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Daily Consumption Smoothing? New Evidence from a Payment Diary

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Abstract

This paper shows that consumption and income data in the *Diary of Consumer Payment Choice* (DCPC) cover high percentages of U.S. data, forecast well in real time, and replicate the literature's estimation and general rejection of PIH models with time-aggregated data. Novel estimates reveal evidence of *daily* consumption smoothing after accounting for three features of daily data: 1) discrepancy between consumption and expenditures (e.g., bill payments); 2) discrete daily expenditures and income; and 3) asynchronous consumption and income. Convenience samples used in the literature appear to reflect selection effects related to payment choices (cash or mobile) that affect model inference. Relative to bank transactions data, the DCPC is more representative, publicly available, and offers other advantages.

JEL Codes: E21, D12, D14

Keywords: Payment diary, consumer expenditures, consumption, income, payment instruments, budgeting, saving, personal financial management, sample selection

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1 Introduction

Research on household consumption and financial behavior using micro transactions data has surged as the "big data revolution" (Pistaferri, 2015, p.97) makes data increasingly available from a variety of sources (Baker and Kueng, 2022). For example, the Opportunity Insights Economic Tracker public data base makes it feasible to do high-frequency, granular analysis of the COVID-19 Pandemic (Chetty et al., 2024).[1] Transactions data often have longitudinal panels with many agents and time periods, broad coverage of the population and concepts, deep granularity, and relatively low measurement error that reveal new insights about consumer preference heterogeneity, consumption smoothing, liquidity and credit constraints, expenditure shocks, policy effectiveness, and budgeting skills. However, transactions data may have shortcomings: 1) proprietary with limited access; 2) unrepresentative convenience samples with unobserved selection effects; 3) anonymity and non-verifiability; 4) retrospective with fixed historical application; and 5) not amenable to continuous improvements.

Lesser known, but essentially equivalent, transactions data without these limitations are found in daily consumer payment diaries. Originally designed to measure the transformation of payments from paper to electronic, the diaries unexpectedly yielded high-quality micro transactions data similar to bank accounts. Payment diaries *record all* expenditures authorized by payment instruments (including cash) in real time better than recall-based expenditure questions (Browning et al., 2003) and more broadly than selected samples (e.g., Chetty et al., 2024). Aggregate payment values are similar to nominal GDP in advanced economies (Bagnall et al., 2016). Precisely identified *consumption* expenditures provide real-time estimates of U.S. personal consumption expenditures (PCE) that cover more of PCE than the Consumer Expenditure Survey (Schuh, 2018). Relative to other transactions data, the Federal Reserve's *Survey/Diary of Consumer Payment Choice* (S/DCPC) has advantages: 1) publicly available; 2) representative of most consumers; 3) verifiable accuracy; 4) real time and ready for forward-looking implementation; and 5) amenable to continuous measurement improvement. "However, the survey [S/DCPC] has limitations compared to the proprietary data obtained from financial institutions, given its much smaller sample size and time window..." (Baker and Kueng, 2022, page 50); Pistaferri (2015) also critiques "small sample sizes" in existing surveys.

Although intriguing, Schuh (2018) begs three important questions. First, was the 2012 DCPC's relatively accurate match of U.S. PCE a fluke, or would it consistently do so in future years—especially with subsequent improvements to measuring consumption? Second, would

[1] Crossley et al. (2021) use survey data from the UK *Understanding Society* longitudinal panel.

the DCPC's direct recording of daily *respondent* (individual consumer) income starting in 2015 be equally successful in matching aggregate U.S. data, and how would it compare with reported annual income for the respondent's *household*? Third—and more importantly—would DCPC micro transactions data yield plausible estimates of benchmark consumption models consistent with those in the literature using time-aggregated data (annual, quarterly, or monthly) and, if so, allow feasible estimation at the daily frequency?

This paper answers the first two questions by reporting updated and expanded data validation for 2016-2020: 1) coverage of U.S. data; 2) real-time forecast accuracy; and 3) payday and pay frequency effects on consumption. Coverage exercises compare revised and improved aggregate DCPC consumption and new income with official U.S. estimates and leading alternative data sources. The real-time exercise evaluates daily forecasts of monthly DCPC consumption *levels* and new forecasts of U.S. PCE *growth* rates to quantify usefulness for macroeconomic analysis. The payday exercise compares DCPC estimates to the literature on payday effects on consumption (Stephens Jr, 2003; Gelman et al., 2014; Olafsson and Pagel, 2018) and pay-cycle length on within pay-cycle borrowing (Baugh and Correia (2022)).

The paper answers the third question by estimating consumption models with DCPC data at annual, weekly, and daily frequencies for validation. We use the analytical solution to a simple Euler equation derived from a benchmark Permanent Income Hypothesis (PIH) model (Jappelli and Pistaferri, 2017) with constant interest rates (due to data limitations). We estimate explicit income models with life-cycle effects for further insights and validation, guarding against mis-specification by using four income models. We also estimate standard model extensions for aggregate shocks (Cochrane, 1991; Mace, 1991; Townsend, 1994), permanent-transitory decomposition of income shocks (Blundell et al., 2008; Kaplan et al., 2014), uncertainty and risk (Dynan, 1993), and non-separability of consumption and leisure (Attanasio and Weber, 1995).

To our knowledge, the daily estimates are the first reported for a PIH model with micro transactions data.[2] Our paper is perhaps closest to others that estimate structural models of consumption with micro transaction data: Baker (2018) and Ganong and Noel (2019) with time-aggregated (quarterly, monthly) data from convenience samples, and Eika et al. (2020) with administrative records.[3] All three studies estimate consumption models with

[2] Brown et al. (2023) use micro transactions data from a Swiss consumer payment diary to estimate cross-section models with time-aggregated data to quantify the effects of cashless (electronic) payments on discretionary consumer spending.

[3] Baker (2018) uses data from a personal finance account aggregator and Ganong and Noel (2019) use data from the very large JPMorganChase bank. Eika et al. (2020) use government micro tax and administrative records data to estimate the consumption implied from the accounting identity with income and wealth.

panel data and superior wealth variables to analyze the effects of income shocks on debt (Baker, 2018) and distribution of consumption across households (Eika et al., 2020). In contrast, we focus on the lesser known daily frequency and estimate explicit income models. Daily data reveal an asynchronous frequency mismatch between consumption (daily) and income (weekly or less often) that highlights a potential role for budgeting in consumption and expenditure decisions that is absent from most textbook models.

Validation of DCPC data for 2016-2020 confirms the 2012 results and affirms the DCPC's value as a reliable ongoing resource for consumption *and* income. While all survey data underestimate population totals to some extent, aggregate DCPC data for October covered unexpectedly high percentages of official U.S. consumption (83 percent of PCE) and income (76 percent of disposable personal income, DPI) in comparable categories.[4] Consumption coverage declined from 92 percent of PCE in 2012 (Schuh, 2018) due to improved measurement in the diary instrument. But coverage of aggregate DCPC data remained superior or comparable to alternatives: 20 percentage points higher than the Consumer Expenditure (CE) Survey and 2 percentage points higher than IRS Statistics of Income, SOI. Thus, the CE Survey no longer is "the only data set with comprehensive and detailed information on household expenditure...[and income]" (Pistaferri, 2015).

Daily DCPC consumption provides accurate real-time forecasts of monthly DCPC consumption and PCE. As in 2012, daily projections of October DCPC consumption converge statistically to the final monthly estimate by about October 10-15. Because DCPC consumption underestimates PCE, we analyze daily projections of 12-month growth in DCPC consumption as real-time (daily) forecasts of PCE growth. Daily DCPC growth projections also converge to PCE growth rates long before the government the PCE data are published in late November. However, growth rate convergence occurs later (end of October) and with less precision (errors of about 5 percentage points in absolute value). DCPC data show promise but need further refinement for real-time analysis.

The effects of paydays and income frequency on DCPC consumption are qualitatively consistent with the literature but quantitatively different. Consumers spend more on paydays for non-bill and total expenditures, as in Olafsson and Pagel (2018) and Gelman et al. (2014), but the more representative DCPC estimates are lower. The DCPC data have uniquely comprehensive bill payments, which increase on paydays about four times more than non-bill expenditures (Gilyard, 2023). Consumers with longer pay cycles (less frequent income) also

[4] Naturally, coverage is lower in categories excluded or significantly different from official U.S. estimates because the DCPC was not originally intended to match U.S. estimates. DCPC coverage could be increased with more intentional, straightforward revisions to design of the survey instruments.

tend to have greater credit card borrowing, as in (Baugh and Correia, 2022), but DCPC estimates are about half as large.

At first glance, estimates of benchmark PIH models with time-aggregated annual and even with raw daily data are highly consistent with the literature. The preferred income specification yields a statistically insignificant annual MPC (elasticity) out of expected income of 0.19 (0.47), compared with a mean MPC of 0.26 for all micro data studies (Havranek and Sokolova, 2020). More precise daily data yield an MPC of 0.009 but a very significant elasticity of 0.019. Daily estimates are an order of magnitude smaller due to the mechanics of time aggregation. The estimated MPC declines as data frequency increases and time aggregation decreases (0.18 annual, 0.08 weekly, 0.01 daily). In any case, the DCPC data generally reject the null hypothesis of consumption smoothing due to excess sensitivity to predicted changes in income – except for consumers unconstrained by wealth (or credit), as typically observed. Estimates of model extensions are mostly consistent with the literature as well, but none can fully explain excess sensitivity of consumption. Daily data reveal smaller roles for permanent income shocks, consumption volatility, and (with limited data) non-separabile utility.

Upon closer examination, however, the DCPC data reveal some evidence of daily consumption smoothing. We re-estimate the models by controlling (as best we can) for unique features in daily data: 1) discrepancy between consumption and expenditure (Aguiar and Hurst, 2005); 2) discrete daily expenditures and income; and 3) asynchronous consumption and income. We address expenditure discreteness by including time effects in both income and consumption models, but these alone do not explain excess sensitivity. We address the consumption-expenditure discrepancy by dividing the expenditure data into bill payments, which are inherently discrete (typically monthly), from smoother non-bill payments. MPCs are similar (0.004-0.005) and insignificant, but elasticities for non-bills (0.052) are small and insignificant, while those for bills (0.670) are large and highly significant. This result suggests consumers smooth expenditures that are more like consumption (non-bills) than those inherently discrete (bills).

Finally, we address asynchronous consumption and income by dividing the data into income frequencies (weekly to monthly). For consumers receiving income weekly or bi-weekly, estimated MPCs and elasticities are less than 0.03 in absolute value and insignificant but consumers receiving income less often have MPCs and elasticities mostly greater than 0.05 and usually significant. This result suggest consumers paid more often are more likely to smooth consumption, regardless of constraints from wealth or credit. Apparently, budgeting of daily expenditures (and consumption) with discrete income payments may play a role in consumption smoothing. Confirming the importance of asynchronous expenditures and income, the MPC (elasticity) for weekly time-aggregated data—i.e., synchronous expenditures and income—is 0.311 (0.571) and rejects consumption smoothing.

Leveraging the relatively more representative nature of the DCPC reveals evidence of potentially important selection effects in convenience samples of transactions data. We construct subsamples of the DCPC based on respondent characteristics that either approximate criteria that define prominent convenience samples of transactions data in the literature (e.g., mobile payments and credit card ownership) or reflect less-often observed decisions (cash use and revolving debt). These simulated convenience samples produce MPCs from expected income that are economically and/or statistically significantly different from those in the complementary samples. This finding suggests that research using convenience samples of transactions data may not give representative estimates.

This paper has at least two potentially important implications. First, fully understanding the linkage between daily and lower-frequency consumption-saving decisions may require explicit introduction of budgeting and personal finance between discrete paydays. In particular, employers or perhaps public policy makers who increase the frequency of income payments may assist consumers' efforts to smooth consumption within income cycles.[5] Second, there appears to be a public good value of expanding and further improving the DCPC. Originally designed to measure payment choices, its success yielded superior coverage of official U.S. consumption and income data, enable reliable and insightful estimation of consumption models. Redeveloping and expanding the S/DCPC to increase sample sizes and frequency should yield an even more superior product.[6]

2 Related Literature

This paper is related to many distinct branches of the literature that are too broad and deep to review comprehensively. Instead, this section provides a brief summary introduction to each branch and its key relevance. Other specific citations are provided throughout the paper where appropriate.

Transactions data. The quantity and quality of transactions data used to study household finance and consumer expenditure behavior has increased tremendously. Baker and Kueng (2022) provides a comprehensive review of these data sources and their use in the

[5] Gelman et al. (2024) also find more consumption smoothing with higher frequency government transfers.

[6] Beyond this discussion, there is potential to address even broader measurement needs, such as the lack of fully integrated coverage of household financial statements (Samphantharak et al., 2018).

literature. Transactions typically refer to the records of bank transaction and credit card accounts obtained directly from financial institutions or indirectly from other sources (personal financial management software, retail scanner data, etc.). In some cases, transactions data are accompanied by balance sheet records as well. Most often, transactions data have very large sample sizes that offer unusually precise statistical inference. However, most transactions data sets are convenience samples (i.e., not drawn from the universe of agents using sampling theory), so they may not be representative or immune from sample selection effects.

Payments data. Motivation for consumer payment data was the long-awaited transformation of payments from paper to electronic forms (Rysman and Schuh, 2017). Understanding the decline in U.S. paper check use (Gerdes and Walton, 2002; Benton et al., 2007; Schuh and Stavins, 2010) and consumer adoption and use of payment instruments (e.g., Koulayev et al., 2016) prompted central banks and other researchers to collect data. Initial surveys were supplemented with daily diaries using representative probability samples of respondents (Bagnall et al., 2016). Payments data contain the same information as bank transactions data plus related consumer decisions. When designed to measure economic concepts, payments data identify consumption and income accurately as well (Schuh, 2018; Brown et al., 2023). Baker and Kueng (2022) note that payment diary data are promising but have limited sample sizes and time spans compared to transactions data.

Measuring consumption. Econometric models of consumption depend crucially on good data. Central issues are proper measurement of consumer *expenditures* (Browning et al., 2003, 2014; Pistaferri, 2015) and the adequacy of the Consumer Expenditure (CE) Survey and Diary (Council, 2013); see also the BLS Gemini Project. The S/DCPC has similarities and differences with the CE approach to collecting consumer expenditures. The insightful distinction between consumption and expenditures (Aguiar and Hurst, 2005) becomes highly relevant at the daily frequency. Like most data sources, the S/DCPC only measures expenditures and not consumption.[7]

Consumption theory. The paper follows the theory and notation of benchmark consumption models described in Jappelli and Pistaferri (2017) to the extent possible. Jappelli and Pistaferri (2010) provide a comprehensive review of the well-known and voluminous literature on the Permanent Income Hypothesis (PIH) and Life-Cycle Hypothesis (LCH) models of consumption. The benchmark models predict that consumption follows a martin-

[7] See our companion paper (Gilyard and Schuh, 2025) for an exploration of the theoretical implications of differences between consumption and expenditure with the available data.

gale unless consumers face departures, such as liquidity and credit constraints or hyperbolic discounting. Consumption models implicitly assume simultaneous (synchronous) receipt of income and consumption, which does not hold daily where consumption is continuous (daily) and income is discrete (weekly or lower frequencies).

Estimating consumption models. Most econometric estimates reject the PIH model, with consumption displaying excess sensitivity to expected changes in income (see Havranek and Sokolova, 2020, for an extensive review). Estimated MPCs are about one-half in aggregate data and about one-quarter in micro data. Most estimation uses time-aggregated, lower-frequency data (monthly, quarterly, or annual) in which income receipts and consumption expenditures are synchronous (occur in the same period). To our knowledge, there are no estimates of daily consumption and income, which is asynchronous in that expenditures occur daily while income is discrete and its size is dependent on paycheck frequency.[8] Aggregating irregular income payments to lower frequencies can induce autocorrelation (Crawley, 2020), which is avoided using daily data.

Daily consumption. Increased availability of transactions data has enabled exciting new analyses of daily consumption and income dynamics. Daily data reveal similar excess sensitivity of consumption to income on paydays (Stephens Jr, 2003; Gelman et al., 2014; Kueng, 2018; Olafsson and Pagel, 2018; Gelman, 2021, 2022); consumption responses to unanticipated income (Baker and Yannelis, 2017; Baker, 2018; Olafsson and Pagel, 2018, 2019; Ganong and Noel, 2019; Gelman et al., 2020); and consumer responses to the COVID Pandemic (Chetty et al., 2024). Additional benefits accrue from observing high-frequency consumption choices with more details on consumer financial positions, especially credit card debt (Hundtofte et al., 2019). Perhaps most importantly, daily data resolves the problematic mismatch of frequencies between consumption and income found in the CE Survey (Pistaferri, 2015, p.110). However, high- frequency granular data on consumer expenditures often come from convenience samples: a single bank (e.g., JP Morgan Chase); software apps (e.g., personal financial management); or subsets of transactions (e.g., credit and debit card transactions in Chetty et al., 2024).

[8] When comparing MPCs and elasticities on paydays in Gelman et al. (2014) to other studies, the authors note that longer estimation horizons display larger MPC estimates. However, the statistical precision of these estimates are not impacted by the horizon choice.

3 Consumer Payments Data

The primary data are from the U.S. *Survey and Diary of Consumer Payment Choice* (S/DCPC), which are similar to other programs worldwide (Bagnall et al., 2016).[9] An unintended and unexpected benefit of the DCPC is its unique ability to accurately identify consumer expenditures from other payments (Schuh, 2018).

3.1 Instrument Design

Like the Consumer Expenditure Survey (CE), the S/DCPC includes two modes of data collection. The SCPC is an annual (2008-present) *recall*-based survey in which respondents complete a 30-minute online questionnaire about current and recent activity. The DCPC is a daily (October 2012, 2015-present) *recorded* diary in which respondents complete a 20-minute per day mixed-mode survey (daytime tracking with physical memory aids, nighttime online questionnaire) about daily activity for three consecutive days.[10] The S/DCPC also includes comprehensive data on household demographics from a quarterly online questionnaire of panel members. Respondents earn \$20 for the SCPC and \$20/day for the DCPC.

The S/DCPC collect overlapping and complementary data. The Survey measures two main types of payment activity. One is *current* (time of the survey) bank accounts, payment instruments and related services on the extensive margin (*adoption*) plus dollar values of currency, checking, and prepaid card. The other type is recall-based estimates of the most *recent* number of payments on the intensive margin (*use*) by each type of payment instrument or account during a "typical" period (week, month,or year). The SCPC also collects data on consumer assessments of the characteristics of payment instruments and other information related to payments and household finance, including total assets and liabilities. The SCPC data supplement analysis of the DCPC.

The Diary *records* seven core variables for each payment transaction during the day: 1) time (hour and minute); 2) dollar amount; 3) payment instrument; 4) in-person (Y/N); 5) device used (e.g., none, card terminal, computer); 6) payee type (expenditure category); and 7) payee name. [11] Payments values are analogous to bank transactions for deposit

[9] The S/DCPC were developed originally by the Federal Reserve Bank of Boston in 2003, and now are managed by the Federal Reserve Bank of Atlanta: `https://www.atlantafed.org/banking-and-payments/consumer-payments/survey-and-diary-of-consumer-payment-choice`.

[10] For more details about the DCPC, see Greene et al. (2018), Schuh (2018), Samphantharak et al. (2018), Briglevics and Schuh (2020), Greene and Stavins (2021), and the Federal Reserve Bank of Atlanta.

[11] Collecting payment values implicitly measures the number of payments, which can be compared with the recall-based Survey.

accounts—expenditures, asset transfers, withdrawals, and deposits including income. The main difference is that payments are recorded for consumer expenditure *categories* rather than the name of the exact payment recipients, such as a specific retailer, merchant, service provider, or financial institution. The nightly online survey allows respondents to self-enter the seven variables for each payment, answer follow-up questions, and check for errors.

Diary expenditures are total payment values, which may include one particular good (gasoline) or service (haircut) or many (basket of groceries). Unlike Browning et al. (2003), which recommends asking for total expenditures and selected detailed expenditures, the DCPC collects intermediate values that cover all consumer expenditures better by reducing granularity and respondent burden. The CE Diary collects highly detailed product-specific prices and quantities to construct price indexes, such as two gallons of milk at $3/gallon equals $6 of expenditure. The DCPC does not collect per-unit prices, so expenditures are the final amount paid for all items (e.g., grocery basket). The DCPC also collects three types of data not in bank transactions: 1) currency holdings and transactions outside the bank; 2) consumer expenditures not in the national income and product accounts; and 3) unique real-time interviews of respondents about their decisions for each transaction ("point of sale").[12]

Since the initial 2012 DCPC, the diary instrument has undergone years of redevelopment. Innovations were motivated by initial research results (Greene et al., 2018; Schuh, 2018; Samphantharak et al., 2018) and feedback from a Board of Advisors. Two innovations were most important.[13] One is the addition of recording income received by *respondents*, which supplements estimates of gross annual *household* income in the SCPC. Respondent income is classified into several types, some of which differ from IRS and Bureau of Economic Analysis (BEA) definitions. Another innovation is improvements to the classification of payment recipients, also called "merchants," to more precisely match external consumption definitions and distinguish them from non-consumption expenditures. For example, the new categories now separately identify bill payments as consumption (e.g., electricity or internet bills) versus non-consumption (credit card bills).

To summarize measurement, the Diary is unique because it directly collects all key information about respondents' daily liquid cash flows (Schuh and Townsend, 2020). Consumption expenditures are obtained from payment values in the memory aids. All deposits (includ-

[12] For each payment, these data include: instruments (including cash values) carried in their wallet at the time of payment; preferred instrument (hence account); whether the transaction was unexpected and, if so, whether it could be postponed; and other related information. Briglevics and Schuh (2020) use the DCPC to estimation a dynamic optimizing model of daily consumer expenditure, payment choice, and cash management.

[13] See Table A11 of Appendix A for a complete summary of innovations in the DCPC survey instrument.

ing income), withdrawals, and current asset values are obtained from nightly online surveys about liquid transaction accounts (primary checking and cash held outside the bank). Thus, the DCPC enables construction of exact daily cash flows for liquid assets rather than implicit estimation from two of the components of cash flow (e.g., Dutz et al., 2025).

3.2 Sampling Design

Since 2015, the primary sampling frame for the S/DCPC has been the *Understanding America Study* (UAS) developed by the USC Dornsife Center for Economic and Social Research (CESR).[14] The UAS is a bi-lingual longitudinal internet survey panel with approximately 14,000 U.S. adults ages 18-years and older (as of 2024) that is built with best-practices for panel recruitment and bears similarities to the UK *Understanding Society* Household Longitudinal Study (UKHLS). CESR uses address-based sampling for prospects and an extensive 14-step protocol to recruit UAS panelists developed from field experiments (Angrisani et al., 2024). About 7-19 percent of invited households became panelists in 2014-2023. The resulting UAS panel is a cutting-edge sampling frame that is highly representative of U.S. households and consumers relative to other private-sector alternatives and offers selected oversamples (e.g., Native American).[15]

The sampling unit of the UAS panel is a household. During recruitment, all eligible individuals in a household are invited to participate, although not all members accept.[16] Panel members are monitored for active participation; retention efforts (including monetary incentives) continue for a year before termination. Roughly half or more of all members remain active since the year they joined. The sampling unit for the S/DCPC is a consumer (respondent). First-time S/DCPC participants are selected randomly from the universe of UAS members who had not previously participated in the S/DCPC. Thus, new entrants should be as representative of the U.S. population as the UAS panel. The UAS includes post-stratification weights to match the Current Population Survey (CPS).

[14] From 2008-2015 (including the 2012 DCPC), the primary sampling frame was RAND's American Life Panel (ALP). In 2015, ALP and UAS were used to smooth the transition between panels. The 2015 UAS sample is less than half that 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).

[15] Private-sector survey vendors generally do not have access to the exhaustive lists of individuals and businesses maintained by the federal government (Census Bureau, IRS, etc.) needed to achieve the most representative samples. A rare exception is the Federal Reserve's Survey of Consumer Finance (SCF), which is implemented by NORC and contains administrative data on high income households (Bricker et al., 2016).

[16] "A household is broadly defined as anyone living together with the initial person who signed up to become a participant in the UAS." (See UAS.)

3.3 Annual Implementation

The S/DCPC are implemented jointly once per year. In September, respondents complete the SCPC and indicate their willingness to participate in the subsequent DCPC. About 84-91 percent of Survey respondents agree to participate in the Diary. Each SCPC respondent who opts into the DCPC is randomly assigned to a consecutive three-day period (wave). There are 33 sequentially staggered waves that begin each day starting on September 29 and ending October 31, as depicted in Appendix Figure A1. Each day also contains an approximately equal share of respondents on the diary days (1, 2, and 3) to eliminate potential diary-day effects in reporting (e.g., "diary fatigue" that may reduce reporting). This random assignment process ensures representatives samples of U.S. consumers all 31 days in October.

The night before their Diary period begins ("Day 0"), respondents complete a brief online survey to update some of their data SCPC data since it was completed in September. Given the sample and implementation designs, the gap between SCPC and DCPC could be between one and almost 60 days, which could involve economically significant changes. Updating involves recording the latest currency and account balances plus income payments.

3.4 Longitudinal Panels

Within the month of October, the S/DCPC sample is a *balanced* longitudinal daily panel with pre-scheduled turnover. Nearly all SCPC respondents (92 percent) who agreed to participate in the DCPC did so, and nearly all DCPC respondents (94 percent) completed all three Diary days (Greene and Stavins, 2021; Foster et al., 2020). Although payments data for individual respondents are limited to three days, the sampling and implementation design permits consistent measurement of aggregate transactions that are representative of U.S. consumers each day. Total expenditures and respondent income each day are weighted sums of all transactions and respondents in one of the three waves completing the diary on that day, giving a daily aggregate time series for October 1-31. Daily aggregate transactions are unweighted sums across all 31 days that form representative estimates of aggregate transactions for the month of October.

Across years (2012-2020), the S/DCPC sample is an *unbalanced* longitudinal panel. Each year, the prior year's respondents are invited to continue in the current year and than 90 percent do so. First-time respondents are recruited randomly from the UAS universe (excluding previous S/DCPC participants) to fill the desired sample size (2,000-3,000 respondents per year). Acceptance rates for randomly recruited new S/DCPC respondents are similarly high. However, this random replacement design does not ensure fully representative replacement of exiting panelists in the S/DCPC panel over time, as recommended by Hsiao (2022).[17] We exclude S/DCPC data after 2020 because the DCPC stopped collecting respondent income in 2021 but it was reinstated in 2023.

3.5 Representativeness

The preceding subsections suggest the UAS panel and random S/DCPC samples should be relatively representative among private-sector alternatives. Of course, no sample derived from any subset of the population is perfectly representative, every random selection contains sampling error, and every survey/diary likely contains measurement error. Therefore, it is instructive to quantify extent to which the S/DCPC is representative of observable respondent characteristics.

Table 1 shows the extent to which S/DCPC samples represent characteristics of the U.S. population as measured by the Current Population Survey (CPS) in the first numeric column. (The table reports estimates only for 2015-2016 due to limitation in the availability of some data on subsample characteristics.) The second and third columns show the same statistics for the full S/DCPC samples as ratios to the CPS estimate. Most characteristics in the S/DCPC are within 5 percentage points (absolute value) of the CPS. Exceptions are high-school education and lowest income (both more than 5 percentage points higher) and bachelor's degree (12-14 percentage points lower). Unlike the Survey of Consumer Finances (SCF), the S/DCPC does not have access to administrative records on the very highest income individuals (Bricker et al., 2016).

Given the relatively representative nature of the S/DCPC, the likely representativeness of convenience samples of transactions data used in the literature can be approximated by subsamples of the S/DCPC shown in columns four through eight. Adoption of personal financial management (PFM) software is comparable to data from account aggregators (Baker, 2018; Olafsson and Pagel, 2018); Visa credit card adopters is comparable to Visa transactions data (Einav et al., 2021); and mobile payment (MP) users is comparable to data from mobile apps (Gelman et al., 2014; Xing et al., 2023). These convenience samples all exhibit higher education and higher income than the CPS, and higher employment probabilities (except Visa). While not directly comparable, adoption of commercial bank and brokerage checking accounts is approximately similar to JPMorganChase accounts (Ganong and Noel, 2019). The commercial bank convenience sample tends to be roughly representative except for lowest income, but the brokerage adopters—probably more similar to JMPC customers—are

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

very high employment, education, and income consumers. Aggregate estimates of convenience sample data sources can be constructed with *ex post* stratified weights to correct approximately for deviations from the CPS in terms of observable demographics. However, this adjustment does not guarantee that subsample data sources are free from unobserved sample-selection effects that may influence estimation.

Table 1: Summary Statistics, 2015-2016

	Representative			SCPC Subsample				
	CPS	SCPC	DCPC	PFM	Visa	M.P.	Checking Account	
							Commercial	Brokerage
Panel A: Fraction of CPS								
Age	47.2	1.00	1.01	0.89	1.05	0.85	1.02	0.96
Male	48.2%	1.00	0.98	0.96	0.99	1.00	0.99	1.06
White	78.4%	0.95	0.95	0.86	0.99	0.91	0.99	0.87
Employed	61.3%	0.98	0.98	1.16	1.02	1.25	1.02	1.28
High-School	29.3%	1.13	1.07	0.41	0.93	0.61	1.07	0.08
Bachelor's	20.0%	0.86	0.88	1.53	1.15	1.30	0.95	2.26
$Y^H < 25k$	20.2%	1.06	1.07	0.56	0.54	0.55	0.79	0.30
$Y^H \geq 100k$	24.2%	0.98	0.98	1.68	1.35	1.60	1.06	1.74
Panel B: Fraction of SCPC								
PFM		6.48%	1.01	NA	1.23	2.68	1.10	1.13
Visa		41.99%	1.05	1.23	NA	1.21	1.09	1.10
M.P.		13.83%	1.05	2.68	1.21	NA	1.08	1.92
Checking Account								
Commercial		58.28%	1.00	1.10	1.09	1.08	NA	NA
Brokerage		1.12%	1.10	1.13	1.10	1.92	NA	NA
Cash User		24.9%	0.98	0.56	0.68	0.53	0.80	0.51
Shop Resp: All		39.3%	1.01	1.01	1.03	1.00	1.03	0.94
Sav/Inv. Resp: All		35.3%	1.01	1.23	1.04	1.05	1.07	1.27
Panel C: Fraction of DCPC (2016)								
$2000 Emergency: Savings Account			$ 411.34	1.50	1.24	1.38	1.09	1.40

[1.] Table reports selected demographics comparisons to the October Current Population Survey for 2015 and 2016. The first column shows the average age in the CPS, followed by the percent of respondents within the CPS who are male, white, employed, have a high-school diploma, bachelor's degree, income under $25,000, and income greater than or equal to $100,000. Columns two and three calculate the same statistics for the DCPC and SCPC respectively, and are converted to a fraction of the CPS. The remaining columns report demographics as a fraction of CPS statistics for the following subsamples: personal financial management, Visa credit-card adopters, mobile payment users, commercial checking account adopters, and brokerage accounts. Mobile payment users are defined as using a mobile app to make a payment within the last 12 months. Panel B reports different shares of subsamples within the datasets. As these variables are not included in the CPS, shares are reported for the SCPC, and the remaining columns report the fraction relative to the SCPC. The first rows report the cross-tabulation of subsamples within each subsample. *Cash users* are defined by those who make more than 50% of their monthly retail payments in cash. The remaining rows show the share of respondents who reported having all the household responsibilities in various categories. Panel C reports the average amount consumers could pay for a $2,000 emergency expense from their savings account. This question is only asked in the 2016 DCPC, and thus the CPS, SCPC, and 2015 DCPC is excluded.

3.6 Data Cleaning

Throughout the paper, we use the publicly-available data posted on the Atlanta Fed website to allow easy replication. The Atlanta Fed uses proprietary data cleaning methods for their official S/DCPC publications, which may result in changes to economically valid data points. The Fed cleaning scripts were not publicly available at the time of this paper but were shared confidentially with the authors for the analysis in this paper. Appendix B.1.1 analyzes robustness of the results to data cleaning methods. The core results in the paper remain qualitatively similar when using cleaned or raw data. Quantitative differences are noted later when relevant.

4 Measurement and Data Construction

This section explains how the DCPC data are use to measure consumption and income, describes aggregation of the data over agents (average consumer) and time (from daily to monthly), and introduces the aggregate DCPC consumption and income data.

4.1 Identifying Variables

The following subsections explain how each variable associated with an economic concept is obtained from DCPC variables. See Appendix A and Tables A3-A10 for more details about the meticulous process of identifying consumption, income, and other variables.

4.1.1 Consumption

Consumption expenditures are a subset of the total dollar value of payments. The payment expenditure value (variable #2 in Section 3.1), X_t, includes:

$$X_t = X_t^c + X_t^o = [C_t^n + C_t^d] + [X_t^u + \Delta A_t + \Delta L_t] \ .$$

Consumer expenditures, X_t^c, includes nondurable goods and services, C_t^n, and consumption of consumer durables, C_t^d [first bracket]. Non-consumption (other) expenditures, X_t^o, includes unofficial consumption expenditures (e.g., underground economy), X_t^u, plus changes in assets and liabilities (debt) [second bracket], ΔA_t and ΔL_t. The latter include payments and transfers to/from other people (person-to-person), such as gifts or allowances.

Identification of C_t^n and C_t^d is possible through careful examination of several other parts of the Diary survey. The payee (variables #6 and #7 in Section Section 3.1), or "merchant," who received the payment identifies the type of consumption expenditure. The exact merchant is not identified (e.g., Whole Foods in Boston, MA) but rather an industry category (e.g., Grocery Stores). DCPC industry categories were constructed based on several input criteria: NAICS codes, official consumer expenditure categories (PCE and CES), and the goals of payments research. Merchant categories are further refined using variables with information about the reason and purpose for the payment. Purpose variables were added in 2015 to better identify expenditure types when merchant categories are broad. For example, financial service expenditures can be C_t^n (e.g., bank fees) or $\Delta L_t < 0$ (e.g., loan repayments).

4.1.2 Income

Income is measured two ways. Since 2008, the SCPC includes a standard recall-based estimate of annual gross *household* income, Y_t^H, from the quarterly UAS survey of respondent demographics ("My Household Questionnaire"). Starting in 2015, the DCPC collected *respondent* income, Y_t^R as part of deposits received via cash, check, direct deposit (ACH payment), gifts (person-to-person), or other payment instrument.[18] It is not possible to determine whether Y_t^R is gross or net of taxes (disposable), but most employment income deposits are likely disposable. The two income types are related by the identity,

$$Y_t^H = Y_t^R + Y_t^O$$

where Y_t^O is the residual income of all other household members (if any). Because respondents only participate in the Diary for three days, the quantitative relationship between annual gross Y_t^H and three-day disposable Y_t^R is unclear. However, the SCPC asks respondents where their individual income ranks within the household, qualitatively from most to least. Still, the data do not indicate clearly the extent to which a respondent has access to Y_t^O for consumption except in single-member households where the consumer and household are the same.

[18] Gross household income may be easier and more accurate to recall and report, at least for some households and respondents. But concerns have been raised about the accuracy of such measures (Moore et al., 2000; Meyer et al., 2015). Angel et al. (2019) shows that survey income 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. The authors argue that income should be validated, so recorded DCPC income may be less prone to misreporting compared to household income.

4.1.3 Balance Sheet and Cash Flow

Each day the DCPC records all elements of cash flow for liquid asset accounts, A_t^l:

$$\Delta A_t^l = D_t^l - W_t^l$$

where D_t is deposits and W_t is withdrawals. In 2015-2020, A_t^l included two main types: 1) cash (currency) carried by the respondent (in pocket, purse, or wallet) or stored elsewhere (home, car, office, or other); and 2) primary checking account balance.[19] Respondents report exact account balances at the beginning and end of their Diary wave, and every night for cash carried (by denomination). D_t and W_t are dollar-value transactions recorded by the payment instrument, or "derivative media" of money (Tobin, 2008), that is used to authorize the exchange of A_t^l from one party to another (buyer and seller). Thus, payment instruments link line items of the balance sheet and income statement through cash-flow relationships (Samphantharak and Townsend, 2010; Samphantharak et al., 2018).

Deposits and withdrawals are linked to payment expenditures. Deposits are

$$D_t = Y_t + D_t^o \ ,$$

which mainly includes all forms of income. Other deposits, D_t^o, include currency (bills and coins), account-to-account transfers from non-recorded asset accounts, tax refunds, or other miscellaneous deposits. Withdrawals include the two basic payment types,

$$W_t = [X_t^c + X_t^n] + W_t^o \ ,$$

where X_t^n includes account-to-account transfers and W_t^o includes cash and miscellaneous withdrawals. Because account-to-account transfers may include non-liquid accounts, A_t^n, such as retirement or investment funds, the ΔA_t^l liquid cash flow identity may have errors.

Annually, the SCPC collects recall-based estimates of total assets,

$$A_t = A_t^h + A_t^o$$

where A_t^h is the value of the primary home (if homeowners), and $A_t^o = A_t - A_t^h$ is a derived

[19] Other liquidity is not collected consistently. Primary prepaid card balances are available for some years, and the 2019 DCPC included primary savings account balances.

estimate of all other assets. The liquid assets pertaining to payment expenditures,

$$A_t^l = A_t^o - \widetilde{A}_t^o$$

are a subset of other non-housing assets and could include non-primary checking accounts, savings accounts from which payments can be made (e.g., MMDAs), and other payment-related assets. Similarly, the SCPC also collects total liabilities,

$$L_t = L_t^h + L_t^o$$

where L_t^h is unpaid mortgage debt on the primary home and $L_t^h = L_t - L_t^o$ a derived estimate of all other debt. Thus, net worth is

$$NW_t = A_t - L_t \ .$$

All asset and liability data are converted to inflation-adjusted $2012.

4.2 Aggregation and Frequency

The rich structure of the DCPC requires unavoidably detailed notation and derivations. Let X_{ijdmt}^c denote consumption expenditures for respondent (consumer) $i = \{1, \ldots, N_t\}$ in consumption category $j = \{1, \ldots, J_t^c\}$ where J_t^c reflects time variation in expenditure categories. Discrete time periods are represented by days of the month, $d = \{1, \ldots, d_m\}$, months (Sep through Nov), $m = \{9, 10, 11\}$, and years, $t = \{2012, \ldots, 2020\}$.[20] Also, let Y_{ijdmt}, denote income received, which is recorded from deposits, D_t, and presumed to be net of taxes (disposable) and other pre-deposit deductions. Here, subscript $j = \{1, \ldots, J_t^y\}$ denotes the 10 income categories found in Appendix Table A1; employment income is most common. 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.

Daily data reveal frequency mismatches in transactions data. Consumer expenditures are discrete whereas consumption presumably is continuous (Aguiar and Hurst, 2005). The typical respondent reports about two payments per day on average (60/month), some of which are consumption expenditures. Most income is received at weekly to monthly frequencies, which the S/DCPC tracks. As a result, a significant number of respondents do not receive

[20] 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.

any income on a given day, in which case the Diary records the date of their last and next income payments. Appendix Table A2 shows that 20.7% of respondents reported receiving income during 2016-2020 and 22.3% of income types are unidentified (missing). See Appendix A.3 for more details.

Aggregation of data *within* respondents does not require sampling weights. For individual i, daily consumption is $X^c_{idmt} = \sum_{j=1}^{J} X^c_{ijdmt}$ and three-day consumption is $X^c_{imt} = \sum_{\delta=d_{i1}}^{d_{i3}} X^c_{i\delta mt}$. Aggregation across respondents requires representative sampling weights for the Survey and Diary (w^S_{it} and w^D_{idt}). Daily DCPC sampling weights sum to the number of respondents, N_{mt}, participating in the Diary for the month: $N_t = \sum_{i=1}^{I_{dt}} w^D_{idt}$ where I_{dt} is the number of individual respondents on each day.[21] See Angrisani et al. (2018) for technical details about sampling weights.

To obtain daily aggregate consumption in October, estimates 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 consumption per capita (denoted by overline) is

$$\overline{X}^c_{dmt} = \frac{\sum_{i=1}^{I_{dt}} w^D_{idt} \cdot X^c_{idmt}}{\sum_{i=1}^{I_{dt}} w^D_{idt}},$$

where w^D_{idt} is day-of-the-week weights that account for weekly seasonal fluctuations and demographic differences in respondents across waves. Average consumption per capita for the month is:

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

where $D_{10} = 31$ for October.

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). Monthly aggregate U.S. consumption in October is $X^c_{10,t} = \overline{X}^c_{10,t} \cdot P_t \cdot D_{10}$, and annual aggregate U.S. consumption is $X^c_t = \overline{X}^c_{10,t} \cdot P_t \cdot 365.25$ because there are 365.25 days in a year.[22] Analogous procedures are used to construct aggregate DCPC respondent income.[23]

[21] These daily weights can be converted to the U.S. population by using a population estimate to scale up the number of Diary respondents.

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

[23] 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

5 Data Validation

This section extends beyond 2012 the data validation exercises in Schuh (2018). The first exercise quantifies S/DCPC data coverage of official U.S. data. The second exercise constructs real-time daily forecasts of the level and growth of consumption. The third exercise replicates estimates of payday and pay-cycle effects on consumption for comparison with the literature.

5.1 Exercise #1: Coverage of U.S. Data

This subsection quantifies the extent to which aggregate DCPC data cover the more comprehensive U.S. estimates of PCE and personal income. Both official U.S. data sources are designed to be the most comprehensive estimates of aggregate activity, thus contain higher estimates than the DCPC and alternative sources of CE consumption and IRS income. The Panel Study on Income Dynamics (PSID) also includes detailed consumer expenditures but only covers about 70-90 percent of the CE data (Pistaferri, 2015, p.107).

Figure 1 depicts five-year (2016-2020) average levels of aggregate real consumption and income ($2012 billions, left axis) plus the average propensity to consume (ratio, right axis).[24] The figure compares three data sources: an official U.S. benchmark (PCE and BEA), the DCPC, and one leading alternative source (CE and IRS); DCPC(h) is household and DCPC(r) is respondent. Each variable has multiple groups of bars.[25] *Total* (green) includes all categories of each source. *Adjusted* (red) excludes categories not in all data sources.[26] Income taxes are an excluded category, thus adjusted income is disposable. *Comparable* (blue) only includes categories in adjusted consumption with classification schemes or definitions that clearly match well between the official and alternate sources.[27] Percentages reported in bars are indexed to official U.S. data (100%). Standard error bands (orange lines) are provided for DCPC data. Average propensity to consume (APC) is X^c/Y.

calculating household income estimates.

[24] Appendix Figures B1 and B2 present the annual time series of DCPC aggregate consumption and income data relative to official U.S. data. Both consumption and income shares fluctuate non-trivially year-to-year.

[25] Consumption bars correspond to Appendix Table B1 and income bars to Appendix Tables B2 and B3.

[26] Most excluded consumption categories 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 for owned dwellings. Additional unique categories removed from the DCPC include taxes, payments to person, non-classifiable payments, and loan repayments.

[27] Comparable consumption categories generally follow the BLS correspondence between CES and PCE. DCPC consumer expenditures are matched to PCE and CES categories as best as possible using merchant categories (see Tables A8 and A9). Non-comparable categories mainly are related to payments for medical, insurance, vehicle-related purchases, tuition, professional services, and other miscellaneous categories that are difficult to compare directly. For details on the exact categorization, see Table A8.

Figure 1: 5-year Consumption and Income Averages

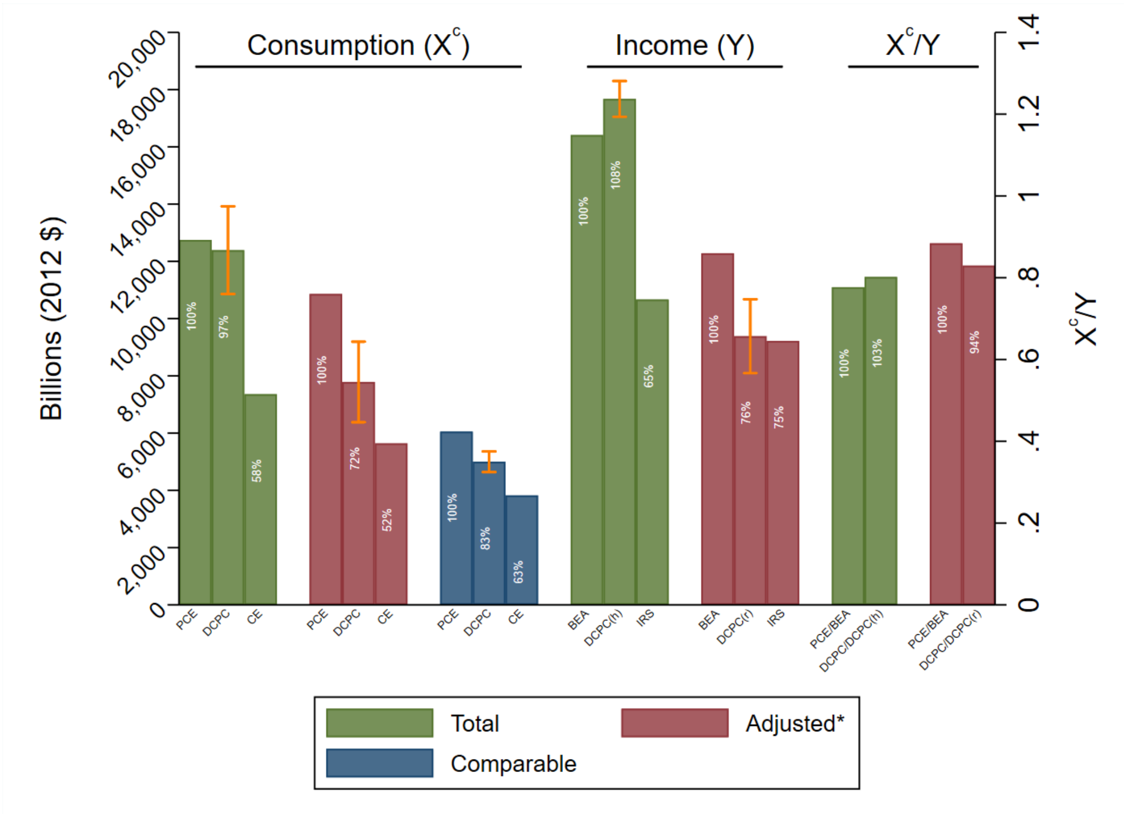


Figure shows the five-year consumption (DCPC, PCE, and CE) and income (DCPC, BEA, IRS) corresponding to Appendix tables B1, B2, and B3. The x-axis shows different categories of expenditures and incomes, while the first y-axis is 2012 dollar values corresponding to Consumption (C) and Income (Y) results. Percentages reported are all indexed to PCE for consumption and BEA for income. Orange range plots are 95% confidence intervals for DCPC estimates. DCPC(r) is respondent income, while DCPC(h) is household income. The second y-axis corresponds to the consumption divided by income estimates (X^c/Y group). These data labels correspond to the second y-axis, as a % of PCE/BEA. The groups under C/Y (Total, Adjusted) correspond to the consumption measurement, where total consumption is divided by total income. Adjusted ratios are both divided by adjusted income. *Note: adjusted income is disposable income plus adjustments. Total consumption and income are totals reported by each dataset. Adjusted consumption and income remove categories which are not in each dataset. Comparable consumption are the most comparable expenditure categories.

5.1.1 Consumption

Qualitatively, Figure 1 is similar to Schuh (2018), verifying 2012 was not a fluke. All three DCPC consumption aggregates continued to cover PCE better than CE data. Total DCPC consumption covered 97 percent, while the CE only matched 58 percent. After adjustments, DCPC consumption was 72 percent of PCE but still higher than CE (52 percent). In comparable categories, the DCPC also covered 20 percentage points more of PCE than CE (83 and 63 percent, respectively). Over the five years, DCPC consumption is 31% higher on average than CE consumption for comparable consumption categories.

Quantitatively, however, DCPC aggregate consumption for 2016-2020 did not compare as favorably relative to PCE. In 2012, adjusted DCPC was 92 percent (Schuh, 2018), about 20 percentage points higher. The more recent results reflect important effects of improvements to the Diary survey instrument in measuring official consumption definitions through merchant categories and other revised and expanded information, which reclassified certain expenditures from consumption to non-consumption (e.g., credit card bill payments).[28]

5.1.2 Income

Figure 1 shows, for the first time, that DCPC income also covers U.S. data relatively well, (similar to Fisher et al., 2019, for the UKHLP). For total (gross) income, DCPC(h) actually covers slightly more of BEA income (108 percent). Total IRS income covers much less (65 percent) because it only includes taxable income and thus excludes some types found in BEA (Ledbetter, 2004). For adjusted (disposable) income, DCPC(r) and IRS cover about three quarters of BEA income (76 and 75 percent, respectively, statistically the same). Thus, DCPC adjusted income covers a similar portion of U.S. data as DCPC adjusted consumption (76 and 72 percent, respectively).[29]

5.1.3 Average Propensity to Consume

Figure 1 shows that DCPC estimates of the APC are notably close to U.S. estimates for total and adjusted data (103 and 94 percent, respectively). For proper comparison, consumption is divided by its respective income category. The APC is slightly higher for adjusted data (0.88 and 0.83) than total data (0.78 and 0.80) because disposable income is less than gross income.

[28] Percentages relative to PCE (and BEA) are slightly lower when using cleaned data. Comparable consumption and adjusted income are approximately 7% and 5% lower, respectively, when using the Federal Reserve's adjustments for outliers.

[29] In addition to taxes, adjusted income excludes 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).

Thus, DCPC estimates of the APC are similar to U.S. data regardless of the accounting for income. DCPC estimates of APCs by categories of household income are qualitatively similar to those in the CE (Sabelhaus and Groen, 2000; Sabelhaus et al., 2015).[30]

5.1.4 Life-Cycle and Daily Data

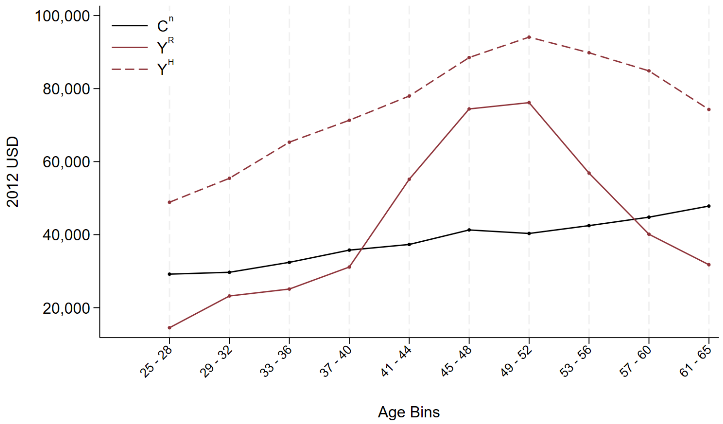
Figure 2 offers a sneak peak at DCPC data over the life cycle and day-to-day. Panel (a) plots life-cycle profiles of consumption and income estimated with controls for consumer demographics using standard methodology in the literature (see figure footnote for details). Overall, DCPC profiles mirror those reported in the literature (e.g., Gourinchas and Parker, 2002). Household income (Y^H) displays the usual hump-shaped pattern that peaks during prime working ages (50s). Individual respondent (consumer) income (Y^R) displays three economically important differences: 1) it is about half of household income on average; 2) it varies relatively more over the life-cycle; and 3) it peaks slightly earlier in the life-cycle. Nondurable consumption (C^n) expenditures, which are most directly comparable to respondent income (Y^R), rise steadily throughout life rather than having a hump shape as in CE data. Aguiar and Hurst (2013) reveal that certain goods and services do not decline late in life and the more representative DCPC has relatively more of them.

Panel (b) reveals perhaps the most striking feature of daily data: consumer expenditures are much smoother than income. The figure plots average aggregate DCPC per consumer (per capita) using nondurable consumption expenditures, $\overline{C}_t^n$ and respondent income, $\overline{Y}_t^R$. The data are for each day in October (bottom axis) concatenated across the years 2016-2020 (top axis). Income is received discretely across heterogeneous pay frequencies. The ratio of standard deviations of daily DCPC consumption to income is 0.2 compared with monthly and quarterly data (0.5 and 0.4, respectively) for aggregate PCE and BEA disposable income during this period. The relative volatility of consumption was lower during 2016-2020, a period mostly of economic expansion, during the full sample 1959-2024 for aggregate PCE (0.9 monthly and quarterly), which includes excess sensitivity during recessions.

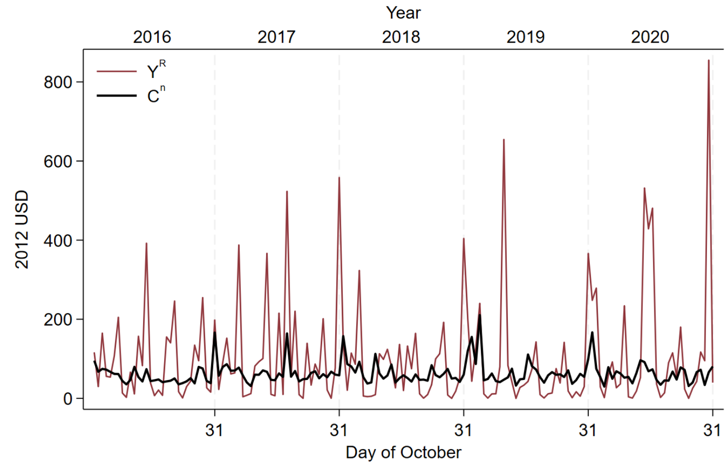
[30] Compare Appendix Figure B3, which uses gross (household) income, to Figure 8.3 in Sabelhaus et al. (2015), which uses disposable. The DCPC estimates of APC are lower due to the different income concepts in the denominator. However, the nonlinear decline in APCs as income rises is notably similar. We thank Edmund Crawley for suggesting this comparison.

Figure 2: Aggregated Consumption Patterns

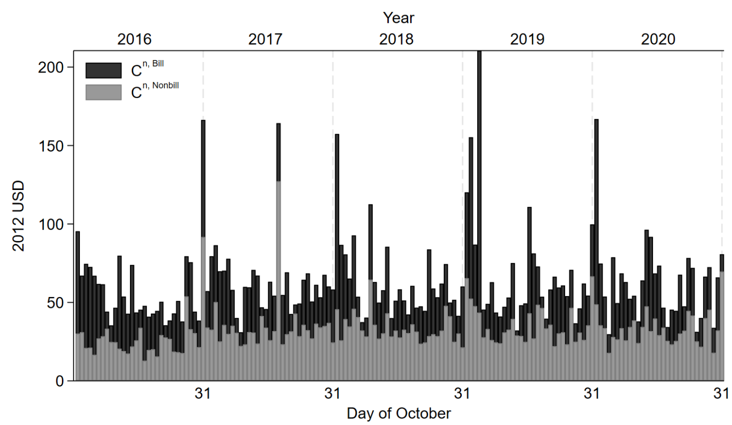
(a) Life-Cycle C^n, Y



(b) Daily C^n, Y^r



(c) Daily C^n by bills and non-bills



Panel (a) plots life cycle profile within the DCPC. C_d^n and Y_d^R are aggregated within consumers (see section 4.2), averaged by age group and date, summed monthly, and annualized. Age bins include 18–25, and bins shown in x-axis of figure. Values are predicted from regressions of log consumption and income on age groups, controlling for year fixed effects and cohort characteristics (household size, marital/retirement status). Consumption regressions also control for shopping responsibility, while income regressions control for within-household income ranking. Consumption estimates are calibrated to respondent having full shopping responsibility. All values are smoothed using a two-bin moving average. Panel (b) plots daily DCPC nondurable consumption C^n and respondent income. Years are concatenated. Panel (c) plots C^n from panel (b) by bill and non-bill consumption expenditures.

Panel (c) drops income and zooms in on daily consumption, which actually is consumer expenditures. Panel (b) obscures the important fact that daily consumer expenditures can exhibit considerable volatility and discreteness like income does. The stacked-bar time series decomposes total non-durable consumption (top of black bars) into non-bill payments (gray shading) and bill payment (remainder). Much, but not all, volatility in total consumer expenditures stems from bill payments, most of which occur monthly – even when consumption is daily (e.g., electricity or water services). Thus, non-bill consumption (expenditures) are even smoother than total consumption appears in Panel (b).

5.2 Exercise #2: Real-Time Forecasts

The DCPC's relatively high coverage of U.S. data motivates *ex post* investigation of potential advantages in leveraging real-time DCPC data, such as for macroeconomic forecasting.[31] This section reports results of two real-time forecasting exercises to further validate and illustrate the value of the DCPC data.[32]

5.2.1 Aggregate DCPC Consumption

The first exercise updates the methodology in Schuh (2018) through 2016-2020 to produce daily forecasts of the final estimate of the level of October DCPC adjusted consumption per capita, $\overline{X}^{c}_{10,t}$. The daily projection (caret) is

$$\widehat{\overline{X}}^{c}_{dmt} = \sum_{s=1}^{d} \left(\frac{31}{d} \right) \overline{X}^{c}_{smt} \ .$$

Where $31 = D_{10,t}$. This univariate projection is inefficient because it does not include prior information, notably $\widehat{\overline{X}}^{c}_{9,t}(30)$, due to data limitations (October only), or other data like income, interest rates, or other business cycle factors.

The left panel (a) in Figure 3 plots daily real-time projections of October 2018 DCPC consumption as an example. Dashed lines are 95 percent confidence intervals. As in 2012 (Schuh, 2018), daily projections of October consumption in 2018 converged quickly to their final estimate on October 31. The projection falls within the standard error band by about October 10. Results are similar overall for 2016-2020, with moderate variation in starting

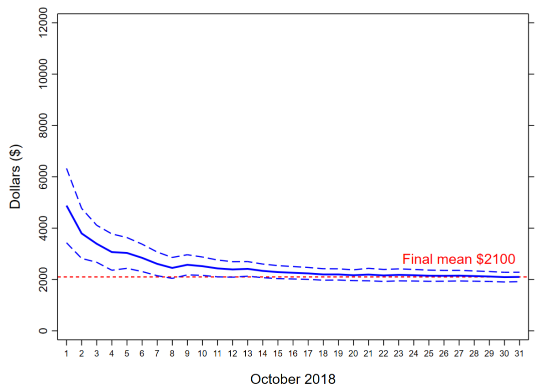
[31] Exercises in this section are analogous to the Atlanta Fed's GDPNow estimates of daily real GDP growth stemming from Faust and Wright (2009), which compared the Fed's Greenbook projections with forecasts of the FOMC's four projection variables based on large-scale real-time data sets. See GDPNow.

[32] For exercise # 2 and #3, we utilize the Fed scripts for cleaning DCPC data outliers.

values and convergence to statistical precision.[33] Thus, real-time access to DCPC data offers an early, reliable forecast of monthly DCPC consumption, albeit an underestimate of PCE. For comparison, PCE data for October are not published until late November and subject to revisions.

Figure 3: Daily Estimates and Annual Forecasts: 2018

(a) Daily Estimate of Monthly Payments



(b) Forecasting Annual DCPC Growth

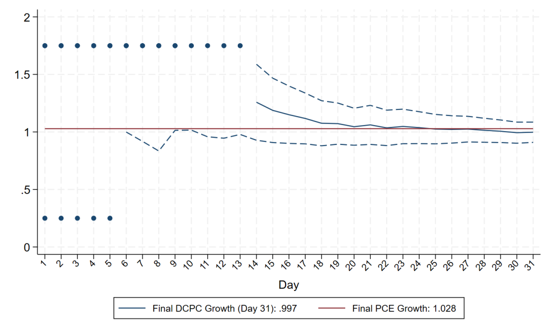


Figure 3 reports the daily estimates of annual DCPC growth for 2018 (right panel) and the daily estimates of monthly payments per consumer for 2018 (left panel). The solid blue line in the right panel represents G_{dmt} for each day of the diary, while the red line shows PCE growth G^*_{mt}. In the left panel, dashed lines indicate 95% confidence intervals, and the dotted red line is the final mean. Scatter points cap estimates above 1.75 and below .25 for display purposes. 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. The estimation procedure from Schuh (2018) is used for calculating standard errors in panel (a).

5.2.2 PCE Growth

A second exercise quantifies how well daily DCPC consumption data can forecast monthly PCE, the more comprehensive measure of aggregate consumption. We use adjusted consumption, for which the DCPC covers only 72 percent of adjusted PCE, so daily projections of DCPC consumption may not be useful for real-time forecasts of the monthly *level* PCE. However, because the DCPC is a relatively representative sample, the *growth* of DCPC consumption might be good predictor of PCE growth. Data limitations require forecasts of annual growth rates.

Let C_{mt} denote PCE adjusted consumption, which is only available monthly. Projecting monthly PCE growth in October, $G^c_{10,t} = (C_{10,t} - C_{9,t})/C_{9,t}$, would require monthly DCPC

[33] See Appendix Figure B4 for the full set of projections in 2012 and 2016-2020. Recall that 2012 data included consumption expenditures that were identified improperly at the time, so the final 2012 estimate is significantly higher than 2016-2020.

growth in October, $G^x_{10,t} = (X^c_{10,t} - X^c_{9,t})/X^c_{9,t}$. However, $X^c_{9,t}$ does not exist because the Diary is implemented only in October each year.[34] Instead, we construct the daily projection of 12-month growth rates of DCPC adjusted consumption,

$$\widehat{G}^x_{d,10,t} = \left[\frac{\sum_{s=1}^{d} \left(\frac{31}{d}\right) \overline{X}^c_{s,10,t}}{\overline{X}^c_{10,t-1}} \right]^{\frac{31}{d}} ,$$

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

$$G^c_{10,t} = \left[\frac{C_{10,t} - C_{10,t-1}}{C_{10,t-1}} \right] ,$$

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

The right panel (b) of Figure 3 plots daily projections of $\widehat{G}^x_{d,10,t}$ for 2018 as an example. Scatter points denote values outside the reported range and are truncated for display. The solid blue line is DCPC estimates of $\widehat{G}^x_{d,10,t}$ and dashed blue lines are standard error bands. The red line is the *ex post* monthly (constant) PCE estimate of G^c_{mt}. Like projections of DCPC consumption levels, $\widehat{G}^x_{dmt}$ converges to its end-of-month estimate, which is close to PCE growth. Again, results are similar for other years; though relatively quick in 2017, convergence takes longer in later years. See Appendix Table B5 for the full set of annual projections for 2017-2020.

Although promising, projections of PCE growth are less accurate than DCPC level projections. Growth projections take at least half month or more before converging to the actual PCE estimate. Accurate estimates of PCE growth by October 31 would be valuable advance notice of real-time consumption activity. However, the standard error bands are too large to provide confident projections, especially early in the sample. The mean forecast error, $\widehat{G}^x_{mt} - G^c_{mt}$, is relatively small: $-.028$ for four years and .012 excluding the 2020 outlier. However, the error sometimes is 5 percentage points in absolute value, which limits the usefulness of DCPC projections for real-time forecasting and policy analysis. More development of the Diary and larger sample sizes are needed to produce more accurate real-time forecasts.

[34] 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. However, the short, noisy, and less representative two-day DCPC sample makes the exercise unacceptably imprecise.

5.3 Exercise #3: Income Timing and Consumption

This subsection follows the literature to estimate how the timing of income payments influences consumption. Our estimates using more representative DCPC data are compared with those from convenience samples in the literature.

5.3.1 Payday Effects on Consumption

Prior studies using daily individual-level transaction data (Stephens Jr, 2003; Gelman et al., 2014; Olafsson and Pagel, 2018) document an economically significant payday effect in which average consumption expenditures are greater on days when expected income is received. We estimate an equation found commonly in the literature:

$$\frac{X^c_{idmt}}{\overline{X}^c_i} = \sum_{s=-7}^{7} \beta_s I_i(Paid_{d+s,mt}) + \eta_i + \lambda_t + \lambda_{DOW} + \lambda_{WEEK} + \varepsilon_{idmt} \tag{1}$$

where $X^c_{idmt} \;/\; \overline{X}^c_i$ 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 (1) at the consumer level and daily frequency.[35] For comparison with the literature, we estimate equation (1) with data on total (all) consumption, non-recurring spending (excludes bill payments), and fast food/restaurant spending. Bill payments are often regarded as commitment expenditures (Chetty and Szeidl, 2007; Baugh and Wang, 2018; Vellekoop, 2018; Gilyard, 2023) that are different from a payday effect on more discretionary spending. However, bill payments are interesting in their own right and included for comparison.

Payday effects in the representative DCPC data are positive and statistically significant but economically different from the literature, as shown in Figure 4 which plots the estimated β_s coefficients of around paydays for all spending categories. Consistent with the literature, DCPC consumption expenditures are about 60 percent higher on paydays relative to average

[35] 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.

Figure 4: Consumption Response to Income Payments

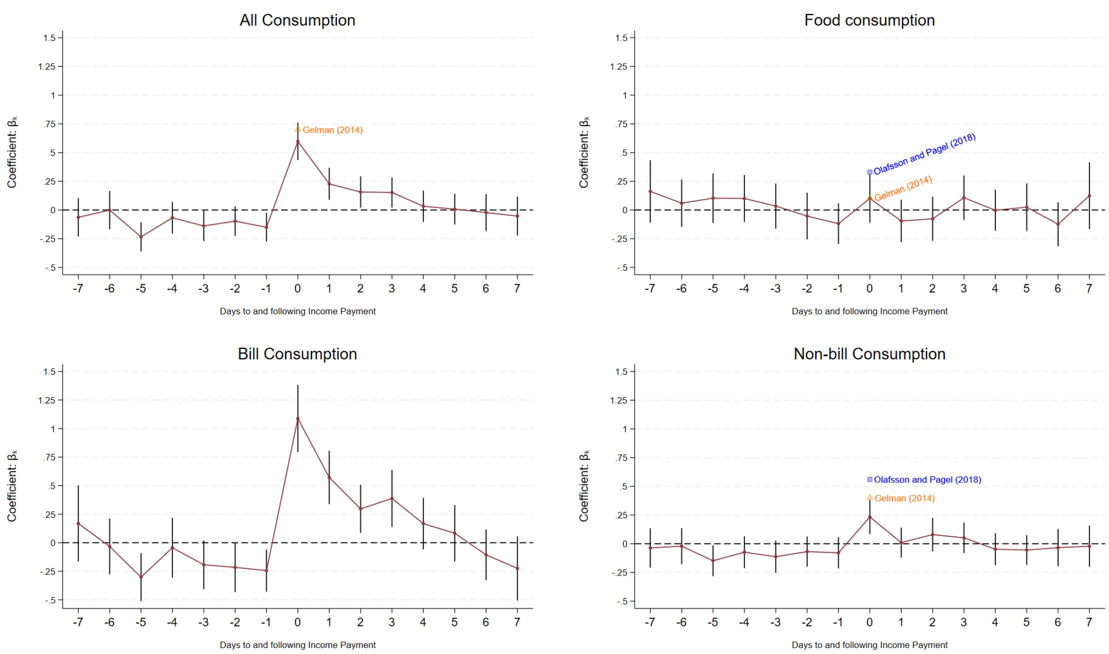


Figure 4 reports the β_s coefficients from equation 1 over the four consumption categories. Negative days denote days before income payment (-7 through -1), while positive days denote days after income payment (1 through 7). paydays. Black lines denote 95% confidence intervals. Results from Gelman et al. (2014) are included in orange, and Olafsson and Pagel (2018) are reported in blue where applicable. Results from Gelman et al. (2014) are taken from their Figure 2 and are approximate. Results from Olafsson and Pagel (2018) are the average of four salary quartile estimates from their Table 2. Stephens Jr (2003) utilizes dollar values, and thus these results are not included.

daily expenditures. Most of this effect is attributable to bill consumption expenditures, which are more than double (109%) on paydays but less discretionary. For this reason, the literature focuses on non-bill expenditures, where the DCPC effect is 23 percent higher on paydays, and food, where the DCPC effect is 10 percent but insignificant. Non-bill $\widehat{\beta}_s \approx 0$ for $s \neq 0$, so the effect on discretionary spending is unique to paydays. The magnitude and persistence of payday effects on bill consumption suggests consumers may align bill payments with income payments. See Gilyard (2023) for a more detailed analysis of bill payments.

DCPC payday effects are lower than in the literature, as shown in the figure. Discretionary non-bill effects are 40 percent in Gelman et al. (2014) and 56 percent in Olafsson and Pagel (2018), and the total consumption effect is 70 percent in Gelman et al. (2014); the insignificant food consumption effect is similar to Gelman et al. (2014).[36] We cannot assess the statistical significance of differences between DCPC estimates and the literature without the data or standard errors. However, given the relative representativeness of the DCPC, the results may suggest economically non-trivial quantitative selection effects.

5.3.2 Pay-Cycle Borrowing

A recent literature has found that when consumers exhibit time-inconsistent preferences, consumers behave differently within and across pay-cycles (Baugh and Wang, 2018; Baugh and Correia, 2022; Parsons and Van Wesep, 2013). Baugh and Correia (2022) extend the model of pay frequencies established by Parsons and Van Wesep (2013) by allowing a hyperbolic-discounting agent to save with an illiquid savings vehicle. The model predicts that agents with higher pay frequencies borrow less (or repay more debt) than consumers with lower pay frequencies, which they verify with analyses of credit card borrowing and repayment across and within consumers. Following Baugh and Correia (2022), we collapse the more representative DCPC data into frequency-day bins based on respondents' survey responses.[37] Then, we run the following specification in dollars and in percentages of monthly income:

$$Z_{fdt} = \phi' Freq_f + \lambda_{DOW} + \lambda_d + \lambda_t + \varepsilon_{fdt} \tag{2}$$

where Z_{fdt} is credit card expenditures or debt repayment, and λ denote day-of-week, day, and annual fixed effects for frequency bin f. $Freq_f$ is a set of indicator variables for each income frequency bin, with monthly as the omitted variable. Thus, the model predicts a

[36] Gelman et al. (2014) finds a modest increase in food spending a number of days after the payday.

[37] When collapsing, we weight by day-of-week weights while Baugh and Correia (2022) weight by the number of observations within each bin. A respondent is included in frequency bin f if they reported having any of the ten income types with such frequency.

decline outcome variables with an increase in pay frequency.

Table 2: Paycheck Frequency Analysis

	Rolling Borrowing				Rolling Repayment			
	(1) % of Y (p.p)	(2) % of Y (p.p)	(3) $/day	(4) $/day	(5) % of Y (p.p)	(6) % of Y (p.p)	(7) $/day	(8) $/day
Panel A: Gilyard and Schuh								
Semi-Monthly	-0.012	0.003	4.103	0.938	-0.077	-0.115	2.396	-3.953
	(0.036)	(0.043)	(1.860)	(2.537)	(0.087)	(0.080)	(4.246)	(4.451)
Weekly	-0.104	-0.097	-3.244	-4.630	-0.188	-0.205	-6.708	-9.487
	(0.039)	(0.041)	(1.896)	(1.930)	(0.082)	(0.078)	(3.578)	(3.707)
Monthly Income (Y^H_{fmt})		-0.000		0.002		0.000		0.003
		(0.000)		(0.001)		(0.000)		(0.001)
R^2	0.09	0.09	0.11	0.12	0.16	0.16	0.15	0.16
Adj. R^2	-0.00	-0.00	0.02	0.03	0.07	0.07	0.07	0.07
F	5.15	5.45	8.62	5.14	3.52	3.62	4.11	3.80
$p - value$	0.01	0.00	0.00	0.01	0.03	0.03	0.02	0.02
Panel B: Baugh and Correia (2022)								
Semi-Monthly	-0.175	-0.172	-4.309	-3.870	-0.426	-0.455	-12.110	-12.470
	(0.007)	(0.007)	(0.267)	(0.276)	(0.020)	(0.020)	(0.877)	(0.882)
Weekly	-0.395	-0.348	-16.330	-8.921	-0.935	-1.430	-43.710	-49.740
	(0.007)	(0.023)	(0.257)	(0.832)	(0.019)	(0.045)	(0.832)	(1.701)
Monthly-Income		0.000		0.010		-0.001		-0.008
		(0.000)		(0.001)		(0.000)		(0.002)
R^2	0.501	0.502	0.534	0.556	0.714	0.743	0.735	0.737
Adj. R^2	0.495	0.497	0.529	0.551	0.711	0.74	0.732	0.734
F	1828.32	328.33	2217.69	108.28	1410.32	603.71	1947.42	429.13
$p - value$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

[1] Table reports the results on the cross-sectional differences of pay-check frequency on borrowing and repayment for this paper (Panel A) and Baugh and Correia (2022) (Panel B). Regressions are calculated at the paycheck frequency group - day level. Rolling borrowing refers to credit card expenditures, while rolling repayment refers to credit card repayments. % of income reports dollar values divided by monthly household income, while $ / day refers to daily dollar values (2012 USD for this paper). Even columns control for household income. Results are robust to heteroskedasticity. F reports the F statistic for the joint probability of paycheck frequencies, and p-value reports this F statistic p-value.

Table 2 reports estimates of equation (2). Estimates in Panel A (this paper) are from DCPC data and estimates in Panel B are from Baugh and Correia (2022).[38] The reported F-value (and associated p-value) correspond to a joint significance of the two indicator variables. The first four columns (Rolling Borrowing) report results for the credit card borrowing dependent variable, while the remaining columns report the debt repayment dependent variable.

In general the DCPC estimates reveal a similar relationship between credit activity and pay frequency as found in Baugh and Correia (2022) but smaller magnitudes. Consumers with weekly pay frequencies exhibit less rolling borrowing and repayments, while semi-monthly pay frequencies report little differences in the dollar value measurement. Our statistical precision is variable, with the weekly indicator corresponding to generally lower standard errors than semi-monthly. The R^2 and F statistic in Panel A is much smaller than reported in Panel B, likely due to many less observations in our sample. Results in Panel A suggest

[38] Y^H_{fmt} is respondents' annual household income divided by twelve in $2012. It is unclear whether Baugh and Correia (2022) use nominal or real values. We use all income sources of consumers, and include a consumer in a frequency bin if they have any of the frequency bin types. Following the authors, we combine consumers who get paid twice a month and every other week in the semi-monthly category.

that consumers exhibit similar time-inconsistent preferences as found in Baugh and Correia (2022). However, lower magnitudes in the more representative DCPC data may suggest that time-inconsistent preferences are more prevalent in convenience samples.

6 Consumption and Income Models

The relative success of the DCPC in matching aggregate U.S. data begs the question: how well do consumption models fit these high-frequency micro data? One way to answer is by estimating the benchmark permanent income hypothesis (PIH) model, which is designed to fit consumer decisions at lower frequencies (annual, quarterly, or monthly) and typically estimated with aggregated data. This section describes the benchmark model by generally following the style and notation of Jappelli and Pistaferri (2017).[39]

6.1 Theoretical Model

Equations 4.1 - 4.2 of Jappelli and Pistaferri (2017) lead to the well-known consumption Euler equation is:

$$U'(C_t) = \beta(1 + r)\mathbb{E}_t U'(C_{t+1}) \tag{3}$$

where $U(\cdot)$ is the utility function, C is consumption, and $\mathbb{E}_t$ is the expectations operator. We assume the real interest rate, r, subjective rate of time preference, δ, and hence discount factor, $\beta = (1 + \delta)^{-1}$, are all constant.

This special case of the Euler equation is restrictive given the conventional specification of stochastic fluctuations in discount rates (Attanasio and Weber, 1993). However, the S/DCPC does not have data on consumer-specific rates that would enable estimation of traditional Euler equations, which are not without controversy.[40] Furthermore, daily interest rates are smaller and less volatile—especially within discrete income periods—than lower frequency rates, which raises questions about their importance in governing intertemporal substitution of consumption across days versus longer time periods.

Further analysis requires specification of the utility function. Assuming linear marginal

[39] The benchmark PIH model abstracts from the rich, granular details of daily decisions documented in the DCPC. See Gilyard and Schuh (2025) for a more general model of daily consumption behavior that nests the benchmark (PIH) model and incorporates more details of the DCPC data.

[40] For examples, see Carroll (2001) and Attanasio and Low (2004). Also, GMM estimation of Euler equations can be biased in small samples (e.g., Fuhrer et al., 1995).

utility and $\delta = r$ for analytical purposes, consumption follows a random walk:

$$C_t = C_{t-1} + e_t \tag{4}$$

with innovation e_t.[41] With an infinite horizon, the solution for e_t is:

$$\Delta C_t = e_t = \frac{r}{1+r}(\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{\tau=0}^{\infty} \frac{Y_{t+\tau}}{(1+r)^\tau} = \zeta_t + \frac{r}{1+r} v_t \tag{5}$$

where Y is income and ζ_t, v_t are permanent and transitory income shocks respectively. Consumers smooth consumption and only change consumption in response to income shocks, responding fully to permanent shocks, ζ_t, and less to transitory shocks, v_t.

Two approaches to identifying permanent versus transitory income shocks are common in the literature. The traditional strategy is to model the income process explicitly; contemporary efforts use actual data on observed income that plausibly identify various types of unexpected changes.[42] Inferring the nature of shocks from observed data offers less structural interpretation but avoids deleterious misspecification errors that can arise from modeling income. However, the S/DCPC data do not have sufficient information to feasibly identify the nature of shocks to individual consumer or household income. Instead, we model income as the sum of expected and unexpected components,

$$Y_t = \mathbb{E}_{t-1} Y_t + u_t \ ,$$

where $u_t = \zeta_t + v_t$. Then we use the common reduced-form specification of the PIH (Jappelli and Pistaferri, 2017, Chapter 8)

$$\Delta C_t = \beta_0 + \beta_1 \mathbb{E}_{t-1} \Delta Y_t + \beta_2 u_t + \varepsilon_t \tag{6}$$

$$\mathbb{E}_{t-1} \Delta Y_t = \Delta Y_t - u_t \tag{7}$$

where the PIH predicts $\beta_1 = 0, \beta_2 > 0$. Evidence in the literature overwhelmingly rejects $H_0 : \beta_1 = 0$, repeatedly documenting excessive sensitivity of consumption to predicted (expected) income (Jappelli and Pistaferri, 2010; Havranek and Sokolova, 2020), although

[41] Under more realistic convex marginal utility, a second-order Taylor expansion with CRRA utility results in an additional precautionary savings motive (Kimball, 1990; Carroll and Kimball, 1996), $\frac{(1+\gamma)}{2}\mathbb{E}_t(\Delta c_{t+1})^2$. This term is likely correlated with predicted income, which can lead to spurious rejections of the PIH (Carroll, 1997). 90 percent of the studies in Havranek and Sokolova (2020) use the first-order approximation. We report results with and without the precautionary savings motive and compare our results with the literature.

[42] Notable examples of the first approach include Hall and Mishkin (1980) and Blundell et al. (2008). An example of the second approach is Baker (2018).

credit or liquidity constraints and omission of precautionary saving motives (Carroll, 1997, 2001) can at least partly explain the rejection. The magnitude of β_2 depends on the relative importance of permanent and transitory shocks: $\beta_2 u_t = \phi_1 \zeta_t + \phi_2 v_t$.[43]

To guard against and assess potential misspecification errors on benchmark PIH model estimates, we estimate multiple income models. Several specification appear in the literature and it is unclear *a priori* which fits the DCPC data best. Therefore, we consider four options for constructing expected income:

$$Y_t = \mathbb{E}_{t-1} Y_t \tag{M0}$$

$$Y_t = \alpha + Y_{t-1} + FE + TE + u_t^{M1} \tag{M1}$$

$$Y_t = \alpha + Y_{t-1} + \rho_2 (Y_{t-2} - Y_{t-3}) + FE + TE + u_t^{M2} \tag{M2}$$

$$Y_t = \alpha + \rho_3 Y_{t-1} + FE + TE + u_t^{M3} \tag{M3}$$

M0 is perfect foresight. In addition to serving as a benchmark, it may be plausible for high-frequency data if forthcoming income payments are virtually certain given employment stability and payroll lags. M1 specifies a unit-root process, implying that all shocks are fully persistent, as in a permanent-income specification (Meghir, 2004). Although simple and parsimonious, stochastic trend models are not estimated precisely over shorter time periods like the DCPC data, and may not be suitable at the micro level due to finite life cycles. M2 is an instrumental variables approach popular in the applied micro literature (Deaton et al., 1992; Jappelli and Pistaferri, 2017). Although this specification may be optimal with many time-series observations, the annual model only has five years. M3 is an AR(1) process. In all models, we include time-invariant fixed effects (FE) and time effects (TE) discussed further below. Although these models do not identify ν_t and ζ_t, they produce estimates of $\mathbb{E}_{t-1} \Delta Y_t$ and u_t.

6.2 Econometric Models

Given their unique panel structure, the daily DCPC micro data support estimation of two main frequencies of econometric models: annual and daily. Let $Z_{idmt} = \{C_{idmt}, Y_{idmt}\}$ denote

[43] Appendix C shows that when income is an AR(1), $\Delta C_t = \left(\frac{r}{1+r}\right)\left(\frac{1+r}{1+r-\rho}\right) \cdot u_t = \Omega \cdot u_t$, where ρ is the AR(1) coefficient that can be viewed as a proxy for permanent versus transitory shocks (Jappelli and Pistaferri, 2017). When $\rho = 1$, $\Omega = 1$ and income innovations are fully realized as changes in consumption, suggesting permanent income shock. When $\rho = 0$, $\Omega = \frac{r}{1+r}$. This analytical model does not necessarily capture all the nuances of a fully specified income process, but it gives a simple benchmark with which to evaluate econometric tests. Results are reported in the footnote of the benchmark consumption estimation table. The PIH from (5) predicts $\beta_1 = 0$, $\phi_1 = 1$, and $\phi_2 = \frac{r}{1+r}$. Extensions such as convex marginal utility predict smaller values for ϕ_1 and larger values for ϕ_2, but with similar conclusions in that $\phi_1 > \phi_2$.

DCPC variables for consumer i on day $d = \{1, \ldots, 31\}$ of month $m = \{1, \ldots, 12\}$ in year $t = \{2016, \ldots, 2020\}$. *Daily* DCPC data, $Z_{id,10,t}$, are available for October 1-31 in 2016-2020. The October panel segments can be concatenated across years and treated as pseudo-continuous, except for October 1 each year. *Monthly* data are time-aggregated sums of daily activity:

$$Z_{i,10,t} = \sum_{d=1}^{31} Z_{id,10,t} \ .$$

Although $Z_{i,10,t}$ does not represent the entire year, $\Delta Z_{i,10,t} = Z_{i,10,t} - Z_{i,10,t-1}$ represents the *annual* (12-month) change between Octobers.[44] More generally, annual and daily changes are, respectively:

$$\begin{aligned} \Delta_m^{12} Z_{imt} &= (Z_{imt} - Z_{im,t-1}), \qquad m = 10 \\ \Delta_d^{1} Z_{idmt} &= (Z_{idmt} - Z_{id-1,mt}), \qquad 1 < d \leq 31 \ . \end{aligned}$$

Following theoretical equations (6) and (7), the annual and daily econometric PIH models, respectively, are:

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

$$\Delta_d^{1} C_{id,10,t} = \beta_0 + \beta_1 \widehat{\Delta_d^{1} Y_{id,10,t}^R} + \beta_2 u_{id,10,t} + TE + \varepsilon_{id,10,t} \ . \tag{9}$$

where $C_t = C_t^n$ is consumer expenditures on nondurable goods and services (defined in Section 4.1), and the caret denotes predicted (expected) income changes,

$$\begin{aligned} \widehat{\Delta_m^{12} Y_{i,10,t}^H} &= \Delta_m^{12} Y_{i,10,t}^H - u_{i,10,t} \\ \widehat{\Delta_d^{1} Y_{id,10,t}^R} &= \Delta_d^{1} Y_{id,10,t}^R - u_{id,10,t} \ , \end{aligned}$$

which are constructed from first-stage estimation of the income models (M0-M3). TE refers to daily time effects that capture, in a reduced form way, the distinction between continuous consumption and discrete expenditures. PIH models do not include fixed costs associated with shopping time that would lead to some infrequent expenditures like gasoline, groceries, and especially monthly bill payments.

In both annual and daily models, consumption changes are only for consumption by consumer i. Changes in daily income, ΔY^R, also are only consumer i (respondent) income, and thus match the dependent variable. However, changes in annual income are for the household,

[44] The Federal Reserve fielded the DCPC in October precisely because it has minimal seasonal factors in aggregate real economic activity.

$\Delta Y^H = \Delta Y^R + \Delta Y^O$. Y^R is utilized at the daily frequency as Y^H only varies by survey year. Like the typical benchmark PIH model, the annual model abstracts from household structure and implicitly assumes individual consumers have full access to ΔY^O when making their own consumption decisions.[45] Successful estimation and inference of equations (8) and (9) depends on accurate, efficient estimation of the income process.

Estimating the PIH model with daily data is novel because it usually is estimated with lower frequency data (annual, quarterly, or monthly). Even studies with daily data typically time-aggregate transactions to lower frequencies for testing models (e.g., Baker, 2018; Ganong and Noel, 2019; Gelman, 2021). Applying the PIH model to daily data provides the opportunity to account for the effects of time aggregation on consumption smoothing, which are hidden in low-frequency data (Crawley, 2020). In particular, the benchmark model assumes consumption occurs simultaneously with the receipt of income (synchronous). In reality, consumption occurs daily while income arrives discretely at lower frequencies (asynchronous). This consumption-income frequency mismatch highlights the importance of personal financial management that are not explicit in the benchmark PIH model, such as payday effects (Gelman et al., 2014; Olafsson and Pagel, 2018) and bill payment effects (Gilyard, 2023).

The econometric models are estimated using OLS in two stages. In the first stage, income models M0-M3 are used to estimate changes in income, ΔY. The predicted income changes are used as generated regressors in the second-stage equations (8) and (9), whose standard errors are corrected for the use of the predicted income changes.[46] The models are estimated with data in dollar values (uppercase C, Y), which yield estimates of the *MPC* under linear marginal utility from equation (4), and in logs (lowercase c, y), which yield estimates of *elasticity* resulting from convex marginal utility. For the analysis, we utilize the Fed scripts for cleaning DCPC data outliers.

6.3 Synthetic Cohorts

The DCPC unbalanced longitudinal panels (overlapping diary waves) prevents direct estimation of the econometric models with daily data at the consumer level.[47] Although daily samples are representative of consumers, each individual consumer (respondent) only records data for three randomly selected days in October. Three days are insufficient time series for estimation, even for five years (15 observations). Moreover, a one-tenth sample (3 of

[45] Average monthly household income ($Y_{it}^H/12$) is used to match the frequency of consumption.

[46] The second-stage standard errors are bootstrapped with 1000 replications.

[47] The DCPC can support estimation of models at the transaction-level *within* days (Briglevics and Schuh, 2014).

31 days) is unlikely representative of the consumer's monthly activity. For examples, many respondents do not receive income (even those paid weekly), some expenditures are weekly (gas or restaurants), and many bill payments are monthly. For these reasons, the DCPC data must be converted to synthetic cohorts.

To obtain continuous daily time series with sufficient observations at the individual level, we construct synthetic cohorts, which have been used to study life-cycle behavior within the literature, especially with repeated cross-sections (Blundell et al., 1994). The S/DCPC sampling design is ideal for aggregating daily respondent-level data with finite time series within cohorts denoted by subscript $k = \{1, 2, \ldots, K\}$. For continuously valued variables like consumption, the cohort-level variable is the average over all consumers in the respondent:

$$\overline{C}_{kdmt} = \frac{\sum_{i=1}^{I_{kdt}} w_{idt}^{D} \cdot C_{idmt}}{\sum_{i=1}^{I_{kdt}} w_{idt}^{D}} , \tag{10}$$

which balances longitudinal panel to have k cohorts with 31 continuous time series observations each October. The cohort-level balanced panel of daily data can be used for estimation or to construct time-aggregated data at lower frequencies.

Cohorts are defined by respondent characteristics that are essentially exogenous and fixed across time. K is an arbitrary specification chosen judgmentally based on available characteristics to maximize K (heterogeneity) given sample size (number of respondents and time periods). Our baseline estimation uses $K = 14$ (seven ages and two biological genders) with five years of October observations for 70 annual observations, and 155 days for 2,170 daily observations. The median number of respondents per cohort on any given day is 17, which is lower than the amount recommended by Verbeek and Nijman (1993).[48] Other cohort definitions are used and described later. Although synthetic cohorts enable model estimation, they mask heterogeneous consumer-specific events within cohorts.

To replicate the literature, we construct cohorts based on constraints defined in Aguiar et al. (2024), who categorize consumers as constrained by net worth (Zeldes, 1989) and net liquidity (Kaplan et al., 2014). Consumers are constrained (C) by net worth if they have less than two months' household income, or by net liquidity if: 1) their net liquidity is positive but equal to one week or less of household income; or 2) they have a negative liquidity whose

[48] From simulated data, Verbeek and Nijman (1993) find that 100 individuals per cohort obtain minimal bias from small samples. Therefore, while synthetic cohorts allow us to study predictions of consumption models in the DCPC, the lack of individuals per sample may suffer from small sample bias.

absolute value is greater than 16.5% of monthly household income.[49,50] Otherwise, consumers are unconstrained (U). Constraint criteria can be applied to consumers each period (denoted time varying), or over a longer time period (time invariant). In the former, consumers' data moves across constraint categories, which can affect estimation. In the latter, consumers are constrained if they meet the qualifications in any one of the time periods (usually five Diary years), with at least one consumer in each each diary day for all cohorts. We use time-invariant constrained cohorts; Appendix D reports results for time-varying cohorts.

Using synthetic cohort data, separate consumption and income models M0 - M3 are estimated for each cohort k at annual and daily frequencies. Table 3 summarizes FE and TE included in each income and consumption equation (See Appendix D for detailed specifications of each income model.). Each annual income model includes η_{AGE}, life-cycle age fixed effects (excluding biological genders) and their interaction with a linear time trend t for M2-M3 motivated by the time-series graphs of income by age in Appendix Figure D1. Although the time-period is short, incomes exhibit heterogeneous trends that roughly conform with standard life-cycle expectations: higher for younger ages, slower for for middle ages, and flat or slightly decreasing for older ages. To capture the additional complexity of daily data, daily estimates include interacted time and day fixed effects (year-by-day), λ_t and λ_d, cohort fixed effects, η_k, and within-cohort shares of consumer-specific variables, $\vartheta^j_{kd,10,t}$ (superscript j). Each period, the N_j variables include share consumers education levels, income rank within households, paycheck frequency, and income type.[51]

7 Estimation Results

This section presents results for the two-step estimation of models of changes in income (first stage) and changes in consumption (second stage).

[49] Kaplan et al. (2014) look at wealthy hand-to-mouth households who have little liquid assets *and* have a high amount of net-worth. Given our limited sample, we are not able to isolate these individuals specifically into a constrained cohort. Credit card debt is the consumer's reported September value, so there is a mistiming between the liquid asset and liquid debt. However, this specification follows the liquidity definition of Aguiar et al. (2024) as closely as possible.

[50] In defining consumers as liquidity constrained with household income, our income definition differs from other authors Aguiar et al. (2024) who uses labor income plus government transfers. Given the survey questions, we are not able to decompose household income further and thus use total household income.

[51] Every respondent reports whether they receive any of the ten types of income discussed in the appendix regardless of whether they received income during their diary period. Additionally, every respondent reports the frequency at which they receive income: weekly, bi-weekly, semi-monthly, monthly, quarterly, annually, other (one-time, regular, or irregular).

Table 3: Fixed Effects and Time Effects Included in Income and Consumption Models

		Income						Consumption	
		Annual			Daily			Annual	Daily
Variable	Description	M1	M2	M3	M1	M2	M3		
η_{Age}	Age Fixed Effects	X	X	X					
$\eta_{Age} \times t$	Age-Linear Time Trend Interaction		X	X					
η_k	Cohort Fixed Effects				X	X	X		
$\lambda_t \times \lambda_d$	Day-by-Year Time Fixed Effects				X	X	X		
ϑ_{kdt}	Cohort-Share Control				X	X	X		
$\lambda_{DOW} \times \lambda_W$	Day-of-week by Week-of-Month Time Fixed Effects								X

7.1 Income Dynamics

Table 4 reports first-stage estimation results for income models M1-M3 with annual and daily data; dependent variables are the income changes. Rows contain estimates of the autoregressive coefficients (ρ_2 and ρ_3), R^2, and percentage of R^2 accounted for by time and fixed effects. Note that model M0 has no parameters or errors ($R^2 = 1$), and model M1 restricts the implicit coefficient on Y_{t-1} ($\rho_1 = 1$).

Table 4: Predicted Income Estimates

	Annual			Daily		
	M1	M2	M3	M1	M2	M3
Levels						
α_i	399.18**			-101.44**		
	(144.07)			(40.88)		
ρ_2		-0.17			-0.04	
		(0.34)			(0.02)	
ρ_3			0.50***			0.03
			(0.14)			(0.05)
R^2	0.07	0.73	0.42	0.19	0.19	0.55
% R^2 explained by TE, FE, and Controls	71	70	71	100	100	22
Logs						
α_i	0.07***			-3.75**		
	(0.02)			(1.39)		
ρ_2		-0.10			-0.04	
		(0.29)			(0.03)	
ρ_3			0.60***			0.03
			(0.13)			(0.02)
R^2	0.08	0.71	0.37	0.28	0.28	0.63
% R^2 explained by TE, FE, and Controls	63	78	73	100	96	33

[1] Table reports coefficients of income prediction models specified in M1-M3. Each model reports R^2 estimates as a goodness-of-fit measurement. Models include time-invariant fixed effects and time effects. Models are then run to exclude any fixed and time effects to calculate % of R^2 due to these controls. M1 estimates reported are the base category for fixed effects.

Overall, model M3 fits the income data best. Model M1 has very low annual R^2 and relatively low daily R^2 for both level and log specifications. Most likely, the relatively short time period (2016-2020) is inadequate to identify a stochastic-trend process well. Model M2 fits better, achieving the highest annual R^2 (0.73, 0.71), which is consistent with the literature using micro data at relatively low frequencies. However, with discrete income at the daily frequency, a two-period (two-day) lag reduces instrument relevance and the daily R^2 are much lower (0.19, 0.28).[52] Furthermore, the M1 and M2 models rely inordinately on time and fixed effects to explain income changes (about 70 percent for annual data and 100 percent for daily data), leaving little room for economic time series behavior.

In contrast, model M3 has consistently high fit, with annual R^2 of 0.37-0.42 and by far the highest daily R^2 (0.55, 0.63). The annual autoregressive coefficients are significant for the M3 model, with ρ_3 estimates implying coefficients on Y_{t-1} of -0.40 to -0.50 ($\rho_3 - 1$). The daily autoregressive coefficients are insignificantly different from zero, so the daily M3 model implies a levels specification for income: $\Delta Y_t = -1.0Y_{t-1} = Y_t$. For all these reasons, model M3 seems best suited to predicting income changes in the applied consumption equations.

Figure 5 plots actual (solid lines) and predicted (dashed lines) aggregate income during 2016-2020 for our preferred model M3. The left column is annual data and the right is daily data; the first row is levels and the second is first differences. Annual data include household (blue line) and respondent (red line) income; the latter accounts for about half of total household income. Annual income is smoother due to time-aggregation (monthly sums) and relatively low seasonality in October. However, daily income changes are predicted notably accurately given the substantial heterogeneity in pay frequencies, types of income, and cohorts across days of the week and month.

7.2 Consumption Dynamics

Table 5 reports estimates of the benchmark PIH model with each income model M0-M3. Panel A contains annual estimates of equation (8), and Panel B contains daily estimates of equation (9). All models are estimated with data in levels (*MPC* sub-panel) and in logs (*Elasticities* sub-panel). In each sub-panel, the first row contains estimates of changes in consumption to changes in *expected* income (β_1) and the second row to changes in *unexpected* income (β_2).

7.2.1 Annual Estimates

Overall, the annual estimates in Table 5 are consistent with the literature but statistically insignificant. Although the β_1 coefficients are statistically insignificantly different from zero,

[52] Income changes two days prior are not good predictors of changes in weekly (or lower frequency) income payments. Instead, income changes seven or 14 days prior may be better instruments (for weekly income) but would dramatically reduce degrees of freedom.

Table 5: Consumption Estimates: Benchmark Results

	M0	M1	M2	M3				
	K=A(7)G(2)				K=A(2)G(2)C(2)			
					C=Net Worth		C=Liquidity	
					U	C	U	C
Panel A: Annual								
MPCs								
β_1	0.117	0.224	0.031	0.191	-0.001	0.081	0.153	-0.151
	(0.102)	(0.267)	(0.115)	(0.150)	(0.212)	(0.247)	(0.369)	(0.285)
β_2		0.110	-0.214	0.062	-0.120	0.268	-0.066	-0.139
		(0.109)	(0.351)	(0.209)	(0.362)	(0.335)	(0.448)	(0.259)
R^2	0.02	0.02	0.03	0.03	0.02	0.13	0.02	0.07
Elasticities								
β_1	0.391	0.583	0.175	0.474	0.076	0.328	0.751	-0.300
	(0.321)	(0.698)	(0.328)	(0.406)	(0.677)	(0.776)	(0.981)	(0.760)
β_2		0.385	-0.423	0.341	-0.181	0.859	-0.150	-0.247
		(0.322)	(0.792)	(0.550)	(1.121)	(1.016)	(1.000)	(0.761)
R^2	0.03	0.04	0.02	0.03	0.01	0.15	0.05	0.03
Panel B: Daily								
MPCs								
β_1	0.006	0.032	0.011	0.009	-0.002	0.058^{**}	0.038^{*}	0.010
	(0.007)	(0.025)	(0.027)	(0.012)	(0.014)	(0.023)	(0.020)	(0.021)
β_2		0.004	0.004	0.003	0.013	0.066	0.010	-0.016
		(0.008)	(0.008)	(0.011)	(0.020)	(0.040)	(0.031)	(0.041)
R^2	0.04	0.04	0.04	0.04	0.10	0.11	0.08	0.10
% R^2 explained by TE	94	82	87	92	95	65	84	82
Elasticities								
β_1	0.019^{***}	0.046^{***}	0.036^{***}	0.019^{***}	0.003	0.029^{***}	0.002	0.007
	(0.003)	(0.012)	(0.013)	(0.005)	(0.007)	(0.010)	(0.008)	(0.008)
β_2		0.017^{***}	0.018^{***}	0.019^{***}	0.017^{*}	0.025	0.007	0.020^{*}
		(0.004)	(0.004)	(0.006)	(0.010)	(0.016)	(0.011)	(0.012)
R^2	0.06	0.06	0.07	0.06	0.14	0.10	0.09	0.13
% R^2 explained by TE	55	42	45	53	76	54	94	57

[1] Panel A: Annual results. Panel B: Daily results. All values are reported in 2012 USD values. Sub-panel MPCs reported differences in levels, while sub-panel Elasticities report differences in logs. Grouping M0 - M3 denote income model used. Grouping K denotes the cohorts used. C denotes the cohort constraint specification, where C is constrained and U is unconstrained. $\beta_{1,2}$ correspond to consumption models (8) and (9).
[2] Let Ω denote the MPC implied by the Permanent-Income Hypothesis given the first stage AR(1) coefficient (ρ) from $\Delta C_t = \Omega \cdot u_t$. The real interest rate is calibrated to a 5-year average of real interest rates (DGS10 from FRED), $\Omega = \frac{r}{1+r-\rho}$. Annual Ω: .005 (.001 SE). Daily Ω: .000017 (.000001 SE).
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each subpanel reports R^2 for each regression, and the % of R^2 explained by time effects (TE). Standard errors are bootstrapped (1000 replications).

Figure 5: Annual and Daily Income: Observed vs. Predicted

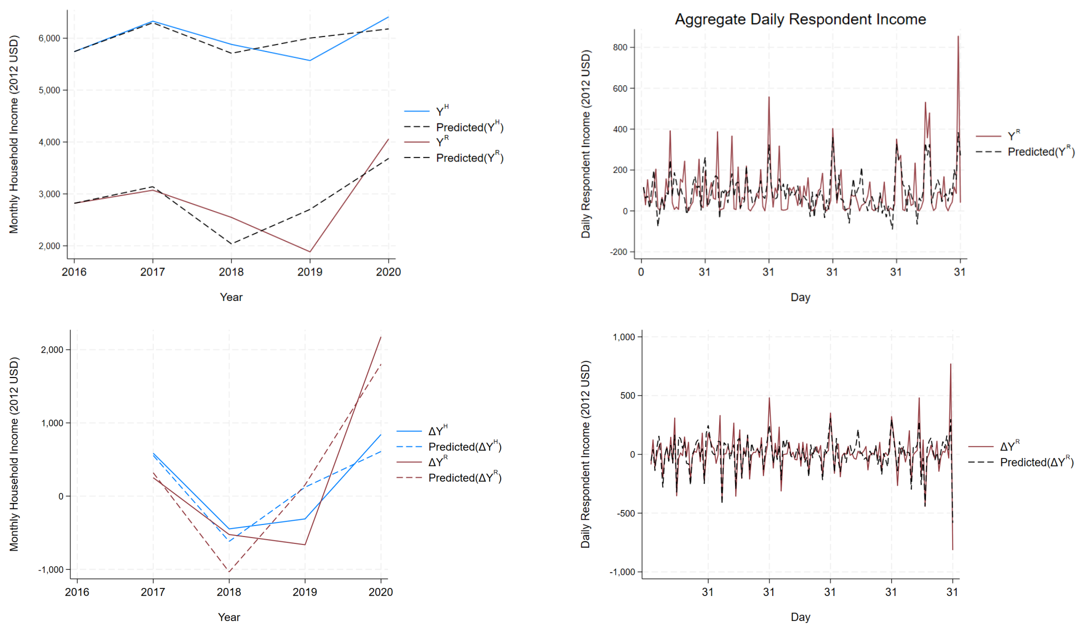


Figure 5 reports monthly income in the first panel and daily income in the second panel over all respondents. The blue line report Y^H, while the red line reports Y^R. The black line in both graphs are the predicted values of each income type at each frequency using a similar specification to M3^t without age cohort controls given the aggregate measurement. The first row reports the levels in income, while the second reports changes in income.

the point estimates in the first four columns are relatively large and consistent across income models, with MPC's of 0.031 to 0.224 and elasticities of 0.175 to 0.583. In fact, the MPC estimates are just slightly lower than the average of .24 for micro data reported by Havranek and Sokolova (2020). These results suggest the model is rejected due to excess sensitivity of consumption to (expected) income.

Annual estimates of β_2 also are imprecise and less consistent across models than β_1, ranging from $-.214$ to 0.110 for MPCs and $-.423$ to 0.385 for elasticities. These results are hard to compare with the literature because $\hat{u}$ combines permanent and transitory components. However, β_2 should be closer to 1 if permanent shocks dominate and closer to 0 if transitory shocks dominate.[53] For comparison, the table footnote reports the analytical response of consumption to income shocks ($\hat{u}_t$) implied by the PIH for income model M3. The calibrated value is $\Omega = r(1 + r - \rho)^{-1} = 0.005$, which is even smaller than the (insignificant) coefficient estimate 0.06; both values suggest the data contain mostly transitory income shocks.[54]

[53] See Carroll et al. (2017), who review estimates of transitory shocks, and Crawley and Theloudis (2024), who review the literature on both transitory and permanent shocks. In both papers, transitory shocks range widely but tend to be lower than permanent shocks. Carroll et al. (2017) estimates the MPC to aggregate transitory shocks at around .20 when accounting for heterogeneity.

[54] We choose the permanent income hypothesis specification for its simplicity and tractability. Estimates

For income model M3 only, the remaining columns (five through eight) report estimates for subsamples of constrained (C) or unconstrained (U) consumers by measures of net worth and liquidity. Consumers constrained by net worth have larger, more positive estimates of β_1 and β_2 than unconstrained consumers. These results are qualitatively similar to the literature but differ quantitatively. Havranek and Sokolova (2020) find excess sensitivity measures are 0.12 lower, on average, for unconstrained consumers.[55] When measured by liquidity, unconstrained consumers have larger, more positive estimates of β_1 and β_2 than constrained, which is not consistent with the literature. One possible explanation is that DCPC liquidity is narrower because it only includes cash (currency) and primary checking account. If consumers with higher income and net worth are more likely to hold lower amounts of non-interest bearing transactions liquidity, and vice versa, then the lower liquidity levels may be associated paradoxically with consumers who are not constrained.

Annual models employ mismatched measures of consumption and income. Consumption changes are for individual consumers (respondent), while the expected income changes are for the total household income, Y^H. The latter potentially includes other household income, $Y^O = Y_t^H - Y_t^R$, which may or may not be accessible to individual consumers in the household for their expenditures. Appendix Table D2 reports the independent effects of expected changes in Y_t^R and Y_t^O on consumer expenditures for all income models. Point estimates for each income type are quite similar but even less precise due to the extra coefficient, thus inhibiting reliable inference.

7.2.2 Daily Estimates

Overall, the daily results in Table 5 are qualitatively similar to the annual results, thus also consistent with the literature, but exhibit two important quantitative differences. First, daily estimates have lower standard errors and thus are statistically more precise due to many more observations (2,170 versus 70). Most elasticity estimates are significant, usually at the 5 percent level, and more consistent across income model specifications. Daily MPCs still are not statistically significant, however. Second, the point estimates of β_1 are an order of magnitude smaller, with MPC's of 0.006 to 0.032 and elasticities of 0.019 to 0.046. Although smaller, the precise β_1 elasticities indicate unequivocal excess sensitivity and rejection of the PIH model. The daily estimates also show modest evidence of failing to reject the PIH

for transitory shocks would be larger under a buffer-stock framework. Ω is calibrated with ρ from $M3^t$ and r as the average real market yield on 10-year constant maturity U.S. Treasury securities (FRED mnemonic DGS10 minus inflation), which averaged .24% over this period.

[55] When constrained categories are time-varying each year, the annual results are less consistent and sometimes contradictory across definitions (see Appendix Table D1).

model for unconstrained consumers (both net worth and liquidity).

Daily estimates of β_2 also are an order of magnitude smaller, precise for elasticities, and relatively consistent across models. The β_2 MPCs are very small and insignificant, hence essentially zero. However, the β_2 elasticities are highly significant and nearly identical, ranging from 0.017 to 0.019 except when distinguishing contraints (β_2 estimates are larger and statistically significant for elasticities of constrained consumers , while insignificant for MPCs.) The daily calibrated Ω reported in the footnote is much less than the annual estimate because the interest rate is much smaller ($r_d = (1 + r_a)^{(1/365)}$).[56]

The model fits reveal additional insights about daily consumption decisions. The R^2 estimates in Table 5 generally are less than 0.10, as is common in micro data econometrics, and broadly similar for annual and daily data. However, the daily models include time effects TE (day-of-week and week-of-month) designed to control for larger discrete consumer expenditures from shopping costs that are not included explicitly in benchmark consumption models. The proportions of R^2 explained by these time effects is at least half, and much higher for MPCs. This finding underscores the prevalence of discrete consumer expenditures (as opposed to consumption) at the daily micro level, which undercuts the hypothesis of consumption smoothing. However, time effects do not alter conclusions about the model radically. Without time effects, Column 4 estimates (standard errors)are: $\beta_1 = .024$ (.011) and $\beta_2 = .003$ (.011) for MPCs; $\beta_1 = .030$ (.004) and $\beta_2 = .019$ (.006) for elasticities. The model is rejected more clearly (positive, significant β_1 for both MPC and elasticity) when it excludes controls for larger, discrete consumer expenditures.

7.2.3 Model Extensions

This section reports estimates for three common extensions of the benchmark PIH model using income model M3:

$$\Delta c_{i\tau} = \beta_0 + \beta_1 \widehat{\Delta y_{i\tau}} + \beta_2 \widehat{u}_{i\tau} + \xi \mathcal{S}_\tau + \varepsilon_{i\tau} \tag{11}$$

$$\Delta c_{i\tau} = \beta_0 + \beta_{2,\phi} \zeta_{i\tau} + \beta_{2,\psi} v_{i\tau} + \varepsilon_{i\tau} \tag{12}$$

$$\Delta c_{i\tau} = \beta_0 + \beta_1 \widehat{\Delta y_{i\tau}} + \beta_2 \widehat{u}_{i\tau} + \beta_3 \widehat{\sigma^2_{i\tau}}(\Delta c_{i\tau}) + \boldsymbol{\beta} \boldsymbol{L}_{i\tau} + \varepsilon_{i\tau} \tag{13}$$

[56] Daily applications of consumption smoothing tests may be insightful given problems with time aggregation. For example, Crawley (2020) addresses for differences in the consumer decision period and observed data by replicating Blundell et al. (2008), finding time aggregation significantly impacts the magnitude of transitory shocks when accounted for. Given consumers make consumption decisions daily, it may be important to account for this by estimating the models at a daily frequency.

where i, τ are general subscripts for agents and time. Equations (11) and (12) quantify consumers' ability to insure against idiosyncratic income shocks. Equation (11) adds aggregate shocks $\mathcal{S}_\tau$. If consumers cannot insure consumption against aggregate shocks proxied by aggregate consumption changes, $\xi \approx 1$.[57] If consumers can fully insure their consumption against idiosyncratic shocks, $\beta_2 \approx 0$. If $\beta_2 > 0$, as typically found in the literature, equation (12) provides a framework to estimate the extent of partial insurance and the separate effects of permanent and transitory income shocks ($\zeta_{i\tau}$ and $v_{i\tau}$, respectively).[58] When $\beta_{2,\phi} > 0$ and/or $\beta_{2,\psi} > 0$, consumers are able to partially insure against permanent or transitory idiosyncratic income fluctuations, respectively.

Equation (13) tests two common explanations for excess sensitivity in the literature. One is the addition of consumption variance, $\widehat{\sigma^2_{i\tau}}(\Delta c_{i\tau})$, which arises from uncertainty and risk aversion.[59] The other is allowing for non-separability of leisure in the utility function, which is captured by labor market variables $\boldsymbol{L}$. When including these labor controls, $\beta_1 \approx 0$ if changes in labor status account for some or all of the excess sensitivity.[60]

Table 6 reports annual and daily estimates (where available) of elasticities from extended models (11) through (13) and compares them with relevant benchmarks from the literature in column (1). Equation (11) is estimated with two proxies for $\mathcal{S}_\tau$: standard aggregate consumption growth (from the DCPC) (Mace, 1991; Townsend, 1994), and the Economic Policy Uncertainty Index (Baker et al., 2025) as an alternative daily measure for robustness. As expected, $\xi > 0$ and significant for $\Delta C_{d,t}$ in column (2). The annual estimate is 1.03, as is common in the literature, but the daily estimate is 0.60, so aggregate shocks pass through less than fully at very high frequency. Estimates of β_2 are essentially unchanged from column (1), the benchmark estimates from Table 5, for both frequencies. These results are consistent with the literature and confirm that consumers cannot fully insure against

[57] This specification follows Mace (1991); Townsend (1994); Jappelli and Pistaferri (2017).

[58] This specification follows Blundell et al. (2008); see also Eika et al. (2020). We estimate ϕ, ψ through an IV estimator as discussed in Blundell et al. (2008) Appendix C and used in Kaplan et al. (2014) where we specify v_d follows an MA(1) process. Blundell et al. (2008) use a minimum distance estimator to identify parameters, while we use the IV estimator due to a limited number of observations.

[59] This specification follows Dynan (1993) (see also, Carroll, 2001; Bertola et al., 2005; Christelis et al., 2020). CRRA utility introduces consumption uncertainty into the Euler equation (Section 6), $[(\gamma+1)/2]\ \mathbb{E}_t(\Delta c_{t+1})^2$, which can cause $\beta_1 > 0$ when excluded if the uncertainty is correlated with income growth. We predict consumption variance by regressing actual consumption variance on age fixed-effects, age fixed-effects interacted with a linear time trend, predicted income growth, and the variance of income residuals from model M3. Then we include this expected consumption variance in our Euler equation tests.

[60] Following Attanasio and Weber (1995), equation (13) includes changes in labor status in $\boldsymbol{L}_{i\tau}$ to proxy for changes in leisure: ΔL_τ and its interaction with lagged consumption, $\Delta L_\tau \cdot c_{\tau-1}$. We use two measures of labor status: cohort employment and unemployment shares. Non-separable consumption and leisure in utility can cause $\beta_1 > 0$ when leisure is omitted if it's correlated with predicted income (Attanasio and Weber, 1995).

idiosyncratic income shocks. Policy risk index results in column (3) are qualitative similar. Estimates of $\xi > 0$ are (logically) negative and significant, although magnitudes are not interpretable for the index, and estimates of β_2 are unchanged.

Given aggregate shocks do not explain failure of the benchmark PIH model, estimates of equation (13) in column (4) reveal the roles of permanent and transitory idiosyncratic income shocks. (Annual data observations are insufficient for estimation; however, daily benchmarks in column (1) are annual data.) With daily data, $\beta_{2,\psi}$ (transitory shocks) is 0.05, almost identical to Blundell et al. (2008) and implying substantial insurance against these shocks; Eika et al. (2020) find a higher value of 0.48 for Norwegian data, however. In contrast, $\beta_{2,\zeta}$ (permanent shocks shocks) is 0.02, far below Blundell et al. (2008) and Eika et al. (2020) (0.64 and 0.66, respectively). Thus, idiosyncratic income shocks have little effect on daily consumption changes, which begs for deeper understanding of the stochastic nature of discrete paydays at the daily frequency.

Neither consumption volatility (column 5) or non-separable utility (columns 6-7) can fully explain excess sensitivity of consumption. Estimates of β_3 are relatively small compared to the literature (Bertola et al., 2005; Christelis et al., 2020) and statistically insignificant, even in daily data. More importantly, estimates of β_1 and β_2 are essentially unchanged. Columns (6-7) include the labor controls (changes in labor force status), which are unavailable in the daily data. The estimate of β_1 falls by about half to 0.23, but none of the estimates are statistically significant.

7.3 Harmonizing Results

The new finding that daily MPC estimates are an order of magnitude smaller than annual estimates warrants explanation. Evidence suggests this result is explained by two features: 1) the high-frequency relationship between consumption and income, and 2) time aggregation. The textbook PIH model implicitly assumes consumption and income are *synchronous*—income is received and consumption occurs *contemporaneously* in period t. At high frequencies, consumption and income are *asynchronous*—income is received discretely (weekly or less often) but consumption and consumption expenditures occur continually (daily). Daily data reject the implicit assumption and require proper accounting for asynchronicity.

Consider first the mechanical effects of time aggregation on MPC estimates with asynchronous consumption and income in a simple calibrated example. Suppose a hand-to-mouth consumer (no saving) earns \$1,400 per week, smooths daily consumption perfectly (\$200 per day or 14.3 percent of income), and expects a 25 percent increase in income, $\Delta Y = \$350$. If

Table 6: Extensions of the Benchmark Model

		Insurance					
		Complete		Partial	Excess Sensitivity		
	(1) Benchmark	(2) DCPC $\Delta C_{d,t}$	(3) Risk Index	(4) ψ, ϕ	(5) Precautionary	(6) Nonsep. Leisure	(7) (5) + (6)
Panel A: Annual							
Elasticities							
β_1	0.474	0.552	0.643		0.483	0.227	0.233
	(0.406)	(0.425)	(0.429)		(0.397)	(0.395)	(0.370)
β_2	0.341	0.511	0.550		0.366	0.491	0.492
	(0.550)	(0.552)	(0.552)		(0.550)	(0.568)	(0.569)
β_3	$[.25, 1.60]^{\dagger}$				0.215		0.249
					(0.688)		(.668)
ξ	$[.74, 1.32]^{\dagger}$	1.033^{**}	-0.215^{**}				
		(0.503)	(0.100)				
Labor Controls						Y	Y
Panel B: Daily							
Elasticities							
β_1	0.019^{***}	0.018^{***}	0.019^{***}		0.019^{***}		
	(0.005)	(0.005)	(0.005)		(0.002)		
β_2	0.019^{***}	0.019^{***}	0.019^{***}		0.019^{***}		
	(0.006)	(0.006)	(0.006)		(0.006)		
$\beta_{2,\psi}$	$[.05, .48]^{\dagger}$			0.048			
				(0.117)			
$\beta_{2,\phi}$	$[.64, .66]^{\dagger}$			0.016^{*}			
				(0.009)			
β_3					-0.013		
					(0.035)		
ξ		0.597^{***}	-0.013^{**}				
		(0.089)	(0.053)				

[1] Table presents several extensions of the Euler equation tests. All results are expressed as elasticities. Panel A reports annual results, while Panel B reports daily results. Column (1) reports the results from Table 5, while estimates in brackets are ranges from the literature (see note † for specific citations). Columns (2) and (3) examine the full insurance hypothesis. Column (2) uses aggregate nondurable consumption (C_t annual, C_d daily) from DCPC data as the independent variable in the Euler equation. Column (3) introduces the Economic Policy Uncertainty Index (Baker et al., 2025, FRED code: USEPUINDXD) as a proxy for aggregate shocks. Column (4) tests for partial insurance following Blundell et al. (2008), using an instrumental variables (IV) approach to estimate the responses to permanent (ζ) and transitory (ν) components of unexpected income shocks. Due to lack of time periods, annual partial insurance estimates are excluded in column (4). Columns (5) through (7) test for potential violations of the Permanent Income Hypothesis (PIH). Column (5) incorporates consumption uncertainty, estimated via a two-stage least squares method. Column (6) includes labor controls (change in employed and unemployed share of cohort), while Column (7) adds both precautionary savings motives and labor controls. Standard errors are bootstrapped (1000 replications).

[2] $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

† Column (1) estimates in brackets report ranges of coefficient estimates from the ltierature. β_3 estimates from Attanasio and Weber (1995); Bertola et al. (2005); Christelis et al. (2020). ξ estimates from Mace (1991); Townsend (1994); Jappelli and Pistaferri (2017). $\beta_{2;\psi,\phi}$ estimates come from Blundell et al. (2008); Eika et al. (2020).

the weekly data MPC is 0.18, the consumer will spend \$63/week (\$9/day) of the expected income change. Thus, the daily data MPC is $0.026 = 9/350$, or roughly an order of magnitude smaller. However, this mechanical explanation of daily MPC magnitudes obscures an important economic effect of income frequencies on consumption smoothing.

To identify this hidden effect, we estimate the benchmark PIH model (M3 income only) with separate samples of synchronous versus asynchronous consumption and income data. Table 7 reports these estimates by data frequency; see Appendix Table D3 for first-stage results (R^2 from 0.48-0.81). Annual and daily results from Table 5 are included for comparison (columns one and four). To clarify, there is a crucial difference between two dimensions of measurement: 1) data frequencies (annual, weekly, and daily); and 2) alignment of consumption and income (synchronous versus asynchronous). Annual data have synchronous consumption and income—that is, 12-month changes in the October values (first column of Table 7). In contrast, daily data exhibit varying degrees of asynchronous consumption and income (columns four onward) that depend on income frequency.

Table 7: Consumption Estimates: Synchronous and Asynchronous C, Y

	Synchronous C,Y			Asynchronous C,Y							
Data Frequency:	Annual	Weekly		Daily							
	Full Sample		Sub Sample	Full Sample			Subsample by Income Frequency				
	K=A(7)G(2)	K=A(7)G(2)	Weekly Income Frequency	K=A(7)G(2)	ΔC: Nonbill	ΔC: Bill	Weekly	Bi-Weekly	Semi-Monthly	Monthly	Misc.
MPCs											
β_1	0.191	0.079*	0.311	0.009	0.004	0.005	0.029	-0.006	0.061	0.011	0.003
	(0.150)	(0.046)	(0.400)	(0.012)	(0.009)	(0.007)	(0.065)	(0.025)	(0.062)	(0.018)	(0.016)
β_2	0.062	0.077	-1.338	0.003	0.013*	-0.009	-0.021	0.037	0.060	0.023	-0.010
	(0.209)	(0.058)	(3.949)	(0.011)	(0.007)	(0.012)	(0.067)	(0.033)	(0.100)	(0.039)	(0.017)
R^2	0.03	0.150	0.540	0.04	0.022	0.039	0.043	0.165	0.111	0.163	0.035
Elasticities											
β_1	0.474	0.062	0.571	0.019***	0.052	0.670***	0.016	0.009	0.060*	0.048**	0.016**
	(0.406)	(0.047)	(0.790)	(0.005)	(0.442)	(0.193)	(0.067)	(0.032)	(0.036)	(0.020)	(0.008)
β_2	0.341	0.144***	-2.620	0.019***	0.855***	0.783**	-0.009	0.040	0.052	0.046	0.009
	(0.550)	(0.054)	(8.024)	(0.006)	(0.329)	(0.365)	(0.053)	(0.033)	(0.038)	(0.036)	(0.008)
R^2	0.03	0.277	0.403	0.06	0.023	0.040	0.043	0.165	0.111	0.163	0.035

[1] Each column is a separate regression. The first two columns estimate regressions when C and Y are aggregated to the same data frequency: annual (first column, from Table 5) and weekly (columns two and three) respectively, where the "Weekly" Sub Sample is estimated for only those consumers who have weekly paycheck frequencies. We refer to these and Synchronous C,Y as consumption and income realizations are measured at the same frequency. The remaining columns estimate regressions for C and Y at the daily data frequency where C occurs daily, while income is measured daily but is in reality discrete dependent on paycheck frequency. We refer to these results as Asynchronous C,Y to denote the misalignment between consumption and income. Column 4 reports the daily estimates from Table 5. Columns 5 and 6 separate nondurables into bills and non-bills for the full sample. Columns 7 - 11 estimate daily regressions for C and Y averaged only across consumers who match the pay frequency denoted by column names. Respondents with multiple income sources are excluded these paycheck cohorts (columns 3, 7-10). Column 11 only includes consumers who had no income reported or multiple income types.

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors or bootstrapped (1000 replications).

To complete the analysis, we construct weekly synchronous data (columns two and three in Table 7) by aggregating the daily data to a weekly daily measurement.[61] These weekly synchronous data are divided into two samples: 1) full (column two), which includes all consumers and utilizes the A(7)G(2) cohorts; 2) weekly subsample (column three), which is a time series for consumers receiving income weekly. The weekly full sample includes some

[61] Specifically, $\overline{X}^c_{kw,10,t} = \sum_d^{D_w} \overline{X}^c_{kd,10,t}$ and $\overline{Y}^R_{kw,10,t} = \sum_d^{D_w} \overline{Y}^R_{kd,10,t}$.

consumers who are paid less often than weekly, so the consumption (weekly) and income (bi-weekly or less often) data are not fully synchronous and thus are most comparable to the full sample of daily data (column four). In contrast, the weekly subsample exhibits approximately synchronous consumption (weekly) and income (weekly) that are most comparable to the annual full sample (column one).[62] However, the trade-off is a small number of observations given the weekly time frequency of only weekly income earners.

Table 7 shows the DCPC data reflect both the mechanical time-aggregation effect and the hidden effect of income frequency on consumption. For synchronous C and Y and full samples, estimates of β_1 MPC (columns one, two, and four) are monotonically declining as income frequency rises: 0.191 annual, 0.079 weekly, and 0.009 daily. However, the weekly and daily full-sample estimates reflect heterogeneity in the underlying synchronicity of consumption and income, whereas the annual full-sample estimate is based on fully synchronous data. The weekly subsample estimate based on synchronous consumption and income data (column three) is 0.311, closer to the annual estimate (0.191), and the model has the highest R^2 by far (0.40). Although neither estimate is statistically significant, the point estimates reveal similar magnitudes for MPCs with comparable synchronous data.

The subtle effect of income frequency on consumption decisions are evident in the last five columns of Table 7. These estimates are from daily subsamples defined by frequency of consumers' income: weekly, bi-weekly, semi-monthly, monthly, and miscellaneous (consumers with none or more than one income frequency). Although none of the daily subsamples has truly synchronous consumption and income, the data become less synchronous as paycheck frequency decreases because income payments are increasingly "misaligned" with daily consumption expenditures. The MPC and elasticity for the weekly subsample (column seven)—the least asynchronous consumption and income—are 0.029 and 0.016 (respectively), insignificant, and thus consistent with the PIH model. Results are qualitatively similar for bi-weekly income (column eight). In contrast, most estimates of MPC and elasticity for semi-monthly and monthly income (columns nine and 10) are larger (0.048-0.061) and the elasticities are statistically significant, clearly rejecting the PIH model.

Finally, Table 7 provides intriguing evidence that failure to account for asynchronous consumption (daily) and consumer expenditures (in some cases less frequent), as noted by Aguiar

[62] Time controls in the first stage income model are changed to reflect differences in paycheck frequency. In all estimations, year fixed effects are included. For weekly and bi-weekly, day-of-week dummies are included with lags of income determined by AIC criteria. For semi-monthly and monthly, specific days of month are included. Since many social security paychecks are paid monthly on Wednesdays, we control for each Wednesday of the month in our monthly specification. For the weekly aggregated regressions, a control for the fourth week is included. See Table D3 for first-stage results.

and Hurst (2005), also may contribute to the rejection of consumption smoothing. Columns five and six report full-sample model estimates for consumption divided into non-bills and bill payments. Non-bill consumption is smoother (Figure 2) but also includes discrete expenditures (e.g., grocery and gas shopping generally do not occur daily) that are only partly accounted for by time effects. The non-bill consumption MPC and elasticity are small (0.004-0.052) and insignificant, thus they do not reject the model – even without controlling for wealth or liquidity constraints or income frequency. In contrast, although the bills MPC is essentially zero, the bills elasticity is 0.670 and significant, clearly rejecting the PIH model.[63]

8 Selection Effects

This section investigates potential sample selection effects on estimates of consumption models from non-representative convenience samples like those in the literature (Pistaferri, 2015, p.117). Although convenience samples can be weighted to match observable demographics from the Current Population Survey (CPS), *ex post* stratification alone does not eliminate selection effects arise from unobserved economic behavior or failure to use that behavior to construct proper sampling weights. Convenience samples are susceptible to selection effects if the reason(s) consumers choose to enter the sample are correlated with the economic behavior being studied. For example, Dutz et al. (2025) find non-response bias can be nontrivial when survey participation is correlated with responses to survey questions.

To quantify these effects, we use selected DCPC variables in Table 1 to construct convenience subsamples similar to those found in the literature and estimate daily benchmark PIH models separately for consumers in each subsample. Convenience samples of mobile payments users and Visa credit card adopters approximate transactions data from phone app and payment card companies in the literature.[64] Convenience samples of heavy cash and revolving debt users stem from the uniqueness of the DCPC and provide transactions data for consumers who may have unobserved budgeting practices ("envelope method") or impatience due to higher discount rates (Fulford and Schuh, 2024), respectively.[65]

Table 8 presents estimates of the benchmark PIH consumption model with daily data for each subsample. Estimation of the convenience and complementary samples is based on four new

[63] Recall that bill payments are consumption and exclude debt payments like credit card balances.
[64] Mobile payment users are consumers who used a mobile app to make a payment in the last 12 months. Visa adopters are consumers who have a Visa credit card.
[65] Cash users are consumers who make more than 50 percent of monthly retail payments in cash. Revolvers are consumers who do not pay their credit card balances in full but carry debt across months and pay high interest rates.

synthetic cohorts: two for age and two for each subsample, the latter to identify membership in the convenience sample (or not). Regressions are run separately for each subsample, so two age cohorts are included in each regression. Membership in the convenience sample is denoted by column headings ("Yes" are members of the convenience subsample). Differences that arise between model estimates from the convenience and complementary samples may indicate the presence of potential selection effects that affect inference.

Table 8: Consumption Estimates: Convenience Sample MPCs and Elasticities

	Used Mobile Payment		Visa Adopter		Cash User		Revolver	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes	(7) No	(8) Yes
MPC								
β_1	0.079*	-0.012	0.020	0.034	0.053**	0.023	0.046*	0.015
	(0.042)	(0.017)	(0.056)	(0.025)	(0.026)	(0.043)	(0.026)	(0.037)
β_2	0.073	-0.010	-0.179*	0.019	-0.016	-0.035	0.010	0.073*
	(0.050)	(0.029)	(0.093)	(0.028)	(0.029)	(0.074)	(0.037)	(0.043)
R^2	0.094	0.048	0.083	0.104	0.093	0.046	0.069	0.136
Elasticities								
β_1	0.026	-0.014	0.010	-0.003	0.005	-0.003	0.001	-0.008
	(0.021)	(0.017)	(0.015)	(0.012)	(0.010)	(0.013)	(0.013)	(0.012)
β_2	0.023	0.025	-0.006	0.018	0.030**	0.002	-0.003	0.006
	(0.023)	(0.022)	(0.018)	(0.016)	(0.013)	(0.018)	(0.017)	(0.016)
R^2	0.112	0.088	0.093	0.144	0.130	0.088	0.088	0.156

[1] Table presents daily consumption equations across subsamples. K = Age(2)Subsample(2). Column groupings denote subsamples. Each column is a separate regression, where each subsample has two age cohorts. Columns labeled "No" regressing only on the subsample of consumers who are not categorize into the subsample, while columns labeled "Yes" do.
[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimates in Table 8 are mostly statistically insignificant, but there is evidence of sample selected effects in convenience samples mobile payment and cash use. Mobile payments users have $\beta_1 \approx 0$ (MPC and elasticity), so the model is not rejected. In contrast, $\beta_1 > 0$ for non-users of mobile payments, especially the significant MPC of 0.079. Similarly, heavy cash users have a relatively small and insignificant MPC of 0.023, so the model is not rejected, while less frequent cash users have a significant MPC of 0.053. Apparently, users of mobile apps (including online banking) and intense cash users are more likely to smooth consumption. One possible explanation is these payment practices support better personal finance management that aids consumption smoothing, but more structural inference is needed to draw firm conclusions. Nevertheless, researchers using transactions data from mobile payment apps or that come from consumers with relatively intense cash usage should beware of this effect. Results for credit card debt suggest that revolvers are more able to smooth consumption than non-revolvers, which is not easy to rationalize, and results for Visa credit card adopters are insignificant and inconclusive.

9 Future Opportunities

Although the S/DCPC was never intended to measure daily consumption and income, the results in this paper confirm their reliability for understanding the daily dynamic relationship between consumption and income. In essence, the S/DCPC satisfies two of the routes to better data recommended by (Pistaferri, 2015, p.111): "starting a new survey from scratch" (#2) and "introduction of novel data collection strategies" (#3). The success of the S/DCPC in addressing many concerns noted in Carroll et al. (2015) is enhanced by the fact that its cost is relatively low compared to the CE and SCF.

9.1 Data Development

Rather than tacitly accepting this unplanned, unexpected success of the DCPC "as is" and waiting patiently for more of the same data, there may be public good value—or even value to the private sector—in actively and intentionally developing the DCPC further. Relative to other sources, especially large proprietary transactions data sets, the S/DCPC has limitations. However, the DCPC has an advantage of being amenable to Continual Process Improvement. The most important opportunities for development of the payment diary are the following.

Sample size. Increasing the number of observations substantially is essential. This task can be achieved with more respondents, more frequent time series, or both. Since 2020, the Atlanta Fed has increased the number of respondents to nearly 5,600 in 2024. Making households the sampling unit, extending individual diary days beyond three, and expanding the sampling frame to cover highest income households would be major improvements. Implementing the S/DCPC at least quarterly would make it useful for business cycle and monetary policy analysis like the Numerator retail sales data (Hoke et al., 2024).

Purpose. The original purpose was to measure the transformation of payments from the consumer perspective. The SCPC now offers nearly two decades of data on the adoption and use of payment instruments. However, the findings here and in Schuh (2018) show unforeseen benefits of consumption and income data, which sparks *ex post* reflection. Perhaps the S/DCPC should be redesigned to measure consumption and income first (and more frequently), then measure consumer payment choices second (continue annually). This approach could be implemented with much smaller and cheaper data instruments for consumption and income—and yield extra data on higher frequency payment choices.

Scope. The original payments purpose limited the need to collect comprehensive household financial information. Even transactions liquidity balances (currency, demand deposits, and revolving credit limits and balances) are not needed to measure consumer payment choices, although assets are necessary for proper modeling of consumer behavior. Samphantharak and Townsend (2010) developed a framework for collecting data to construct fully integrated household financial statements. Samphantharak et al. (2018) and Schuh and Townsend (2020) demonstrate how to create data for such statements with the S/DCPC. The S/DCPC is a blueprint for development and implementation of more fully integrated household financial statements, which would benefit a variety of research programs.

Measurement. Refocusing the purpose and expanding the scope would require improving economic measurement in the survey and diary instruments that create the data. Important tasks include better identification of key theoretical concepts (consumption, income, emergency saving, etc.), expanded coverage of balance sheet items (more types of liquidity and long-term assets and liabilities), and upgraded use of "real-time" transaction interviews each night of data entry.

Sampling unit and information coverage. Converting the sampling unit of the S/DCPC from a respondent (consumer) to a household, as in the SCF, is more expensive but would greatly enhance data quality and research opportunities. Adding more, and more kinds of, "information coverage" (Pistaferri, 2015) about household members and their economic lives would become feasible and offer a complementary enhancement to data quality.

Access. The full value of the S/DCPC cannot be realized without more and better access. The success of DCPC data in real-time forecasting begs for providing real-time access for public data users. Interactive data-user websites have become common and beneficial for many official government data sources, such as Census Bureau and Bureau of Labor Statistics, and benefit the S/DCPC data as well. Access that emulates best practices like the Census Public Use Microdata Samples (PUMS) would be beneficial. These and other data production upgrades would require expanding the professional staff devoted to such tasks.

Given the success value of current data and promise of further improvements, policy makers and private-sector agents may find it profitable to fund this future data development. As the current owner/operator, the Federal Reserve Bank of Atlanta is the natural leader for future development, but thus far it has not adopted the broader vision necessary. Alternatively, other data-producing government agencies, such as the U.S. Bureau of the Census, Bureau of Economic Analysis (BEA), and Bureau of Labor Statistics (BLS), could adopt many of the insights gleaned from the data program and build on them. Private firms such as Numerator, which collects retail sales transactions by capturing images of receipts, also may find elements of this data program profitable.

9.2 Research

Further data development may help rectify the striking under-utilization of the S/DCPC data (outside of payments research) that has prevailed thus far. Some promising directions for future research with the data are the following.

Real-time measurement. With foresight and planning, the S/DCPC can be fielded to consumers before, during, and after upcoming special economic events. Examples in the literature include randomized tax rebates, policy regime shifts, and semi-predictable natural disasters or health pandemics. If combined with incisive real-time interviews tailored to elicit consumer decision making, these projects could yield important new insights. Because the S/DCPC questionnaires are publicly available, anyone or institution can use them to obtain additional data.

Data matching. S/DCPC data can be merged with data from a wide variety of many other UAS surveys using the common respondent identifier. The survey vendor (CESR) also has confidential personally identifiable information (PII) that enable more sophisticated data-merging efforts, such as administrative government data records (via SSNs), exact geographic locations (via residential address), and merging confidential credit bureau data with the S/DCPC (via names and addresses) as in Cole et al. (2018). If the data are made available to the public in real-time (rather than with a one-year lag), researchers could use them for forecasting and business cycle analysis.

10 Conclusions

This paper yields two main conclusions. First, consumers appear to smooth daily consumption when income is relatively more synchronous (weekly and bi-weekly) and discrete consumer expenditures are controlled for (non-bills and shopping time effects). This result is not limited to unconstrained consumers. However, as the data frequency declines, consumption, consumer expenditures, and income payments are time aggregated and become fully synchronous within periods. Low-frequency, synchronous consumption and income data becomes less smooth and the benchmark PIH model is rejected as usual. Theoretical models may benefit from focusing on daily consumption with infrequent shopping trips and expenditures and discrete income receipts, then explicitly time aggregating the daily micro data. Fully understanding the linkage between daily and low-frequency behavior may require explicit introduction of budgeting and personal finance decisions.

A second main result is that a properly designed and implemented consumer payment diary unexpectedly produces remarkable daily data on consumption and income dynamics. This study demonstrates the value of the Atlanta Fed's S/DCPC payments data in measuring and collecting broad-based, accurate micro data on consumption and income dynamics at high frequency. The S/DCPC data match official US data relatively well, forecast aggregate consumption behavior well in real time (daily), and exhibit similar payday effects to those found in proprietary transactions data. This success recommends the S/DCPC as a promising alternative to proprietary transaction data sets. Given the relatively low cost of production, further development and expansion of these invaluable data are needed to make the S/DCPC more useful and a better alternative to other transactions data.

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Technical Appendix

Appendix A Data Construction Details

A.1 Variable Mapping and Definitions

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	20.7%
Recorded Income Unidentified	22.3%
Recorded Income Identified	77.7%
Identified Income by Type:	
Employment	54.7%
Employer paid retirement	4.4%
Self-employment income	12.6%
Social Security	11.9%
Interest and dividends	3.5%
Rental income	2.8%
Government assistance	5.2%
Alimony	.3%
Child Support	2.7%
IRA, Roth IRA, 401K or other retirement fund or other retirement fund	2%

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)

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

Purpose (P)

1 - Credit card repayment
2 - Mortgage
3 - HELOC
4 - Auto or car loan
5 - Installment loan
6 - Zero-interest or no-money-down loan
7 - Payday loan
8 - Student loan
9 - Marketplace or peer-to-peer loan
10 - Loan from another person
11 - Health insurance
12 - Life insurance
13 - Umbrella insurance
14 - Vehicle insurance
15 - Homeowners or renters insurance
16 - Other type of insurance
17 - Parking
18 - Tolls
19 - Public transit
20 - Utilities
21 - Federal taxes
22 - State taxes
23 - Local taxes
24 - Property taxes
25 - Car or vehicle taxes
26 - Charitable donation
27 - Offering, tithe, collection plate
28 - Purchase goods or services
29 - Gift or allowance
30 - Lend money
31 - Split check or share expenses
32 - Make a remittance
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: Durable and Nondurable Consumption Expenditures Classification

	(1) 2016	(2) 2017-2020
Panel A: Durable Consumption C^d		
Adjusted Consumption[†] X^C	Y	Y
Merch	-	M5
Submerch (SM)	SM12, SM13, SM14, SM17, SM18, SM20, SM21, SM25, SM27, SM29, SM40, SM41, SM44	-
Durable Type	-	1 Cars, trucks, motorcycles, other motor vehicles and parts
	-	2 Furniture and furnishings
	-	3 Household appliances
	-	4 Computers, cameras, TVs, other electronics
	-	5 Sports equipment, sports and recreational vehicles, boats
	-	6 Jewelry and watches
	-	7 Therapeutic appliances and equipment
	-	8 None of the above
Panel B: Nondurable classification C^n		
	$C^n = X^C - C^d$	$C^n = X^C - C^d$

[1] Table reports identification strategy for durable and nondurable consumption expenditures, $C^{d,n}$. C^d is identified from payments are already identified to be consumption expenditures (denoted by Y in table). In 2017 forward, respondents are asked if expenditures above \$200 fall into any of the durables types listed in the above listed categories. C^n is then calculated as the remaining consumption expenditures after subtracting identified C^d.

[†] Adjusted consumption defined in Table B1.

A.2 Data Structure

Figure A1: Diary Wave Implementation

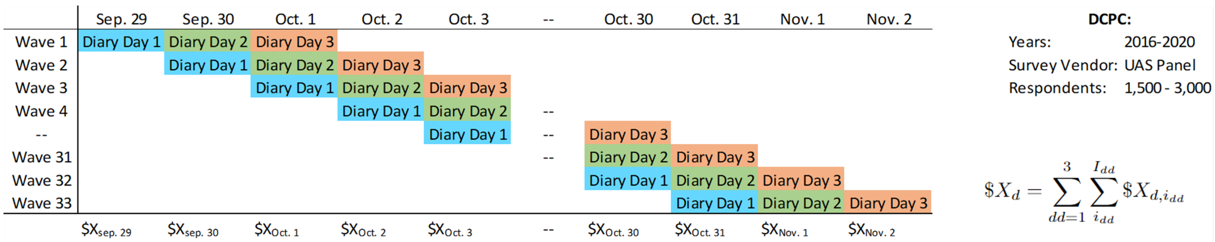


Figure A1 presents a visual representation of wave implementation for the payment diaries. Each wave contains an approximately equal number of respondents who are randomly assigned to each wave. Each wave contains three days where respondents record their daily transactions. The first wave begins September 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

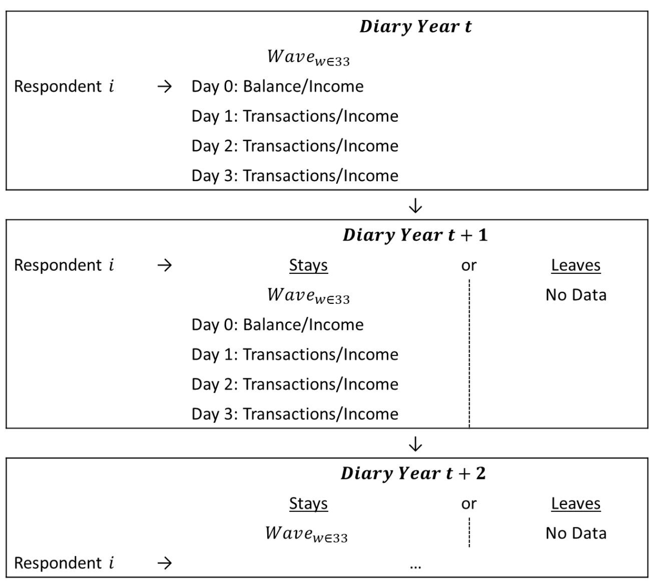


Figure A2 presents a visual representation of the panel structure of the payment diaries. Respondents from the SCPC are offered to take the DCPC. Any respondent i who agrees to participate in diary year t is randomly assigned to one of 33 waves (see figure A1). On the initial diary day 0, account balances 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.

A.3 Changes to the DCPC

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 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.

Table A11: 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 A3: Evolution of Payment Categories in the DCPC

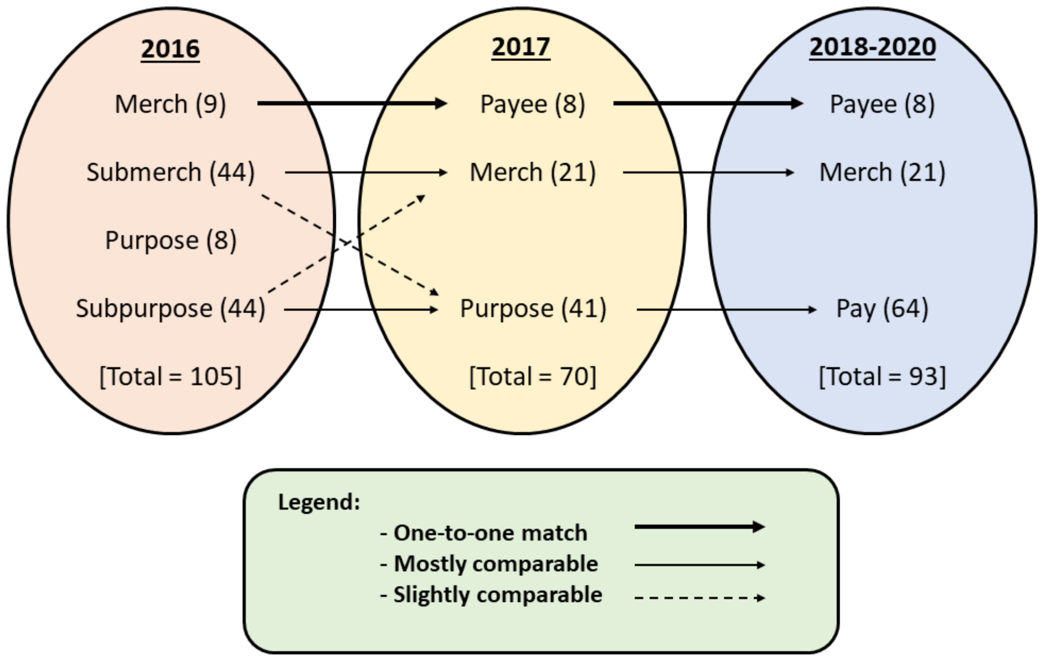


Figure A3 offers a simple overview of changes to DCPC payment categories over the years. In 2012, there were 45 possible merchant categories in which expenditures could be categorized. In 2015, merchant was simplified into 9 categories, and submerch categories were added to add more details to the merchant 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.

A.4 Data Cleaning Procedure

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 B4. 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.

Appendix B Data Validation Details

Appendix B reports additional validation details from Sections 5.1 and 5.2. Tables presented correspond to the Figures in Section 5.1, 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, while column (4) reports DCPC household income. Total income compares the raw estimates before making any adjustments. Categories under adjustments account for unique categories within the datasets. These adjustments are subtracted from total income to arrive at adjusted income.

B.1 Consumption/Income Tables

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** (1)	**DCPC(r)** (2)	**DCPC(r)/BEA** (3)	**DCPC(h)** (4)
Total Income	**16,413**	**9,615**	**.59**	**17,675**
	(313)	(659)		(320)
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)		
Other Income	1,932	2,054	1.06	
	(21)	(177)		
Adjustments				
Employee Contributions to Retirement	298			
	(6)			
Supplements to Wages and Salaries	1,882			
	(22)			
Alimony and Child Support	-	26		
		(5)		
Taxes	1,949	204		
	(19)	(49)		
Adjusted Income (Disposable)	**12,284**	**9,386**	**.76**	
	(277)	(658)		

Table B2 reports the aggregate 5-year average estimates (2016-2020) of BEA and DCPC income results. Total income is all income types from both data sets with no adjustments. DCPC(r) is respondent income, while DCPC(h) is household income. Total BEA and DCPC respondent income is the sum of income categories. Other 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 other income in the 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, which is disposable as taxes are removed. May not sum directly due to rounding. Estimates are in 2012 billions USD, standard errors are reported in parentheses. Column 3 reports the ratio of DCPC respondent income to BEA income.

Table B3: IRS and DCPC Income Estimates

5 Year Income Averages of DCPC and BEA Income (2012 Billions USD)	**IRS** (1)	**DCPC(r)** (2)	**DCPC(r)/IRS** (3)	**DCPC(h)** (4)
Total Income	**10,668**	**9,615**	**.9**	**17,675**
	(228)	(659)		(320)
Wages and Salaries	7,225	4,923	.68	
	(105)	(478)		
Propreitors' 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)		
Other Income	717	2,053	**2.86**	
	(64)	(177)		
Adjustments				
Taxes	1,446	204		
	(27)	(49)		
Child Support	-	24		
		(5)		
Adjusted Income (Disposable)	**9,222**	**9,387**	**1.02**	
	(214)	(658)		

Table B3 reports the aggregate 5-year average estimates (2016-2020) of IRS and DCPC income results. Total income is all income types from both data sets with no adjustments. DCPC(r) is respondent income, while DCPC(h) is household income. Total IRS and DCPC respondent income is the sum of income categories. Other income is multiple categories in the IRS which do not match any definitions from DCPC (other business transfers and supplements to wages and salaries), while other income in the DCPC is income whose type is not identifiable, or child support. Taxes and child support are removed from DCPC while taxes are removed to create adjusted income, which is disposable as taxes are removed. May not sum directly due to rounding. Estimates are in 2012 billions USD, standard errors are reported in parentheses. Column 3 reports the ratio of DCPC respondent income to IRS income.

B.1.1 Data Cleaning Validation

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 B4 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 B4: 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
Adjusted Income	9,386	8,732	1.07	.76	.71

Table B4 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 analogous 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.

B.2 Consumption/Income Figures

Figure B1: Annual Comparable Expenditures

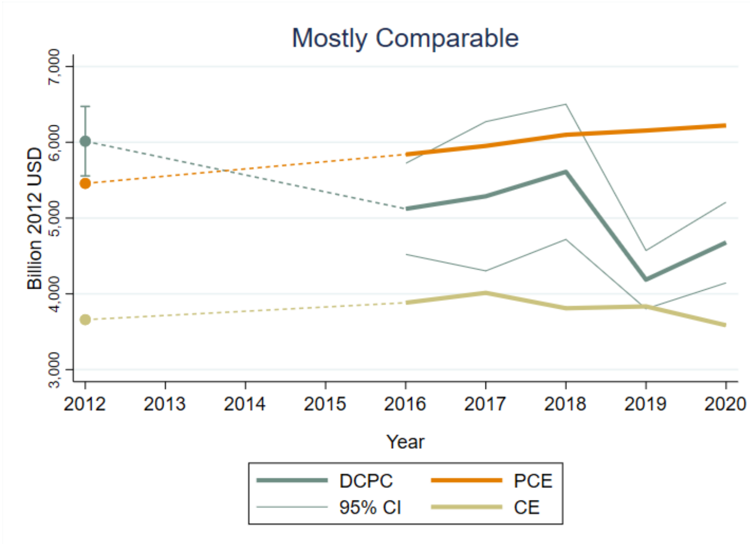
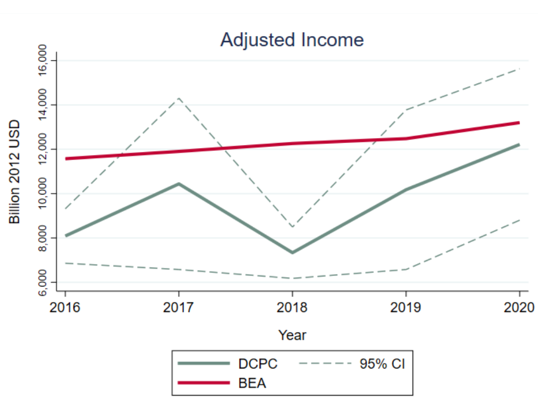


Figure B1 shows the annual estimates of comparable consumption across DCPC, PCE, and CE. 2012 estimates are reported by circles for comparison, with bars indicating confidence intervals in 2012. Dashed lines are to indicate missing values from 2013-2015. Thick solid lines are point estimates, while thin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

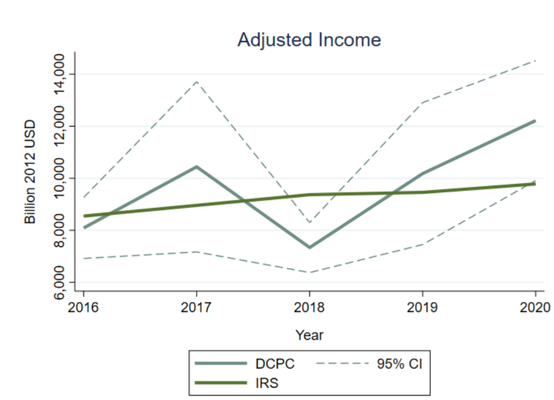


Figure B2 shows the annual estimates of adjusted income across DCPC, BEA, and IRS. Figure B2a compares DCPC and BEA adjusted income, while figure B2b compares DCPC and IRS income. 95% confidence intervals are reported for DCPC by dashed lines. All estimates are reported in billions 2012 USD.

Figure B3: X^c/Y by Household Income Categories

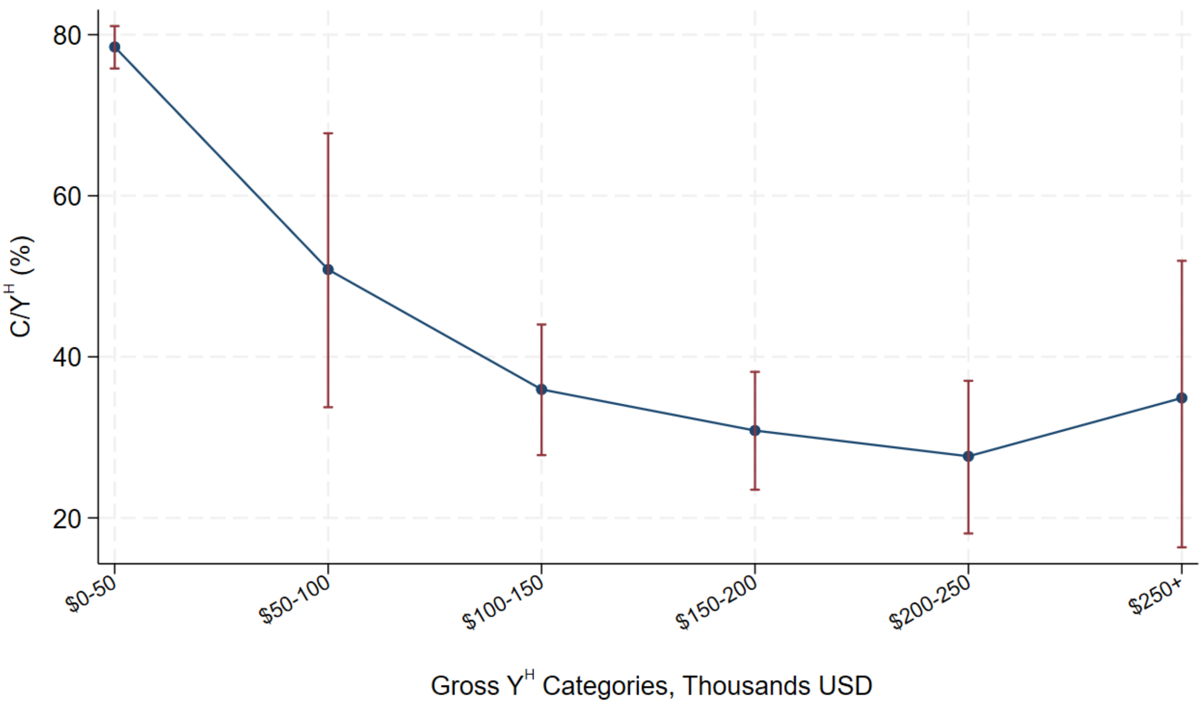


Figure reports consumption expenditures divided by income in the 2016 - 2020 DCPC. Consumption is estimated by using the average adjusted consumption categories (annualized) divided by average household income within each household income category.

Figure B4: Daily Estimate of Monthly Payments per U.S. Consumer

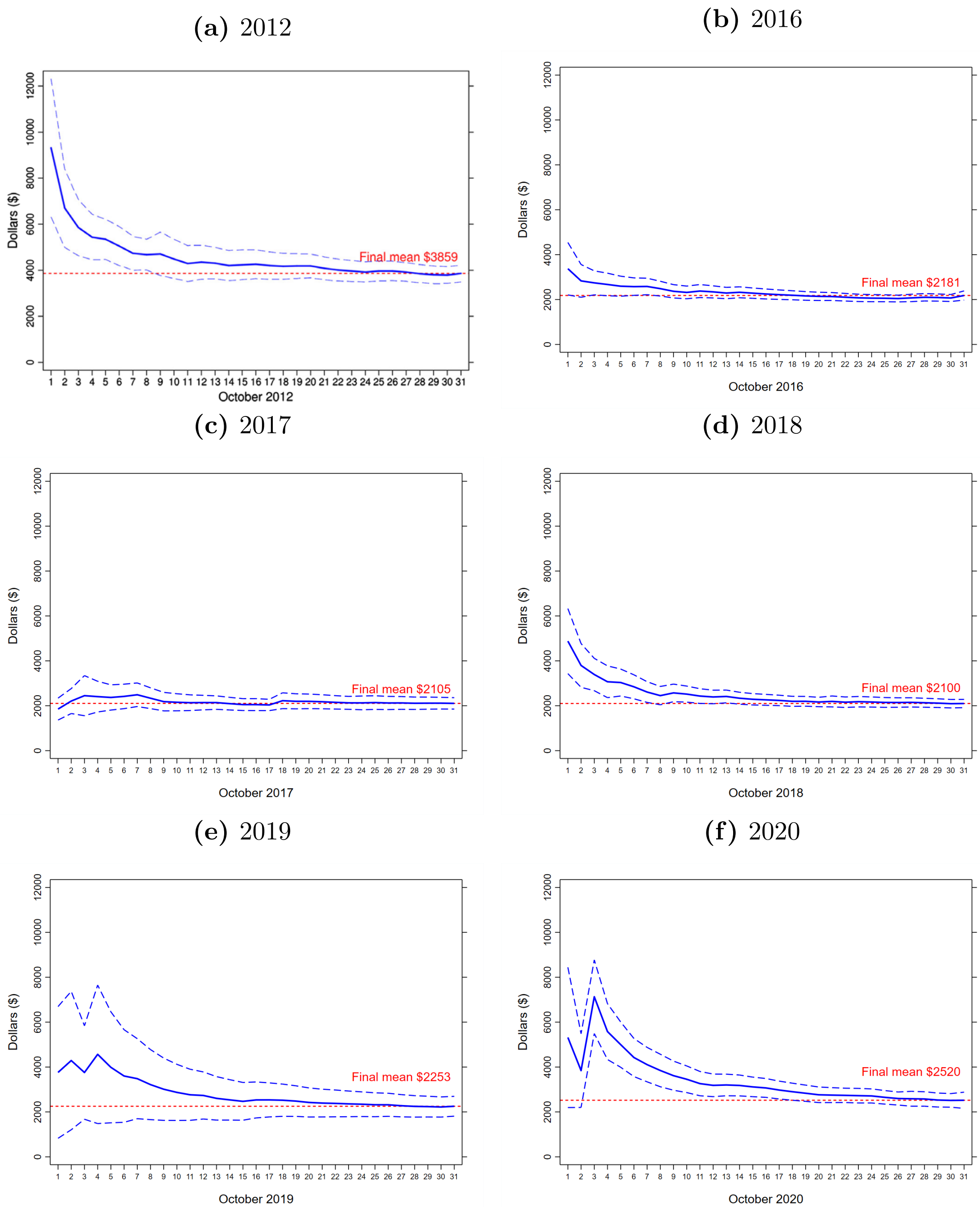


Figure B4 reports the results of the daily estimates of monthly payments per consumer, as discussed in section 5.2.1. Dashed lines indicate 95% confidence intervals, and dotted red lines are the final mean. Subfigure B4a is taken directly from Schuh (2018), while subfigures B4b - B4f are calculated from 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. The estimation procedure from Schuh (2018) is used for calculating standard errors.

Figure B5: Forecasting Annual DCPC Growth

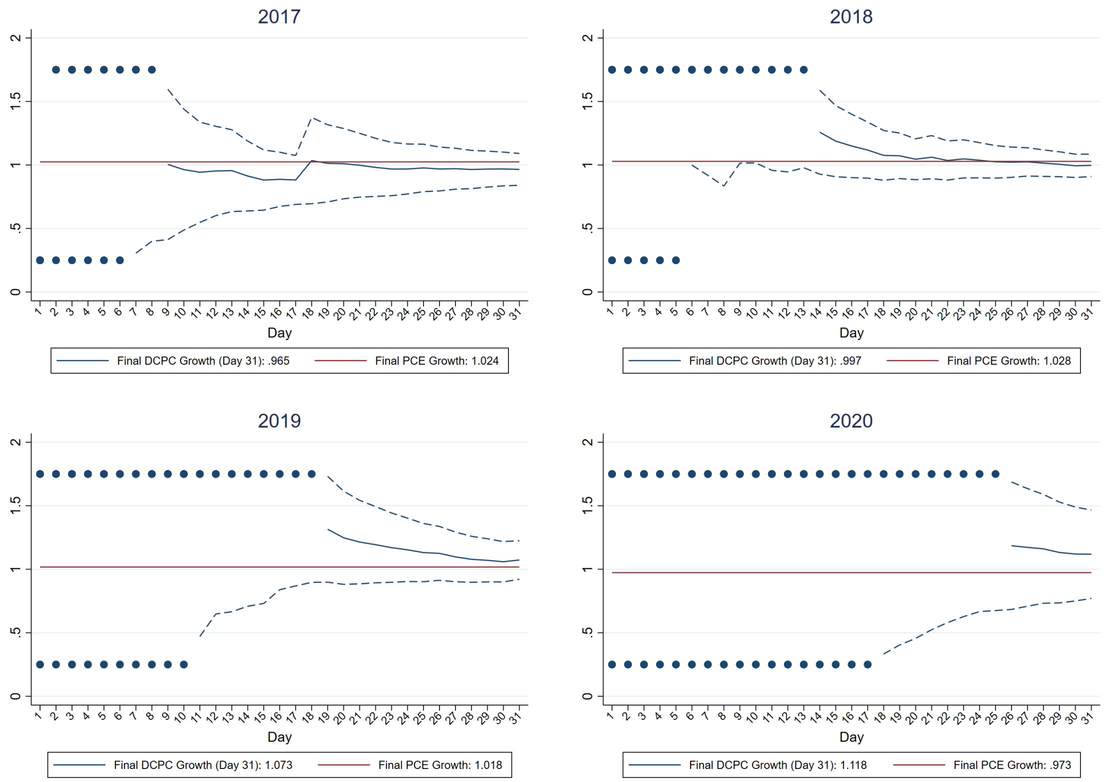


Figure B5 reports the daily estimates of annual DCPC growth. The solid blue line reports G_{dmt} for each day of the diary. The red line reports PCE growth G^{*}_{mt}. The legend reports end-of-month growth estimates for DCPC and the PCE growth rate. Scatter points cap estimates above 1.25 and below .25 for display purposes.

Appendix C Theory Derivation

C.1 Implied MPC from 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.[66]

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

$$Y_t = \sum_{a=1}^{p} \rho_a Y_{t-a} + \sum_{b=0}^{q} \phi_b u_{t-b} \tag{14}$$

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

Which can be written as follows:

$$Y_t = u_t + \sum_{s=1}^{\infty} \psi_s u_{t-s}$$
$$\text{Where} \tag{15}$$
$$\psi_s = \phi_s + \sum_{j=1}^{s} \rho_j \psi_{s-j}$$

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.[67] As u_t is white noise, then it follows that:

$$\mathbb{E}_t Y_{t+s} - \mathbb{E}_{t-1} Y_{t+s} = \psi_s u_{it}$$
$$\Delta c_t = \frac{r}{1+r} \sum_{s=0}^{\infty} \frac{(\mathbb{E}_t Y_{t+s} - \mathbb{E}_{t-1} Y_{t+s})}{(1+r)^s} = \frac{r}{1+r} \left[\sum_{s=0}^{\infty} \frac{\psi_s}{(1+r)^s} \right] u_t \tag{16}$$

Where equation 16 would define the annual innovation. It can be shown as in Flavin (1981) that:

$$\frac{r}{1+r} \left[\sum_{s=0}^{\infty} (1+r)^{-s} \psi_s \right] u_t = \frac{r}{1+r} \left[\frac{1 + \sum_{s=1}^{q} (\frac{1}{1+r})^s \phi_s}{1 - \sum_{j=1}^{p} (\frac{1}{1+r})^j \rho_j} \right] u_t \tag{17}$$

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

$$\frac{r}{1+r} \frac{1 + \frac{1}{1+r}\phi_1}{1 - \frac{1}{1+r}\rho_1} \cdot u_t = \frac{r}{1+r} \frac{1 + r + \phi_1}{1 + r - \rho_1} \cdot u_t \tag{18}$$

In our specification, we model income as a simple AR(1) process. Therefore, $\phi_1 = 0$ in equation 18 and thus:

$$\left(\frac{r}{1+r} \frac{1+r}{1+r-\rho} \right) \cdot u_t = \Omega \cdot u_t \tag{19}$$

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

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

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 estimate the type of income changes apparent in the diaries. When estimating the AR(1) process, we use controls as specified in the primary text. Once ρ is obtained from the regression, we use the delta method to compute standard errors reported in the table.

Appendix D Additional Econometric Results

D.1 Income Specifications

Below are the income specifications used for predicting expected and unexpected income:

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

$$\Delta_d^1 Y_{kd,10,t}^R = \alpha + \lambda_t \times \lambda_d + \eta_k + \sum_{j=1}^{N_j} \gamma_j \vartheta_{kd,10,t}^j + u_{k,10,t}^{M1^d} \tag{M1$^{\mathrm{d}}$}$$

$$\Delta_m^{12} Y_{k,10,t}^H = \alpha + \rho_2 \Delta Y_{k,10,t-2}^H + \eta_{AGE} + t \cdot \eta_{AGE} + u_{k,10,t}^{M2^t} \tag{M2$^{\mathrm{t}}$}$$

$$\Delta_d^1 Y_{kd,10,t}^R = \alpha + \Delta_d^1 Y_{k,d-2,10,t}^R + \lambda_t \times \lambda_d + \eta_k + \sum_{j=1}^{N_j} \gamma_j \vartheta_{kd,10,t}^j + u_{k,10,t}^{M2^d} \tag{M2$^{\mathrm{d}}$}$$

$$\Delta_m^{12} Y_{k,10,t}^H = \alpha + (\rho_3 - 1) Y_{k,10,t-1}^H + \eta_{AGE} + t \cdot \eta_{AGE} + u_{k,10,t}^{M3^t} \tag{M3$^{\mathrm{t}}$}$$

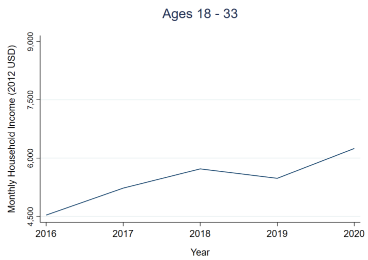
$$\Delta_d^1 Y_{kd,10,t}^R = \alpha + (\rho_3 - 1) Y_{k,d-1,10,t}^R + \lambda_t \times \lambda_d + \eta_k + \sum_{j=1}^{N_j} \gamma_j \vartheta_{kd,10,t}^j + u_{k,10,t}^{M3^d} \tag{M3$^{\mathrm{d}}$}$$

Where η_{AGE} are age fixed effects, and $t \cdot \eta_{AGE}$ is a linear time trend interacted with age. η_k are cohort fixed effects, λ_t are year fixed effects, λ_d are day fixed effects, and ϑ^j are cohort controls. See main paper for list of controls.

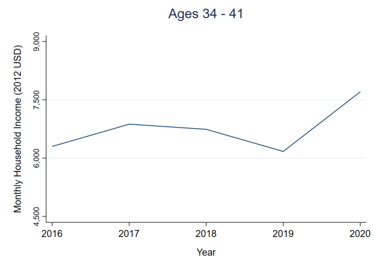
D.2 Additional Results

Figure D1: Income Profiles by Age Cohorts

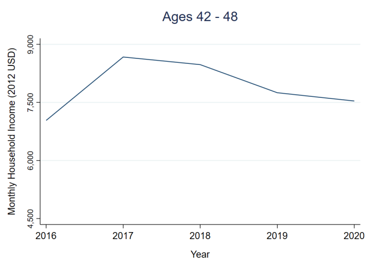
(a)



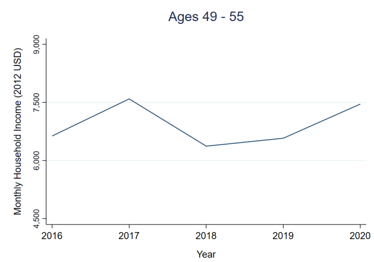
(b)



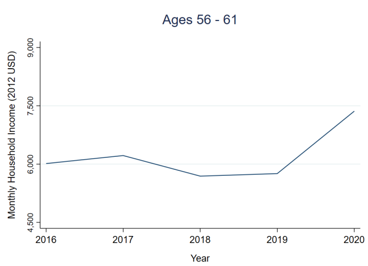
(c)



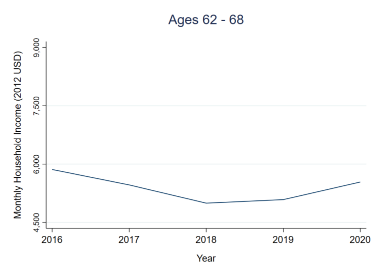
(d)



(e)



(f)



(g)

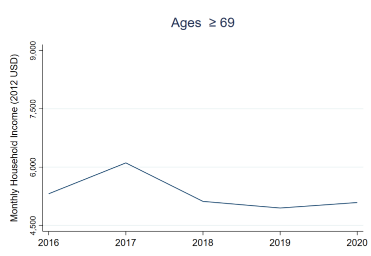


Figure D1 plots the time series of monthly household income for each age cohort from 2016 through 2020. All values are in 2012 USD values.

Table D1: Time-Varying Constraints

	M3: K=A(2)G(2)C(2)			
	C = Net Worth		C = Liquidity	
	(1) U	(2) C	(3) U	(4) C
Panel A: Annual				
MPCs				
β_1	0.088	-0.017	0.291	-0.398
	(0.240)	(0.142)	(0.252)	(0.570)
β_2	-0.053	0.142	0.256	-0.527
	(0.306)	(0.229)	(0.395)	(0.595)
Elasticities				
β_1	0.373	0.006	0.761	-0.686
	(0.790)	(0.428)	(0.626)	(1.275)
β_2	-0.032	0.385	0.662	-0.884
	(0.867)	(0.750)	(0.912)	(1.323)
Panel B: Daily				
MPCs				
β_1	0.002	0.014	0.018	0.034
	(0.021)	(0.012)	(0.017)	(0.024)
β_2	0.016	0.017	0.015	0.028
	(0.024)	(0.029)	(0.023)	(0.044)
Elasticities				
β_1	0.013*	0.025***	-0.000	0.016*
	(0.008)	(0.009)	(0.008)	(0.009)
β_2	0.012	0.012	0.004	0.017
	(0.011)	(0.013)	(0.011)	(0.013)

[1] Panel A: Annual results. Panel B: Daily results. All values are reported in 2012 USD values. Sub-panel MPCs reported differences in levels, while sub-panel Elasticities report differences in logs. Each column grouping reports 2 age cohorts, 2 gender cohorts, and 2 liquidity constrained cohorts. Columns (1) - (2) report constraints based on cohort members' net worth position. Here net worth constraint is based on if the consumer had net worth less than their annual salary. Columns (3) - (4) report constraints based on cohort members' net liquid assets. In all liquidity constrained definitions, respondents are considered constrained if they were observed being constrained in year t . Standard errors are clustered at the cohort level and are bootstrapped (1000 replications).

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In the benchmark estimation, we utilize household income (Y^H) and respondent income (Y^R) for the annual and daily application, respectively. To test for differences in consumption responses between respondent and the rest of the household's income, we calculate other household income as $Y^O_{k,10,t} = Y^H_{k,10t} - \sum_{d=1}^{D} Y^R_{kd,10,t}$ and estimate (8) and (9) as follows:

$$\Delta^{12}_m C_{k,10,t} = \beta_0 + \eta_{k \in age} + \beta^R_1 \widehat{\Delta^{12}_m Y^R_{k,10,t}} + \beta^O_1 \widehat{\Delta^{12}_m Y^O_{k,10,t}} + \beta^R_2 u^R_{k,10,t} + \beta^O_2 u^O_{k,10,t} + \varepsilon_{k,10,t}$$

Where Y^R is aggregated to the monthly level. Note that Y^H varies by diary year only, and thus Y^O cannot be meaningfully calculated at the daily frequency. We repeat models M1-M3 for the first stage, but allow for Y^R to predict Y^O and vice-versa.

Table D2: Separate Components of Y^H

	K=A(7)G(2)			
	M0	M1	M2	M3
Annual				
MPCs				
β^R_1	0.109	0.209	0.074	0.199
	(0.097)	(0.303)	(N/A)	(0.160)
β^O_1	0.088	0.163	0.172	0.152
	(0.109)	(0.371)	(N/A)	(0.193)
β^R_2		0.102	-0.203	0.046
		(0.109)	(N/A)	(0.201)
β^O_2		0.082	-0.232	0.041
		(0.127)	(N/A)	(0.247)

[1] Table reports the annual MPC estimates when including respondent income Y^R and other household income Y^O separately, where $Y^H = Y^R + Y^O$. To obtain the results from the benchmark table, coefficients must be weighted by each income source's share of household income change, and adjusted for differences in intercept terms. Results for elasticities require complicated weighting schemes and thus aren't reported for simplicity. Standard errors are bootstrapped (1000 replications). M2 standard errors cannot be estimated with bootstrapping reliably given the lack of observations using a second lag (28).

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.3 First Stage Results

Table D3: First Stage: Paycheck Frequency Regressions

	Weekly	Bi-Weekly	Semi-Monthly	Monthly	Weekly Synchronous
2017	0.321	-3.572	33.753	-15.701	18.975
	(15.706)	(24.317)	(65.012)	(23.303)	(89.532)
2018	-26.514*	-24.392	50.669	14.401	-209.626*
	(14.135)	(26.892)	(46.202)	(28.800)	(98.315)
2019	-33.012*	-47.121*	-52.002	-14.996	-236.860**
	(19.688)	(25.124)	(40.029)	(25.746)	(74.023)
Monday	24.689*	64.701**			
	(12.943)	(26.225)			
Tuesday	29.348***	9.252			
	(10.466)	(23.137)			
Wednesday	39.411***	54.221			
	(11.786)	(37.529)			
Thursday	133.417***	76.922*			
	(17.084)	(38.919)			
Friday	310.448***	384.912***			
	(39.946)	(118.826)			
Saturday	34.961	68.380			
	(29.072)	(42.776)			
Day 2			-40.009		
			(25.633)		
Day 13			479.613		
			(358.143)		
Day 14			122.244*		
			(69.243)		
Day 15			257.948**		
			(114.671)		
Day 29			159.382		
			(151.394)		
Day 30			-22.154	307.416	
			(23.513)	(291.316)	
Day 31			547.075***	309.170***	
			(163.336)	(98.221)	
Second Wednesday				88.393**	
				(39.870)	
Third Wednesday				93.178*	
				(49.847)	
Fourth Wednesday				101.799***	
				(33.758)	
Fifth Wednesday				4.765	
				(288.037)	
Week 4					82.975
					(63.055)
$Y^R_{d-1,mt}$	-1.113***	-1.155***	-1.076***	-1.218***	
	(0.098)	(0.093)	(0.056)	(0.069)	
$Y^R_{d-2,mt}$				0.646	
				(0.460)	
$Y^R_{d-3,mt}$		-0.154**			
		(0.062)			
$Y^R_{d-4,mt}$				-0.282	
				(0.172)	
$Y^R_{d-7,mt}$		0.211		0.080	
		(0.214)		(0.081)	
$Y^R_{w-1,mt}$					-0.879***
					(0.241)
Observations	150	120	150	120	15
Adjusted R^2	0.810	0.810	0.607	0.634	0.475

[1] MPCs for the first-stage pay-frequency regressions. Includes day and year controls. Each column is a new regression with only 1 cohort: the paycheck frequency. The last column is weekly paycheck frequency, where the data is collapsed to weekly frequency. We record four weeks in October, with the final week containing extra days: days 1-7, 8-14, 15 - 21, and 22 - 31.

[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors or bootstrapped (1000 replications).