP39, SP40, SP41, SP43, SP44	M12, M15, M16, M17*, M18, M19, M20, P11:16, P26:28, P31, P34, P37, P40, P41	M12, M15, M16, M17*, M18, M19, M20, Pay010-3, Pay010-5, Pay010-8, Pay016-1:7, Pay020-1, Pay020-4, Pay030-1:5, Pay040-1, Pay040-3, Pay040-4, Pay041-2:3, Pay041-8:11, Pay050-1:4, Pay082-4:6

[1] Table A8 maps payment coding to consumption categories found in the aggregate consumption results in Table B1. Codes reported correspond to tables A5, A6, A7.
[*] M17 only included if it was also specified the payment was a purchase of a good or service.

Table A9: Mapping PCE and CE Expenditure Categories

Expenditure Categories	PCE and CE
Food and Food Services	Food and beverages purchased for off-premises, Purchased meals and beverages, Food supplied to civilians
General Merchandise	Glassware, Outdoor equipment, Photographic equipment, Sporting equipment, Recreational items, Clothing, Household Products, Personal care services
Housing and Utilities	Furniture and household appliances, Televisions and audio equipment, Computers, Telephones, Rent and utilities, Communication, Childcare, Household maintenance
Transportation	Motor vehicles and parts, recreational vehicles, gasoline, vehicle services
Entertainment and Recreation	Pet products, film and photographic supplies, Information processing equipment, Gambling, Veterinary services
Pharmaceuticals	Pharmaceutical Products
Noncomparable	Financial services and insurance, health, education, social services and religious activities

Table A9 gives a description of the categorization of consumption in PCE and CE. Categories were matched based on the BLS report comparing PCE and BLS, found here.

Table A10: Changes to the DCPC

Sponsor:	Federal Reserve Banks of Boston, Atlanta, and San Francisco
Content Summary:	Payments, income, payment instruments, account balances, instrument carried/available, cash balances, use of instruments (frequency, amount), choice reasons
Measurement Period:	Daily (three consecutive, randomly assigned)
Target population:	Age 18 and above, non-institutional population

	2012	2015	2016	2017	2018	2019	2020
Reporting period	October	Oct, Nov, Dec	October	October	October	October	October
Days in October reported	1st - 31st	16th - 31st	1st - 31st	1st - 31st	1st - 31st	1st - 31st	1st - 31st
Vendor	RAND Corporation	University of Southern California	University of Southern California	University of Southern California	University of Southern California	University of Southern California	University of Southern California
Sampling Frame	American Life Panel (ALP)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)
Outsourced Sampling Frame	-	Growth from Knowledge (GFK)	-	-	-	-	-
Total Respondents	2,468	Total: 1,392 UAS: 1,076 GFK: 316	2,848	2,793	2,873	3,016	1,537
- In October	-	UAS: 238 GFK: 0	-	-	-	-	-
Merchant Categories	Merchant (45)	Merchant (9) Submerchant (34) Purpose (8) Subpurpose (42)	Merchant (9) Submerchant (44) Purpose (8) Subpurpose (44)	Payee (8) Merchant (21) Purpose (41)	Payee (8) Merch (21) Pay Categories (60)	Payee (8) Merch (21) Pay Categories (60)	Payee (8) Merch (21) Pay Categories (60)

Figure A1: Diary Wave Implementation

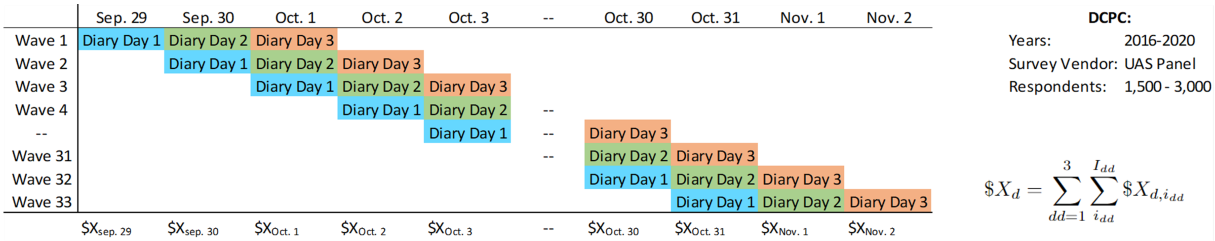


Figure A1 presents a visual representation of wave implementation for the payment diaries. Each wave contains an approximately equal number of respondents who are randomly assigned to each wave. Each wave contains three days where respondents record their daily transactions. The first wave begins September 29th and continues for three days. The second wave begins September 30th, and continues in this manner. As shown by the figure, each day in October has three waves participating such that all transaction information on a given day is composed of respondents from each of the three waves. The total expenditures on a given day (X_d) is the sum of all expenditures of all respondents' expenditures on day d, for each diary day within the waves ($dd \in (1, 2, 3)$).

Figure A2: Panel Structure of the DCPC

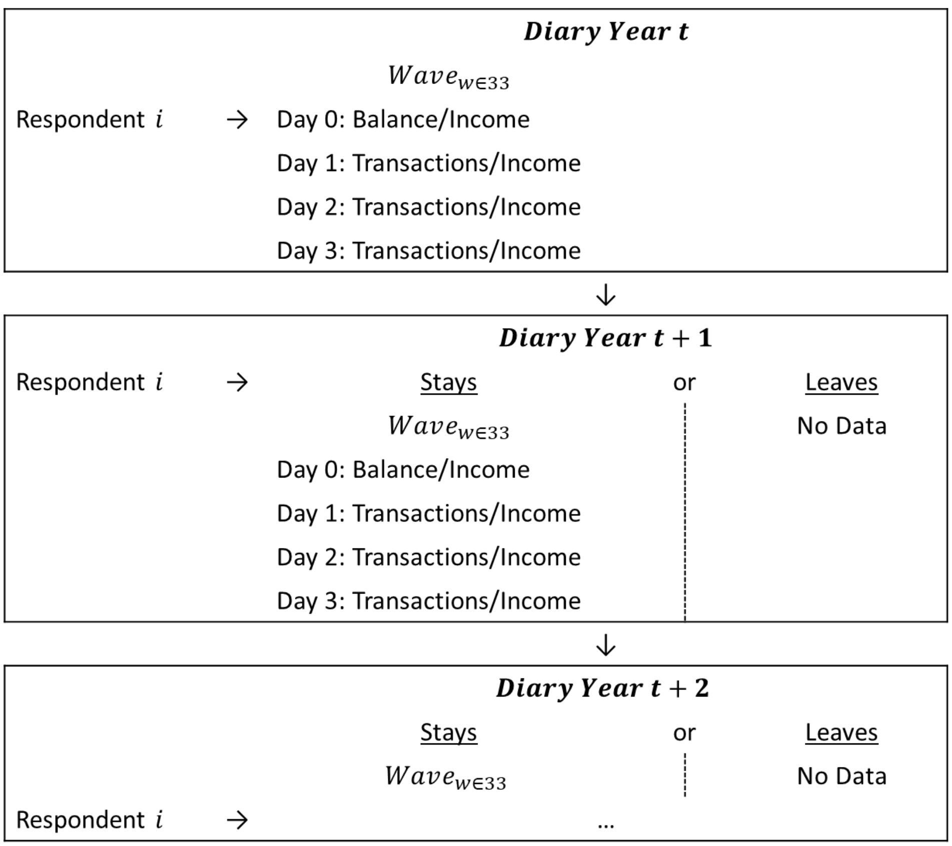


Figure A2 presents a visual representation of the panel structure of the payment diaries. Respondents from the SCPC are offered to take the DCPC. Any respondent i who agrees to participate in diary year t is randomly assigned to one of 33 waves (see figure A1) On the initial diary day 0, account balances are recorded as well as income payments received on that day. For diary days 1-3, transaction and income payments are recorded during each day. During diary year $t+1$, the respondent is invited to take the DCPC again if they completed the survey in year $t+1$. If the respondent says no, or does not take the SCPC, then no data is collected for that respondent and they are not a part of the panel for that year (marked *Leaves* in figure). If they agree to participate, the process of data collection begins again. This structure is continuous for all diary years.

Figure A3: Evolution of Payment Categories in the DCPC

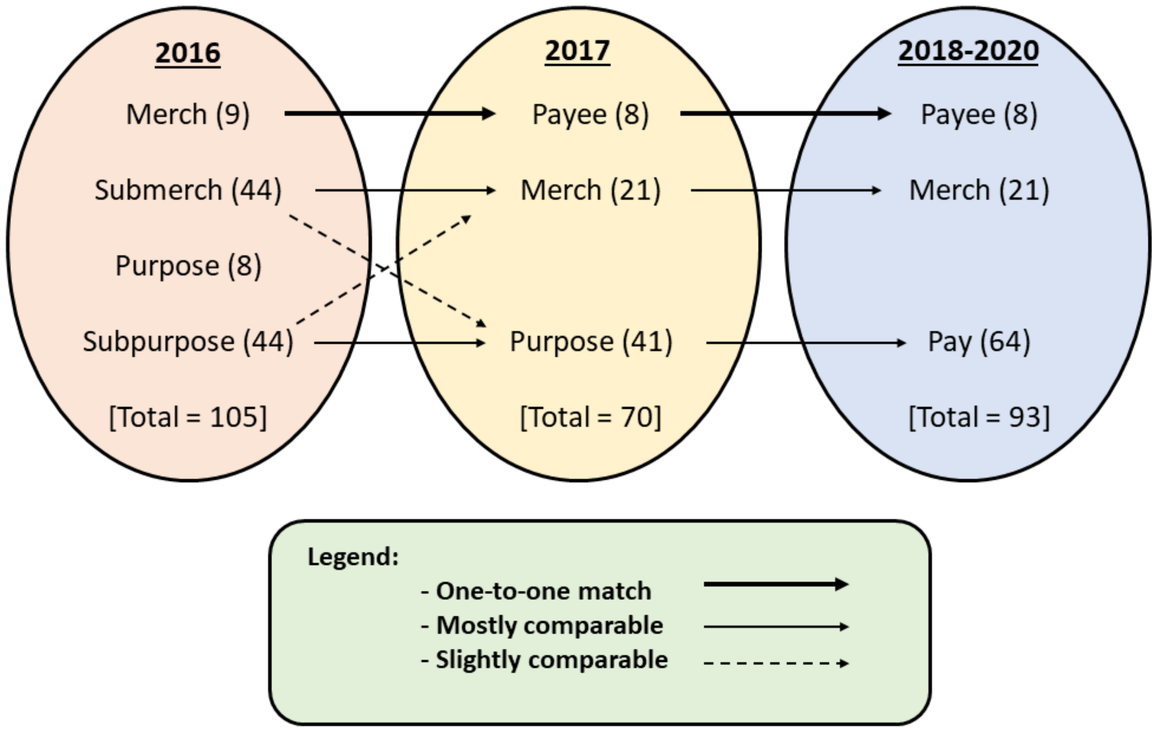


Figure A3 offers a simple overview of changes to DCPC payment categories over the years. In 2012, there were 45 possible merchant categories in which expenditures could be categorized. In 2015, merchant was simplified into 9 categories, and submerch categories were added to add more details to the merchant being paid. Additionally, the diaries began tracking general purposes (Purpose) and more detailed purposes (Subpurpose) about payments. The 2016 diary, shown in the figure, has the same general format as the 2015 diary. In 2017 merchant was changed to payee, and merchant was recategorized to contain aspects of both Submerch and Subpurpose categories from the previous year, while Purpose mainly contains aspects of Subpurpose from 2016. In 2018 through 2020, Purpose was recategorized to reflect the diary questionnaire. Pay categories are offered depending on the Merchant category chosen for payments. Note that Payee from 2017-2020 and Merch are the same categories, but 2016 contains the "Other" options, resulting in 9 Merchant categories in 2016 but 8 Payee categories from 2017-2020.

Appendix B Data Validation Details

Appendix B reports additional validation details from Sections 5 and 6. Tables presented correspond to the Figures in Section 5, and report the detailed 5 year income and consumption results. Additionally, annual time series of comparable consumption and adjusted income are included.

Columns (1) - (3) of Table B1 show CE, PCE, and DCPC estimates of expenditure categories. Column (4) reports the ratio of CE to PCE, while column (5) reports the ratio of DCPC to PCE. PCE estimates in column (2) is split into section for comparable/noncomparable as PCE consumption have additional comparable categories not found in DCPC. Adjusted consumption reports expenditures after removing unique categories in each data set for closer comparison. Mostly comparable are the closest categories within all three data sets, while mostly noncomparable have similar differences but distinct differences. The bottom panel of the table reports the 2012 estimates from Schuh (2018).

Tables B2 and B3 report the income comparisons with the DCPC. Column (3) reports the ratio of the DCPC to the respective income data set. Total income compares the estimates before any adjustments. Total is broken down into comparable and noncomparable categories. Note these comparisons are before any adjustments. Comparable category in this table reports the comparisons of identified recorded income found in the DCPC and the same income types in the other data set.[51] The DCPC tends to match 59% and 90% of BEA and IRS results comparably. However, this comparison is before deducting taxes or supplements to wages and salaries, and therefore this comparison misses important differences between within the income types. After removing taxes and other differences between the data sets, adjusted income reports the disposable income with common income definitions between the DCPC and BEA/IRS.

[51] Therefore, comparable categories here are not the same concept as in the consumption results. Because taxes cannot be subtracted from each income type, and the DCPC income amounts are based on the amount respondents receive, a comparison of each income category can only be achieved before adjustments.

Table B1: 5 Year Averages of Consumption

5 Year Averages (2012 Billions USD)	CE (1)	PCE (2)		DCPC (3)	CE/PCE (4)	DCPC/PCE (5)
Total Expenditures	**7,360**	**12,749**		**12,391**	**.58**	**.97**
	(138)	(151)		(781)		
-Imputed Rent	1,719	1,479				
	(66)	(23)				
-Non-Profit Goods and Services		409				
		(10)				
-Mortgage Payments, Expenses for Owned Dwellings				1,245		
				(103)		
-Taxes, Payments to Persons, Non-Classifiable				463		
				(75)		
-Loan Repayments				2,897		
				(191)		
Adjusted Consumption	**5,641**	**10,861**		**7,786**	**.52**	**.72**
	(96)	(129)		(717)		
Mostly Comparable	**3,825**	**6,089**	**6,054**	**4,999**	**.63**	**.83**
	(70)	(70)	(70)	(30)		
Food and Food Services	981	1,688	1,688	1,172	.58	.69
	(24)	(19)	(19)	(30)		
General Merchandise	447	1,087	1,087	1,228	.41	1.13
	(16)	(9)	(9)	(137)		
Housing and Utilities	1,274	1,520	1,520	1,683	.84	1.11
	(5)	(28)	(28)	(77)		
Transportation	788	915	915	389	.86	.43
	(16)	(12)	(12)	(26)		
Entertainment and Recreation	174	367	367	295	.48	.8
	(4)	(3)	(3)	(54)		
Pharmaceuticals	140	477	477	17	.29	.03
	(39)	(13)	(13)	(2)		
Other*	20	36		215	.57	NA
	(2)	(1)		(23)		
Mostly Noncomparable	**1,816**	**4,772**	**4,807**	**2,788**	**.38**	**.58**
	(117)	(79)	(79)	(689)		
2012 Estimates (Schuh 2018)						
Adjusted Consumption	4,943	9,492		8,729	.52	.92
Mostly Comparable	3,659	5,486	5,093	6,014	.67	1.18
Mostly Noncomparable	1,284	4,006	4,399	2,715	.32	.62

[1] **Table** B1 reports the aggregate consumption estimates of CE, PCE, and DCPC consumption. Columns (1)-(3) report the estimates of CE, PCE, and DCPC consumption respectively. Standard errors are reported in parentheses. Columns (4) and (5) report the the ratio of CE and DCPC estimates to PCE consumption.

[2] Total expenditures are the estimates before any adjustments. Categories below are removed which are not in DCPC or the other data sets (see text for further discussion), equalling adjusted consumption. Adjusted consumption is the sum of mostly comparable categories, and mostly noncomparable. Comparable is further distinguished into multiple consumption categories. 2012 estimates from Schuh (2018) are reported in the final rows. May not sum directly due to rounding.

[*] Other includes other business transfers from CE and DCPC, while includes for DCPC it includes general goods and services which would belong to another comparable category, but cannot be distinguished. Therefore, the ratio of the Other estimate for DCPC to PCE is not included.

Table B2: BEA and DCPC Income Estimates

5 Year Income Averages of DCPC and BEA Income (2012 Billions USD)	**BEA**	**DCPC**	**DCPC/BEA**
	(1)	(2)	(3)
Total Income	**16,413**	**9,615**	**.59**
	(313)	(659)	
Comparable	**14,480**	**7,562**	**.52**
	(294)	(609)	
Wages and Salaries	8,233	4,923	.6
	(135)	(478)	
Proprietor's Income	1,472	409	.28
	(51.40)	(107)	
Retirement, Interest, and Dividends	2,585	786	.3
	(43)	(158)	
Rental Income	623	160	.26
	(6)	(41)	
Social Security	912	1,158	1.27
	(18)	(329)	
Government Assistance	655	126	.19
	(96)	(22)	
Noncomparable	**1,932**	**2,054**	**1.06**
	(21)	(177)	
Unidentifiable Income	-	2,028	
		(177)	
Other	1,932	26	
	(21)	(5)	
Less:			
Taxes	1,949	204	
	(19)	(49)	
Employee Contributions to Retirement	298		
	(6)		
Supplements to Wages and Salaries	1,882		
	(22)		
Alimony and Child Support	-	26	
		(5)	
Adjusted Income	**12,284**	**9,386**	**.76**
	(277)	(658)	

Table B2 reports the aggregate 5-year average estimates (2016-2020) or IRS and DCPC income results. Total income is all income types from both data sets with no adjustments. Total income is the sum of comparable and noncomparable income. Comparable income is any income type that is identifiable in the DCPC, and is match to IRS income types with similar categories. Noncomparable income is multiple categories in the BEA which do not match any definitions from DCPC (other business transfers and supplements to wages and salaries), while noncomparable categories in DCPC is income whose type is not identifiable, or child support and alimony (under other). Taxes, child and alimony are removed from DCPC while taxes, employee contributions to retirement, and supplements to wages and salaries support are removed to create adjusted income. May not sum directly due to rounding. Estimates are in 2012 billions USD, standard errors are reported in parentheses. Last column reports the ratio of DCPC income to BEA income.

Table B3: IRS and DCPC Income Estimates

5 Year Income Averages of DCPC and IRS Income (2012 Billions USD)	**IRS**	**DCPC**	**DCPC/IRS**
	(1)	(2)	(3)
Total Income	**10,668**	**9,615**	**.9**
	(228)	(659)	
Comparable	**9,951**	**7,564**	**.76**
	(173)	(609)	
Wages and Salaries	7,225	4,923	.68
	(105)	(478)	
Proprietor's' Income	935	409	.44
	(8)	(107)	
Interest and Dividends	390	81	.21
	(18)	(52)	
Retirement Income	967	704	.73
	(17)	(148)	
Rental Income	53	160	3.02
	(2)	(41)	
Social Security	305	1,158	3.79
	(11)	(329)	
Government Assistance	66	126	1.91
	(44)	(22)	
Alimony	10	1	.12
	(0)	(1)	
Noncomparable	**717**	**2,053**	**2.86**
	(64)	(177)	
Undentifiable Income	-	2,028	
		(177)	
Other	717	24	
	(64)	(5)	
Less:			
Taxes	1,446	204	
	(27)	(49)	
Child Support	-	24	
		(5)	
Adjusted Income	**9,222**	**9,387**	**1.02**
	(214)	(658)	

Table B3 reports the aggregate 5 year average estimates of IRS and DCPC income results. Total income is the sum of comparable and noncomparable income. Comparable income is any income type that is identifiable in the DCPC, and is match to IRS income types with similar categories. Noncomparable income is multiple categories in the IRS which do not match any definitions from DCPC, while noncomparable categories in DCPC is income whose type is not identifiable, or child support (under other). Taxes and child support are removed to create adjusted income. May not sum directly due to rounding. Estimates are in 2012 billions USD, standard errors are reported in parentheses. Last column reports the ratio of DCPC income to IRS income.

Figure B1: Annual Comparable Expenditures

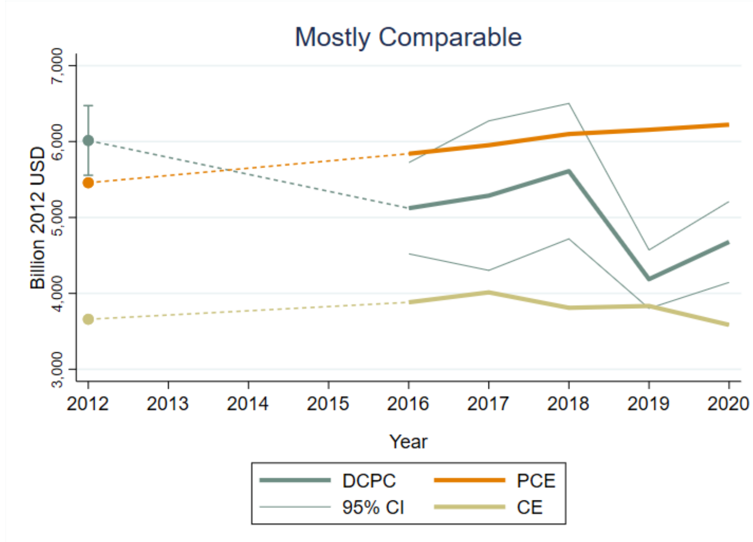
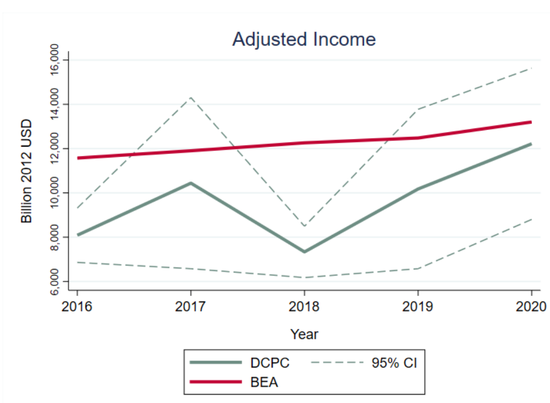


Figure B1 shows the annual estimates of comparable consumption across DCPC, PCE, and CE. 2012 estimates are reported by circles for comparison, with bars indicating confidence intervals in 2012. Dashed lines are to indicate missing values from 2013-2015. Thick solid lines are point estimates, while thin lines are the 95% confidence intervals for DCPC estimates. All estimates are reported in billions 2012 USD.

Figure B2: Annual Adjusted Income

(a) DCPC and BEA Income



(b) DCPC and IRS Income

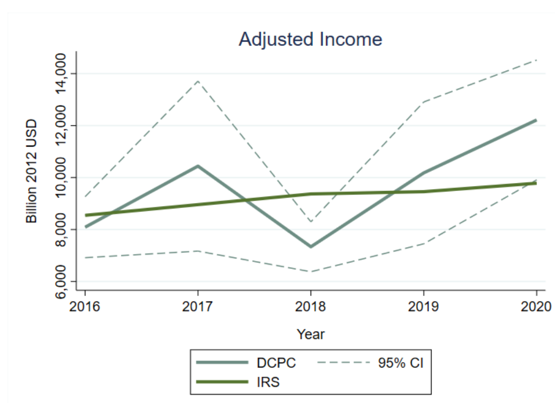


Figure B2 shows the annual estimates of adjusted income across DCPC, BEA, and IRS. Figure B2a compares DCPC and BEA adjusted income, while figure B2b compares DCPC and IRS income. 95% confidence intervals are reported for DCPC by dashed lines. All estimates are reported in billions 2012 USD.

Appendix C Supplemental Consumption and Income Dynamics Details

This Appendix derives the theoretical model used in this paper, as well as deriving the implied coefficient from unexpected income changes.

C.1 Certainty Equivalence Model

The Certainty Equivalence Model (CEQ) is a fundamental model of consumption which has been used extensively in the literature when including uncertainty. We follow Jappelli and Pistaferri (2017) in showing how to derive the model at the annual level, then apply it to the DCPC. The CEQ model offers a closed-form solution for consumption under uncertainty, as the marginal utility of consumption is linear. Due to some strong assumption of the CEQ model, the literature has often moved towards isoelastic utility functions, which introduces a precautionary savings motive to intertemporal optimization, and has been regarded as more realistic in the literature. However, for the purposes of this study, the CEQ model allows us to derive a clear solution for hypothesis testing to compare to benchmark studies.

First, we define consumption, income, and assets at the monthly frequency:

$$C_{kmt} = \sum_{d=1}^{D_m} C_{kdmt} \ , \ Y_{kmt} = \frac{Y_{kt}}{12}$$

Where C is the level of consumption, and Y^H is household income. Y^H will be reported as Y for ease of notation. Note that household income is divided by 12, as in the diaries we observe annual income and thus find the average monthly income. The cohort k maximizes the following:

$$E_{mt} \sum_{s=0}^{MT-mt} (1+\delta_m)^{-s} U(C_{m+s,t}) \tag{13}$$

Where k is dropped for ease of nation. The cohort member is subject to the following budget constraint:

$$\begin{aligned} A_{m+1+s,t} &= (1+r)(A_{m+s,t} + Y_{m+s,t} - C_{m+s,t}) \\ A_{M+1,T} &\geq 0 \end{aligned} \tag{14}$$

Where MT denotes the terminal month and year of the cohort, δ_m is the rate of time preference,and r is the monthly interest rate. Assume consumption take the following form: $U(C_{mt}) = a \cdot C_{mt} - \frac{b}{2}C_{mt}^2$. Finally, let $r = \delta_m$ for simplicity. Optimizing gives the following Euler equation:

$$
\begin{aligned}
U'(C_{mt}) &= E_{mt}U'(C_{m+1,t}) \\
C_{mt} &= E_{mt}C_{m+1,t} \\
C_{m+1,t} &= C_{mt} + e_{m+1,t}
\end{aligned}
\tag{15}
$$

Therefore, consumption follows a martingale process where $e_{m+1,t}$ is the forecast error. The intertemporal budget constraint dictates that:

$$
\begin{aligned}
\sum_{s=0}^{MT-mt} \frac{E_{mt}C_{m+s,t}}{(1+r)^s} &= \sum_{s=0}^{MT-mt} \frac{E_{mt}Y_{m+s,t}}{(1+r)^s} + A_{mt} \\
\rightarrow C_{mt} \sum_{s=0}^{MT-mt} \frac{1}{(1+r)^s} &= \sum_{s=0}^{MT-mt} \frac{E_{mt}Y_{m+s,t}}{(1+r)^s} + A_{mt}
\end{aligned}
\tag{16}
$$

As $E_{mt}C_{m+1+s,t} = C_{mt}$. It follows that:

$$
\begin{aligned}
C_{mt} &= \frac{r}{1+r} \cdot \left(1 - \frac{1}{(1+r)^{(M+1,T)-mt}}\right) \left[A_{mt} + \sum_{s=0}^{MT-mt} \frac{E_{mt}(Y_{m+s,t})}{(1+r)}\right] \\
MT \rightarrow \infty : C_{mt} &= \frac{r}{1+r} \left[A_{mt} + \sum_{s=0}^{\infty} \frac{E_{mt}(Y_{m+s,t})}{(1+r)}\right]
\end{aligned}
\tag{17}
$$

Where we analyze at $MT \rightarrow \infty$ for simplicity and thus is classified under the permanent income hypothesis framework. Subtracting $(1+r)C_{m-1,t}$ and substituting the budget constraint allows for an analysis of the Euler equation in terms of income:

$$
\Delta_1^m C_{mt} = \frac{r}{1+r} \sum_{s=0}^{\infty} \frac{E_{mt}Y_{m+s,t} - E_{m-1,t}Y_{m+s,t}}{(1+r)^s} = e_{mt} \tag{18}
$$

Equation 18 states that only changes in expectations of income will lead to changes in consumption. At time $s = 0$, only unexpected changes in income will change consumption, as is the conclusion of the Permanent Income and Life-Cycle Hypothesis.

However, equation 18 is in terms of monthly changes. In the diaries, we only observe $mt = 10, t$ for all years $t = 2016 : 2020$. Therefore, we examine the *annual difference* in income even though the consumption is optimized *monthly* in the model. Therefore, we derive $\Delta_m^{12} C_{mt}$ in the following analysis. This would be the annual change in monthly consumption, from October in year t from October in year $t-1$.

We know the following from the martingale process:

$$
\begin{aligned}
C_{mt} &= C_{m-1,t} + e_{mt} \\
C_{m-1,t} &= C_{m-2,t} + e_{m-1,t} \\
&\vdots \\
C_{m-11,t} &= C_{m-12,t} + e_{m-11,t}
\end{aligned}
$$

Therefore, substituting recursively:

$$
\begin{aligned}
C_{mt} &= e_{mt} + e_{m-1,t} + e_{m-2,t} + ... + e_{m-11,t} + C_{m-12,t} \\
C_{mt} &= \sum_{\mu=0}^{11} e_{m-\mu,t} + C_{m-12,t} \\
\Delta_m^{12} C_{mt} &= \sum_{\mu=0}^{11} e_{m-\mu,t}
\end{aligned} \tag{19}
$$

Plugging in equation 18 for $e_{mt}, ..., e_{m-11,t}$ we can see that:

$$
\Delta_m^{12} C_{mt} = \frac{r}{1+r} \sum_{s=0}^{\infty} \frac{(\overbrace{E_{mt}Y_{m+s,t} - E_{m-1,t}Y_{m+s,t}}^{e_{mt}} + \overbrace{E_{m-1,t}Y_{m-1+s,t} - E_{m-2,t}Y_{m-1+s,t}}^{e_{m-1,t}} + ... - E_{m-12,t}Y_{m-11+s,t})}{(1+r)^s}
$$

Grouping by the error terms:

$$
\begin{aligned}
\Delta_m^{12} C_{mt} = \frac{r}{1+r} \Bigg[&\sum_{s=0}^{\infty} \left(\frac{E_{mt}Y_{m+s,t} - E_{m-1,t}Y_{m+s,t}}{(1+r)^s} \right) + \sum_{s=0}^{\infty} \left(\frac{E_{m-1,t}Y_{m-1+s,t} - E_{m-2,t}Y_{m-1+s,t}}{(1+r)^s} \right) \\
&+ ... + \sum_{s=0}^{\infty} \left(\frac{E_{m-11,t}Y_{m-11+s,t} - E_{m-12,t}Y_{m-11+s,t}}{(1+r)^s} \right) \Bigg]
\end{aligned}
$$

Isolating $s = 0$:

$$
\begin{aligned}
\Delta_m^{12} C_{mt} = \frac{r}{1+r} \Big[&(Y_{mt} + Y_{m-1,t} + ... + Y_{m-11,t}) - (E_{m-1,t}Y_{mt} + E_{m-2,t}Y_{m-1,t} + ... + E_{m-12,t}Y_{m-11,t}) \\
&+ \sum_{s=1}^{\infty} \left(\frac{E_{mt}Y_{m+s,t} - E_{m-1,t}Y_{m+s,t}}{(1+r)^s} \right) + \sum_{s=1}^{\infty} \left(\frac{E_{m-1,t}Y_{m-1+s,t} - E_{m-2,t}Y_{m-1+s,t}}{(1+r)^s} \right) \\
&+ ... + \sum_{s=1}^{\infty} \left(\frac{E_{m-11,t}Y_{m-11+s,t} - E_{m-12,t}Y_{m-11+s,t}}{(1+r)^s} \right) \Big]
\end{aligned}
$$

Where the current terms (at time mt) have been isolated, as $E_{m+s,t}Y_{m+s,t} = Y_{m+s,t}$. This first line is needed for differencing monthly income annually. Note that in the infinite summation terms, there are overlapping incomes occurrences. Specifically, $Y_{m+s}\ \forall s \geq 1$ is in every infinite summation with different discounting. From the infinite summation terms, we can group terms which contain $\geq Y_{m+1}$.

Grouping $Y_{m+s}\ \forall s \geq 1$ from the infinite summations:

$$
\begin{aligned}
&\sum_{s=1}^{\infty} \frac{E_{mt}Y_{m+s,t}}{(1+r)^s} + \sum_{s=1}^{\infty} \frac{E_{m-1,t}Y_{m+s,t}}{(1+r)^{s+1}} + \sum_{s=1}^{\infty} \frac{E_{m-2,t}Y_{m+s,t}}{(1+r)^{s+2}} + ... + \sum_{s=1}^{\infty} \frac{E_{m-11,t}Y_{m+s,t}}{(1+r)^{s+11}} \\
&\quad - \sum_{s=1}^{\infty} \frac{E_{m-1,t}Y_{m+s,t}}{(1+r)^s} - \sum_{s=1}^{\infty} \frac{E_{m-2,t}Y_{m+s,t}}{(1+r)^{s+1}} - ... - \sum_{s=1}^{\infty} \frac{E_{m-12,t}Y_{m+s,t}}{(1+r)^{s+11}} \\
&\quad = \sum_{j=0}^{11}\sum_{s=1}^{\infty} \left[\frac{E_{m-j,t}Y_{m+s,t}}{(1+r)^{s+j}} - \frac{E_{m-1-j,t}Y_{m+s,t}}{(1+r)^{s+j}} \right] = \sum_{j=0}^{11}\sum_{s=1}^{\infty} \left[\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{m+s,t})}{(1+r)^{s+j}} \right]
\end{aligned}
$$

Where the above specification has grouped all $Y_{m+s}\ \forall s \geq 1$ terms. After this grouping, there still exists common Y_{m-s} for $0 \leq s \leq 10$. Grouping each Y term individually:

$$Y_{mt}: \quad \frac{E_{m-1,t}Y_m}{(1+r)} + \frac{E_{m-2,t}Y_{mt}}{(1+r)^2} + ... + \frac{E_{m-11,t}Y_{mt}}{(1+r)^{11}} - \frac{E_{m-2,t}Y_m}{(1+r)} - ... - \frac{E_{m-12,t}Y_{mt}}{(1+r)^{11}} = \sum_{j=0}^{10} \frac{(E_{m-1-j,t} - E_{m-2-j,t})(Y_{mt})}{(1+r)^{1+j}}$$

$$Y_{m-1,t}: \quad \frac{E_{m-2,t}Y_{m-1,t}}{(1+r)} + ... + \frac{E_{m-11,t}Y_{m-1,t}}{(1+r)^{11}} - \frac{E_{m-3,t}Y_{m-1,t}}{(1+r)} - ... - \frac{E_{m-12,t}Y_{m-1,t}}{(1+r)^{11}} = \sum_{j=0}^{9} \frac{(E_{m-2-j,t} - E_{m-3-j,t})(Y_{m-1,t})}{(1+r)^{1+j}}$$

$$\vdots$$

$$Y_{m-10,t}: \quad \frac{E_{m-11,t}Y_{m-10,t}}{(1+r)} - \frac{E_{m-12,t}Y_{m-10,t}}{(1+r)}$$

Therefore, we can see a repeating pattern for the finite terms. Note that $Y_{m-11,t}$ is only in the last term, and is only available when $s = 0$ and thus the expectation cancels out. For a general differencing period of J, it follows that:

$$
\begin{aligned}
\Delta_J^m C_{mt} = \frac{r}{1+r} \Bigg\{ &\left(\sum_{j=0}^{J-1} (Y_{m-j,t} - E_{m-1-j}Y_{m-j}) \right) + \sum_{j=0}^{J-1}\sum_{s=1}^{\infty} \left[\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{m+s,t})}{(1+r)^{s+j}} \right] \\
&+ \sum_{j=0}^{J-2} \left[\frac{(E_{m-1-j,t} - E_{m-2-j,t})(Y_{mt})}{(1+r)^{1+j}} \right] + \sum_{j=0}^{J-3} \left[\frac{(E_{m-2-j,t} - E_{m-3-j,t})(Y_{m-1,t})}{(1+r)^{1+j}} \right] \\
&+ ... + \left[\frac{(E_{m-J+1,t} - E_{m-J,t})(Y_{m-J+2,t})}{(1+r)} \right] \Bigg\}
\end{aligned}
$$

When $J = 12$:

$$\Delta_m^{12} C_{mt} = \frac{r}{1+r}\left\{\left(\overbrace{\sum_{j=0}^{11}(Y_{m-j,t} - E_{m-1-j,t}Y_{m-j,t})}^{s=0}\right) + \sum_{j=0}^{11}\sum_{s=1}^{\infty}\left[\overbrace{\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{m+s,t})}{(1+r)^{s+j}}}^{\text{Expected Future Income}}\right]\right.$$
$$+ \sum_{j=0}^{10}\left[\frac{(E_{m-1-j,t} - E_{m-2-j,t})(Y_{mt})}{(1+r)^{1+j}}\right] + \sum_{j=0}^{9}\left[\frac{(E_{m-2-j,t} - E_{m-3-j,t})(Y_{m-1,t})}{(1+r)^{1+j}}\right]$$
$$\left. +... + \left[\frac{(E_{m-11,t} - E_{m-12,t})(Y_{m-10,t})}{(1+r)}\right]\right\}$$

The overbrace term "$s = 0$" shows the realization of each income, and the expected of income for each previous month. "Expected Future Income" denotes expectations from $m - 11$ to m of all future income (into infinity, hence permanent income hypothesis). The remaining terms are a collection of expectations for income between the $m - 11$ and and m.

Finally, we collect all Y_{mt} terms from the previous equation. Note that Y_{mt} appears in the "s=0" term above, and in the $\sum_{j=0}^{10}$. Isolating Y_{mt}:

$$\Delta_m^{12} C_{mt} = \frac{r}{1+r}\left\{\left(\sum_{j=0}^{11}(Y_{m-j,t} - E_{m-1-j,t}Y_{m-j,t})\right) + \sum_{j=0}^{10}\left[\frac{(E_{m-1-j,t} - E_{m-2-j,t})(Y_{mt})}{(1+r)^{1+j}}\right]\right.$$
$$+ \sum_{j=0}^{9}\left[\frac{(E_{m-2-j,t} - E_{m-3-j,t})(Y_{m-1,t})}{(1+r)^{1+j}}\right] + ... + \left[\frac{(E_{m-11,t} - E_{m-12,t})(Y_{m-10,t})}{(1+r)}\right]$$
$$\left. + \sum_{j=0}^{11}\sum_{s=1}^{\infty}\left[\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{m+s,t})}{(1+r)^{s+j}}\right]\right\}$$

$$\Delta_m^{12} C_{mt} = \frac{r}{1+r}\left\{(Y_{mt} - E_{m-1,t}Y_{mt}) + \sum_{j=0}^{10}\left[\frac{(E_{m-1-j,t} - E_{m-2-j,t})(Y_{mt})}{(1+r)^{1+j}}\right] + \left(\sum_{j=1}^{11}(Y_{m-j,t} - E_{m-1-j,t}Y_{m-j,t})\right)\right.$$
$$\left. +... + \left[\frac{(E_{m-11,t} - E_{m-12,t})(Y_{m-10,t})}{(1+r)}\right] + \sum_{j=0}^{11}\sum_{s=1}^{\infty}\left[\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{m+s,t})}{(1+r)^{s+j}}\right]\right\}$$

$$\Delta_m^{12} C_{mt} = \frac{r}{1+r}\left\{\sum_{j=0}^{11}\left[\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{mt})}{(1+r)^{j}}\right] + \left(\sum_{j=1}^{11}(Y_{m-j,t} - E_{m-1-j,t}Y_{m-j,t})\right) + ...\right\}$$

$$\Delta_m^{12} C_{mt} = \frac{r}{1+r}\left\{\sum_{j=0}^{11}\left[\frac{(E_{m-j,t} - E_{m-1-j,t})(Y_{mt})}{(1+r)^{j}}\right]\right\} + \frac{r}{1+r}\xi_{mt} = \sum_{\mu=0}^{11} e_{m-\mu,t}$$

Where ξ_{mt} includes expectations of income beyond m, and previously adjusted expectations on $Y_{m-1,t}$ through $Y_{m-11,t}$. Here we have isolated the Y_{mt} term, as it is what's observed in the data.

Therefore $\Delta_m^{12} C_{mt}$ is influenced by changes in income expectations.

C.2 Implied MPC and Elasticity of an Income Shock

Defining the income-generating process can shed light on the consumption response to unanticipated income changes implied by the model. Deaton et al. (1992) and Jappelli and Pistaferri (2017) both show the implied MPC of an income innovation when income is defined as an ARMA(p,q) process, as in Flavin (1981). We briefly describe how we apply this characterization to our data.[52]

Suppose annual household income is defined as an ARMA(p,q) process:

$$Y_t = \sum_{a=1}^{p} \rho_a Y_{t-a} + \sum_{b=0}^{q} \phi_b u_{t-b} \tag{20}$$

Which can be written as follows:

$$\begin{gathered} Y_t = u_t + \sum_{s=1}^{\infty} \psi_s u_{t-s} \\ \text{Where} \\ \psi_s = \phi_s + \sum_{j=1}^{s} \rho_j \psi_{s-j} \end{gathered} \tag{21}$$

Note that here we have replaced the dmt subscript with t. That is, we are examining the annual innovations to income as household income is reported.[53] As u_t is white noise, then it follows that:

$$\begin{aligned} &E_t Y_{t+s} - E_{t-1} Y_{t+s} = \psi_s u_{it} \\ &\qquad \Delta c_t = \frac{r}{1+r} \sum_{s=0}^{\infty} \frac{(E_t Y_{t+s} - E_{t-1} Y_{t+s})}{(1+r)^s} = \frac{r}{1+r} \left[\sum_{s=0}^{\infty} \frac{\psi_s}{(1+r)^s} \right] u_t \end{aligned} \tag{22}$$

Where equation 22 would define the annual innovation of 18. It can be shown as in Flavin (1981) that:

$$\frac{r}{1+r} \left[\sum_{s=0}^{\infty} (1+r)^{-s} \psi_s \right] u_t = \frac{r}{1+r} \left[\frac{1 + \sum_{s=1}^{q} (\frac{1}{1+r})^s \phi_s}{1 - \sum_{j=1}^{p} (\frac{1}{1+r})^j \rho_j} \right] u_t \tag{23}$$

For the simple case of an ARMA(1,1) process, we get the following:

[52] We follow Flavin (1981) in terms of derivation and general notation.

[53] When defining $\Delta_m^{12} C_{mt}$, mt is needed as consumption is the monthly aggregate of cohorts.

$$\frac{r}{1+r}\frac{1+\frac{1}{1+r}\phi_1}{1-\frac{1}{1+r}\rho_1}\cdot u_t = \frac{r}{1+r}\frac{1+r+\phi_1}{1+r-\rho_1}\cdot u_t \tag{24}$$

In our specification, we model income as a simple AR(1) process. Therefore, $\phi_1 = 0$ in equation 24 and thus:

$$\left(\frac{r}{1+r}\frac{1+r}{1+r-\rho}\right)\cdot u_t = \Omega\cdot u_t \tag{25}$$

Where $\Omega = \frac{r}{1+r}\frac{1+r}{1+r-\rho}$, and the subscript 1 from ρ is dropped for ease of notation. Thus, Ω is the consumption response of a shock to income. In this simple specification, the parameter ρ determines the magnitude of the response. When $\rho = 1$, the shock is fully persistent and captures permanent income changes. When $\rho = 0$, then the shocks are transitory in nature. This is described further in Jappelli and Pistaferri (2017). By measuring income in the DCPC through this specification, we can therefore get an estimate of the type of income changes apparent in the diaries. When estimating the AR(1) process, we control for year and age fixed effects, and their interaction. Once ρ is obtained from the regression, we use the delta method to compute standard errors reported in the table.

Income by Age

Figure C1: Income Profiles by Age Cohorts

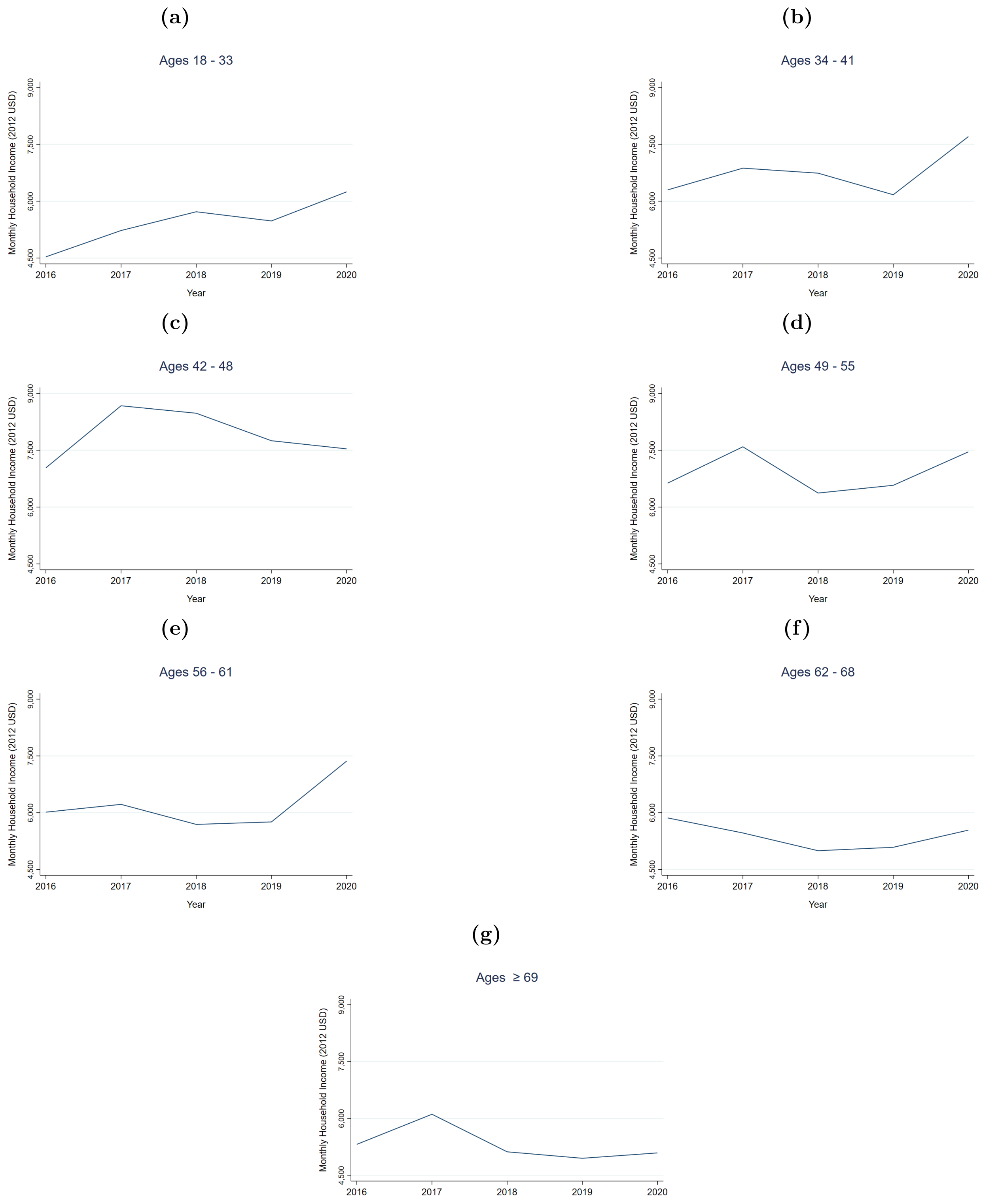


Figure C1 plots the time series of monthly household income for each age cohort from 2016 through 2020. All values are in 2012 USD values.

Appendix D Cleaning Consumption and Income Comparison

The results presented in the main paper use the original expenditure and income amounts available in the public datasets. However, the Boston Fed also publishes research reports annually for the DCPC which summarizes key facts regarding consumer payment choices. In this report, the Boston Fed also cleans the data with respect to large outliers in payment amounts. To examine the robustness of the results relative to outliers influencing the estimates, this section presents estimates of the high level consumption/income categories from the consumption and income tables of the primary paper using the cleaning methods by the Federal Reserve. These estimates are reported in Table D1. Cleaning scripts were obtained from the Boston Federal Reserve. The cleaning method used involves replacing outliers given a threshold determined by a beta distribution. However, in 2020 this method was not used and instead individual observations were removed. One of the observations removed was a car purchase. Because car purchases are included in PCE and CE consumption, this observation was kept for the cleaning results.

Column (1) reports the consumption and income estimates without Fed cleaning (WOFC). Column (2) reports these same estimates using the cleaned Fed estimates (WFC). Column (3) reports the ratio of WOFC to WFC. As shown in column (3), the WOFC estimates are 16% higher for total expenditures and 20% higher for adjusted consumption. When examining income, WOFC estimates are 8 and 7% higher for total and adjusted income respectively. Columns (5) reports the cleaned estimates of the DCPC as a ratio of the PCE estimates for consumption and the BEA estimates for income. The DCPC matches 77% of comparable consumption categories and 71% for adjusted income. The results of Table D1 show that while the WFC effects the point estimates, the core results do not change in that the DCPC still matches a significant amount of aggregate comparable consumption and aggregate income.

Table D1: With Fed Cleaning Comparison

With Fed Cleaning (WFC) and Without Fed Cleaning (WOFC) Comparisons					
	(1)	(2)	(3)	(4)	(5)
(A) 5 Year Consumption Averages	WOFC	WFC	WOFC/WFC	WOFC/PCE	WFC/PCE
Total Expenditures	12,391	10,699	1.16	.97	.84
Adjusted Consumption	7,786	6,466	1.2	.72	.6
Mostly Comparable	4,999	4,637	1.08	.83	.77
Mostly Noncomparable	2,788	1,814	1.54	.58	.38
(B) 5 Year Income Averages					
Total Income	9,615	8,926	1.08	.59	.54
Comparable Income	7,562	6,876	1.1	.52	.47
Noncomparable Income	2,054	2,052	1	1.06	1.06
Adjusted Income	9,386	8,732	1.07	.76	.71

Table D1 reports the consumption and income estimates without fed cleaning (WOFC) which is used in the paper, and with fed cleaning (WFC). Panel A reports the consumption results, while panel B reports the income results. Panel B reports BEA comparable income, while IRS is excluded for space. Column (1) reports the consumption and income results found in the paper, while column (2) reports the same results using the cleaned data. Column (3) reports the ratio of column (1) to column (2). Column (4) reports the ratio of WOFC estimates to PCE in panel A and BEA in panel B, while column (5) reports the ratio of WFC estimates to PCE and BEA income. Dollar values are in 2012 USD billions.