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

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Abstract

This paper extends Schuh (2018) by demonstrating that daily micro transactions in the *Diary of Consumer Payment Choice* (DCPC) contain reliable estimates of consumption and income that cover high percentages of U.S. data, forecast them well in real time, and match payday effects as well as pay cycle borrowing from other transactions data. Annual estimates of a benchmark PIH model of consumption using DCPC data match the literature well, rejecting the model due to excess sensitivity. Novel *daily* estimates of the MPC from expected income are an order of magnitude smaller (as expected) and also reject the PIH—except when income payments are frequent (weekly). Relative to other transactions data, the DCPC is: 1) more representative; 2) publicly available; 3) amenable to continuous measurement and improvement; and 4) flexible for real-time implementation.

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 data have become increasingly available from a variety of sources (Baker and Kueng, 2022). 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. Thus, research is producing new insights about consumer behavior: preference heterogeneity, consumption smoothing, liquidity and credit constraints, expenditure shocks, policy effectiveness, and budgeting skills. However, transactions data can 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 that track all expenditures authorized by account-specific payment instruments, including cash. Although intended to track the transformation of payments from paper to electronic means, payment diaries unexpectedly yielded high-quality micro transactions data. Aggregate payments values are similar to GDP in advanced economies (Bagnall et al., 2016) and precisely identified *consumption* expenditures are valid real-time estimates of U.S. personal consumption expenditures (PCE) that are more accurate than the Consumer Expenditure Survey (Schuh, 2018). Relative to other transactions data, the U.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).

Although intriguing, Schuh (2018) begs four 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 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 does 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 that are consistent with those in the literature using time-aggregated data (annual, quarterly, or monthly)? If so, would they allow feasible estimation at the daily

frequency and reveal new insights about high-frequency behavior?

This paper answers the first two questions by reporting results of three updated and expanded validation exercises using DCPC data for 2016-2020: 1) coverage of official U.S. data; 2) real-time (daily) forecast accuracy; and 3) payday effects on consumption. The coverage exercise compares revised and improved aggregate DCPC consumption and—for the first time—income with official U.S. estimates and leading alternative data sources. The real-time exercise evaluates daily forecasts of monthly DCPC consumption *levels* and—for the first time—forecasts of monthly 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 (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 reporting econometric estimates of benchmark consumption models with the validated DCPC data at the annual and daily frequency. We estimate analytical solutions to the Euler equations derived from a benchmark Permanent Income Hypothesis (PIH) model (Jappelli and Pistaferri, 2017) with various models of the income process. Annual estimates are highly comparable to the literature (Havranek and Sokolova, 2020)—another data validation. Daily estimates are, to our knowledge, the first reported estimation of a PIH model with micro transactions data.[1] In daily data, a frequency mismatch arises between continuous consumption (daily) and discrete income (zero most days and received weekly, semi-monthly, and monthly) introduces an explicit budgeting decision for consumption expenditures that is absent when consumption and income are synchronous.

Extended validation of DCPC data for 2016-2020 confirms the 2012 results were *not* a fluke and affirms the DCPC's value as a reliable 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.[2] Consumption coverage declined from 2012 (92 percent of PCE, Schuh, 2018) due to improved measurement. Nevertheless, coverage of aggregate DCPC data remained superior to alternative consumption measures (20 percentage points higher than the Consumer Ex-

[1] Brown et al. (2023) also use micro transactions data from a Swiss consumer payment diary to study consumption but do not estimate a time-series consumption model. The study estimates cross-section models with time-aggregated data to quantify the effects of cashless (electronic) payments on discretionary consumer spending and finds evidence of present bias.

[2] Naturally, coverage is notably 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 significantly with more intentional, straightforward revisions to the design of the survey instruments.

penditure Survey) and comparable to alternative income (2 percentage points higher than IRS Statistics of Income, SOI).

Daily DCPC consumption also provides remarkably accurate real-time forecasts of the monthly *level* of DCPC consumption. As in 2012, daily projections of monthly consumption converge statistically to the final October estimate by mid-October, sometimes within 10 days (or less). Because DCPC consumption underestimates PCE, we extend the analysis to daily projections of 12-month growth in DCPC consumption as real-time (daily) forecasts of PCE growth. While daily DCPC growth projections also converge to PCE growth rates (adjusted for comparability) long before the government published the PCE data, convergence occurs later in the month and with less precision (5 percentage points in absolute value). Thus, DCPC data show promise for real-time analysis but need further refinement.

The pay-cycle analyses are qualitatively consistent with the literature but the more representative DCPC produces quantitatively different results. Consumers spend significantly more on paydays for non-bill and total expenditures, as in Olafsson and Pagel (2018); Gelman et al. (2014), but DCPC estimates are lower. The DCPC data have uniquely comprehensive bill payments, which increase on paydays about four times more than non-bill expenditures. Consumers with longer pay cycles (less frequent income) also tend to have greater credit card borrowing, as in (Baugh and Correia, 2022), but the DCPC estimates are about half as large as in the literature.

Annual econometric estimates of the benchmark PIH model are consistent with the literature (Havranek and Sokolova, 2020), further validating the DCPC data. The data reject the null hypothesis of consumption smoothing due to excess sensitivity of consumption to predicted changes in income. Our preferred income specification yields a statistically significant MPC of 0.27 out of expected income (elasticity of 0.66), compared with mean MPC of 0.40 (0.26) in the literature for all (micro) data. Unexpected income (shocks) are residuals from the income model predictions. Estimates of the MPC from unexpected income range from 0.13 to 0.49 but statistically insignificantly different from zero, suggesting predominance of transitory income shocks.

Daily data also reject the PIH but reveal new insights. Our preferred income model yields a statistically significant MPC from expected income of 0.023 (elasticity of 0.029). Coefficient estimates on unexpected income range from 0.003 to 0.020 and are statistically significant for some specifications. The fact that daily MPC estimates are about an order of magnitude smaller than annual estimates is due to the asynchronous mismatch between consumption (daily) and income (weekly or less frequency). The MPC estimated with weekly data (syn-

chronous consumption and income) is 0.219, about the same as with annual data. However, when income arrives weekly the MPC is 0.000, but when it arrives biweekly the MPC is 0.030. Thus, *the PIH model is rejected when income is received less frequently.* Whether this finding is attributable to weekly income being less uncertain, weekly planning periods being easier to budget than longer ones, or some other factor requires more research.

As in the literature, annual and daily data show that credit or liquidity constraints explain the rejection of the benchmark model, which further validates the DCPC as a reliable micro data source for studying consumption and income dynamics. When the sample is divided into constrained versus unconstrained consumers using credit and liquidity measures defined in the literature, the benchmark PIH model is rejected for constrained consumers but generally not rejected for unconstrained consumers. Defining liquidity constraints is robust to multiple definitions, with smaller coefficients and larger standard errors for the unconstrained consumers.

Finally, model estimation with sub-samples of the relatively representative DCPC data reveal evidence of potentially important selection effects. We construct sub-samples using respondent characteristics that approximate criteria that define prominent convenience samples of transactions data in the literature (e.g., mobile payment use). These pseudo-convenience samples produce estimates of MPCs from expected income that are economically and/or statistically significantly different in the convenience sample. This result suggests that research with convenience samples of transactions data may not give representative findings despite the richness of the transactions data.

The results in this paper suggest at least two potential policy implications. First, increasing the frequency of income payments may impact consumption in a manner analogous to the frequency of government transfer payments (Gelman et al., 2024). If so, efforts by employers or public policy makers to increase the frequency of income payments may assist consumers in better planning how to smooth their consumption within income cycles. Second, there may be a public good value to supporting further expansion of the DCPC. Originally designed for measuring payments choices, its success has allowed for superior coverage of official U.S. consumption and income data which appear to enable reliable and insightful estimation of consumption models. Redeveloping the S/DCPC with goals of increasing sample sizes and frequency would yield an even more superior product.[3]

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

2 Related Literature

This paper is related to many distinct branches of the literature that are too broad and deep to review comprehensively or even adequately. 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 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 of the population that include most types of consumers and households but are not drawn from the universe of agents using sampling theory. Thus, they may not be fully representative or immune from sample selection effects.

Payments data. An ongoing transformation of payments from paper (cash and checks) to electronic means has prompted central banks and other researchers to collect data on payment choices using daily diaries with representative probability samples of respondents (Bagnall et al., 2016). Payments data essentially contain the same information as transactions data from financial institutions, and in many cases additional data on consumer decision making. When designed properly to measure broader economic concepts, payments data can be used to construct consumption and income accurately as well (Schuh, 2018; Brown et al., 2023). As noted in Baker and Kueng (2022), payment diary data are promising but typically have limited sample sizes and time spans compared to transactions data.

Measuring consumption. Econometric models of consumption depend crucially on good data. A central issue has been proper measurement of consumer *expenditures*, as discussed thoroughly in Carroll et al. (2015). Much concern has been focused on the adequacy of the Consumer Expenditure (CE) survey and diary. 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. However, like most data sources, the S/DCPC only measures expendi-

tures and not consumption.[4]

Consumption theory. The paper follows the theory and notation of benchmark consumption theory as 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 martingale unless consumers face departures such as liquidity and credit constraints or hyperbolic discounting. At least implicitly, consumption models 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 a recent 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. [5] Aggregating irregular income payments to lower frequencies can induce autocorrelation (Crawley, 2020), which is avoided using daily data.

Daily consumption. The increase in availability of transactions data has enabled exciting new analyses of daily consumption and income dynamics. These high-frequency data reveal similar excess sensitivity of consumption to income on paydays (Agarwal et al., 2007; Gelman et al., 2014; Kueng, 2018; Olafsson and Pagel, 2018; Gelman, 2021, 2022) and consumption responses to unanticipated income (Baker and Yannelis, 2017; Baker, 2018; Olafsson and Pagel, 2018, 2019; Gelman et al., 2020). Additional benefits accrue from observing high-frequency consumption choices with more details on consumer financial positions, especially credit card debt (Hundtofte et al., 2019).

[4] For a preliminary exploration of the difference using the available data, see our companion paper.

[5] When comparing MPCs and elasticities on paydays in Gelman et al. (2014) to other studies, the authors note that longer estimation horizons have higher estimates though does not impact the general precision.

3 Consumer Payments Data

Our primary data source is the U.S. Survey and Diary of Consumer Payment Choice (S/DCPC), one of several similar data programs worldwide (Bagnall et al., 2016).[6] Early motivation for consumer payment data was understanding the long-awaited decline in U.S. paper check use that finally started in the late 1990s (Gerdes and Walton, 2002; Benton et al., 2007; Schuh and Stavins, 2010), the transformation of payments from paper to electronic forms (Rysman and Schuh, 2017), and consumer adoption and use of payments (e.g., Koulayev et al., 2016). An unintended and unexpected benefit of consumer payments data is their unique inclusion of consumer expenditures that are reliably separable from other expenditures (Schuh, 2018).

3.1 Survey Instrument Design

Like the Consumer Expenditure Survey (CE), the S/DCPC includes two modes of data collection. The SCPC is an annual (2008-2023) *recall*-based survey in which respondents complete a 30-minute online questionnaire about current and recent activity. The DCPC is a daily (October 2012, 2015-2023) *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.[7] 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 SCPC 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 *recent* (during a "typical month") flow volume of the number of payments on the intensive margin (*use*) by each type of payment instrument or account. 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 to supplement analysis of the DCPC.

At a more granular level, the DCPC measures dollar values of all daily consumer transactions

[6] 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.

[7] 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.

authorized by a payment instrument.[8] DCPC payments are analogous to bank transactions data for deposit accounts—expenditures, asset transfers, withdrawals, and deposits including income—but somewhat less specific about payment recipients. The DCPC also collects two types of data that are not available in bank transactions. First, it tracks currency holdings and transactions beyond deposits and withdrawals to/from bank accounts, giving a more complete cash flow of liquid assets. Second, the DCPC includes unique data from real-time interviews of respondents about their decisions for every payment transaction ("point of sale" in retail).[9] The DCPC data enable measurement of consumption and income.

After the initial 2012 DCPC, the diary survey 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. For this paper, two innovations were most important.[10] 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).

3.2 Sample Design

Since 2015, the primary sampling frame for the S/DCPC has been the Understanding America Study (UAS) developed by the USC Dorsife Center for Economic and Social Research (CESR). [11] 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 using best-practice techniques for panel recruitment. CESR uses address-based sampling for prospects and an

[8] Specifically, data for each transaction include seven key variables: day; time, amount ($); payment instrument (account); location (in-person or not); technology (computer, phone, etc.); and recipient (industry or expenditure category). Implicitly measured is the number of payments.

[9] These data include: payment instruments they were carrying (including cash in their wallet; their 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.

[10] See Table A10 of Appendix A for a complete summary of innovations in the DCPC survey instrument.

[11] From 2008-2015 (including the 2012 DCPC), the primary sampling frame was RAND's American Life Panel (ALP). In 2015, the ALP and UAS both served as a sampling from 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).

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).[12]

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.[13] 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).

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 Figure A1. Each day also contains an approximately equal share of respondents on each diary day (1, 2, and 3) to eliminate potential diary-day effects in reporting (e.g., "diary fatigue" that reduces reporting). This random assignment process ensures representatives samples on each day of October 1-31.

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.

[12] 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).

[13] "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.)

3.4 Longitudinal Panels

Within a year (October 1-31), the S/DCPC sample essentially is a *balanced* longitudinal panel for with 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 the U.S. population 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 (except 2013-2014), the prior year's respondents are invited to continue in the current year and the vast majority do so (greater than 90 percent). 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).[14] We exclude S/DCPC data after 2020 because the DCPC stopped collecting respondent income in 2021.

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 data on subsample characteristics.) The second and third columns show the same statistics for

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

the full S/DCPC samples as ratios to the CPS estimate. Most characteristics in the S/DCPC are within 5 percentage points 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.

Given the relatively representative nature of the S/DCPC, the likely representativeness of convenience samples of transactions data used in the literature can be estimated with the subsamples of the S/DCPC shown in columns four through eight. Adoption of personal financial management software (PFM) is comparable to account aggregators (Baker, 2018; Olafsson and Pagel, 2018); Visa credit card adopters is comparable to Visa transactions (Einav et al., 2021); and mobile payment (MP) users is comparable to (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 JPMorgan-Chase 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 very high employment, education, and income consumers. Aggregate estimates of convenience sample data sources can 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.

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 make 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.

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 out of their savings account. This question is only asked in the 2016 DCPC, and thus the CPS, SCPC, and 2015 DCPC is excluded.

4 Measurement and Data Construction

This section accomplishes three tasks. First, it explains how the DCPC data are use to measure consumption and income that are approximately comparable to the official U.S. data. Second, it describes aggregation of the data over agents (average consumer) and time (from daily to monthly). Finally, it provides an introductory analysis of 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-A9 for more (gory) details about the meticulous process of identifying consumption, income, and other variables.

4.1.1 Consumption

Consumption expenditures are a subset of the dollar value of total payments. The Diary collects seven core variables associated with each payment: 1) time of day; 2) dollar amount; 3) payment instrument; 4) in-person (Y/N); 5) device used (e.g., card terminal, computer, etc.); 6) type of payee; and 7) name of payee. Payment expenditures (#2), X_t, include:

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

Consumption expenditures, X_t^c, includes (first bracket) PCE for nondurable goods and services, C_t^n, and consumption of consumer durables, C_t^d. Non-consumption (other) expenditures, X_t^o, includes [second bracket] unofficial consumption expenditures (e.g., underground economy), X_t^u, changes in assets and liabilities (debt), $\Delta A_t, \Delta L_t$, which includes payments to or from other people, or person-to-person transfers 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 (#6 and #7), 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. First, the SCPC includes a recall-based estimate of annual gross *household* income, Y_t^H, from the quarterly UAS survey of respondent demographics ("My Household Questionnaire"). Second, 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.[15] 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 Y_t^H and 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 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.

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 or stored elsewhere; and 2) primary checking account balance.[16] 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

[15] 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.

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

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 also includes account-to-account transfers and W_t^o include cash and other miscellaneous withdrawals. Because account-to-account transfers may include non-liquid accounts, A_t^n, such as a retirement or investment fund, 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 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, 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^c_{ijdmt} denote consumption expenditures for respondent (consumer) $i = \{1, \ldots, N_t\}$ in consumption category $j = \{1, \ldots, J^c_t\}$ where J^c_t 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, $t = \{2012, \ldots, 2020\}$.[17] Also, let Y_{ijdmt}, denote income received, which is recorded from deposits, D_t, and presumed to be after-tax. Here, subscript $j = \{1, \ldots, J^y_t\}$ denotes the 10 income categories found in Table A1; employment income is most common. Time variation in J^y_t 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 is presumed to be essentially continuous (Aguiar and Hurst, 2005). The typical respondent reports about two payments per day, some of which may be consumption expenditures. Most income is received at between weekly to monthly frequencies, which the S/DCPC tracks. As a result, a significant number of respondents do not receive 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.[18] 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

[17] 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.

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

month. Thus, daily consumption per capita (denoted by overline) is

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

where w_{idt}^D 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 $X_{10,t}^c = \overline{X^c}_{10,t} \cdot P_t \cdot D_{10}$, and annual aggregate U.S. consumption is $X_t^c = \overline{X^c}_{10,t} \cdot P_t \cdot 365.25$ because there are 365.25 days in a year.[19] Analogous procedures are used to construct aggregate DCPC respondent income.[20]

5 Data Validation

This section updates and 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.

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

This subsection quantifies the extent to which aggregate DCPC data cover the comprehensive U.S. estimates of PCE and personal income. In both cases, official U.S. data are designed to be the most comprehensive estimates of activity and thus are inherently greater than the DCPC and alternative sources (CES consumption and IRS income). To provide a useful

[19] 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.

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

comparison, all data sources are *adjusted* to remove categories that are not included in the other data sources.[21] Even after removing non-comparable elements of all data sources, some remaining categories are more comparable than others because the data sources have different classification schemes and definitions. A second comparison is made among the *comparable* categories that are most similar among data sources.[22] For the similar income categories, the diaries report net income while BEA and IRS estimates are gross. Therefore, while they are conceptually comparable, their dollar amounts are not directly. We call this comparison of similar income categories *analogous* income categories.

Figure 1 depicts five-year average (2016-2020) levels of real ($2012) consumption and income.[23] The figure includes the three data sources—official U.S., DCPC, and alternatives—and four aggregates: total (green), adjusted (red), comparable consumption (blue), and analogous income (purple). Percentages reported are indexed to the official U.S. data (100%). Total income includes DCPC household (h), which cannot be adjusted or made comparable like respondent (r). Standard error bands (orange lines) are provided for DCPC data.[24] The figure also reports consumption expenditures divided by income for PCE and DCPC measurements.

5.1.1 Consumption

Qualitatively, the results in Figure 1 are quite similar to those in Schuh (2018), verifying that 2012 was not a fluke. All three DCPC consumption aggregates continued to match PCE significantly better than CES data. Total DCPC consumption matched 97 percent of PCE, while the CES only matched 58 percent. After adjustment DCPC consumption was only 72 percent of PCE, statistically significantly lower but still notably higher than CES (52 percent). In comparable categories, the DCPC and CES aggregates match more of PCE

[21] Most items are related to housing, non-profits goods and services, and consumer loan servicing. Imputed rent and non-profit goods and services are in PCE but not DCPC, and vice versa for mortgage payments and expenses for owned dwellings. Additional unique categories removed from the DCPC include taxes, payments to person, non-classifiable payments, and loan repayments.

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

[23] The consumption bars are PCE, DCPC, and CES estimates corresponding to Appendix Table B1, which reports a detailed comparisons of consumption categories. The income bars are BEA, DCPC, and IRS estimates corresponding to Appendix Tables B2 and B3, which report detailed comparisons of income categories.

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

on average (83 and 63 percent, respectively), but the DCPC continues to be notably closer than CE. Over the five years, the DCPC is approximately 31% higher than CE consumption results on average for comparable consumption.

Quantitatively, however, DCPC aggregate consumption does not compare quite as favorably relative to PCE. Adjusted DCPC was 92 percent in 2012, 20 percentage points higher than during 2016-2020. This result reflects the important effects of improvements to the Diary survey instrument in measuring official consumption definitions through merchant categories and other revised and expanded information.[25]

5.1.2 Income

Figure 1 also shows, for the first time, that DCPC income covers U.S. data remarkably well. All three DCPC aggregates represent a majority of BEA income, but the extent of coverage varies more than for consumption. For total income, the IRS data only includes taxable income and thus excludes some income types found in BEA income (Ledbetter, 2004). DCPC total income, however, varies widely. Household income, which likely includes taxes other categories not in IRS, slight exceeds the BEA (108 percent). Respondent income, which likely excludes taxes and types that are hard-to-measure with the Diary, falls well below (59 percent) but is statistically insignificantly different from IRS. If we assume the ratio of gross to adjusted income is the same in both datasets, we can get a broad estimate on what the diary gross income would be using BEA income. This calculation is reported by the transparent bar, where the calculated gross respondent income would match 78% of BEA gross income.

Income coverage in the other two categories is similar but less variable. Adjusted DCPC respondent income (76 percent) covers the U.S. data even better than adjusted consumption (72 percent) and is essentially the same as IRS (75 percent). Adjusted income converts all measures to after-tax (disposable) and excludes a few categories that are not in all three income sources.[26] In analogous categories, DCPC income falls notably and statistically significantly short of IRS (52 versus 69 percent). However, these estimates are net for the diaries and gross for the BEA and IRS. When we use the BEA ratio of total to adjusted income to estimate gross analogous respondent income, we see that the diaries would match 76% of BEA income (purple transparent bar).

[25] 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.

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

5.1.3 Average Propensity to Consume

The last group X^c/Y in Figure 1 reports total and adjusted consumption divided by their respective income categories, whose fraction is reported on the right y-axis. The fraction of total expenditures to total income is similar between BEA and DCPC household at .80 and .78 respectively. For respondent income, we see a value of .96 when using estimated gross respondent income, significantly higher than the PCE fraction. When we compare adjusted consumption and income (which is net), we see similar fractions of X^c/Y of .88 and .83 for PCE and diary respectively. Thus, after accounting for taxes, we see similar relationship between consumption and income in the diaries found to that in the PCE and BEA.

In Appendix Figure B3, we plot expenditures by household income categories, similar to Figure 8.3 in Sabelhaus et al. (2015) who examine the ratio of total spending to net income across a continuous measurement of disposable income. Our measurement uses the adjusted consumption measurement divided by total household income. Therefore, our ratio is lower given the use of gross household income. We see a similar pattern to Sabelhaus et al. (2015), where the ratio of spending to income is highest for those with the lowest income. It is easy to imagine that at higher household incomes, we'd expect to see a higher savings rate. However, we do not see a significant difference in the spending ratio at higher incomes, likely due to the diaries not capturing the highest income consumers.

While the above analysis presented 5-year averages (and annual estimates in the Appendix), in Figure 2 we present the daily averages of adjusted consumption expenditures and respondent income in the diaries. The figure presents the diary years concatenated, with years denoted in the top x-axis. We see that consumption expenditures are much more smooth compared to income payments, which are more discrete given the nature of paychecks. The standard deviation of the consumption expenditure over the respondent income payments is .30, suggesting consumption is much more smoother than income. Quarterly and monthly PCE to BEA disposable income during this time period were .4 and .5 respectively, highlighting we can observe much more smooth incomes at the daily frequency.

5.2 Exercise #2: Real-Time Forecasts

DCPC data are essentially real-time information. Respondents complete online questionnaires every diary night to enter their recorded activity, including the exact time of day for all transactions (payments, cash management, and related activities). In theory, DCPC data are available in approximately real time, or with a one-day lag. At present, however, the Atlanta Fed and CESR have real-time access. In practice, the DCPC data are proprietary

for about a year until the Fed releases them publicly. The relative success in matching official U.S. data (Section 5.1) motivates *ex post* investigation of potential advantages in leveraging real-time DCPC data, such as for macroeconomic forecasting.[27] This section reports results of two real-time forecasting exercises to illustrate the potential value of DCPC data.

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 $\overline{C}_{10,t}$, the level of October DCPC adjusted consumption per capita. The daily projection (caret) is

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

This projection is inefficient because it does not include prior information, notably $\widehat{\overline{C}}_{9,t}(30)$, 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.[28] 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 values and convergence to statistical precision.[29] Thus, real-time access to DCPC data offers a very early, reliable forecast of monthly consumption. For comparison, PCE data for October are not published until late November and subject to revisions.

5.2.2 PCE Growth

A second exercise extends the analysis to assess how well daily DCPC consumption data can forecast monthly PCE, the broader and more important measure of aggregate consumption. Section 5.1 revealed that DCPC adjusted consumption covers only 72 percent of adjusted PCE, so daily projections of DCPC consumption may not be useful for real-time forecasts of

[27] 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.

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

[29] 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.

the *level* of PCE. However, because the DCPC is a relatively representative sample of U.S. consumers, the *growth* of DCPC consumption data might be good predictor of PCE growth.

Constructing the growth rate of DCPC consumption involves additional challenges stemming from limited data availability. Let C^*_{mt} denote adjusted PCE data, which is the best unbiased estimate of U.S. consumption but only available publicly at the monthly frequency. Projecting monthly growth of October PCE, $G^*_{10,t} = (C^*_{10,t} - C^*_{9,t})/C^*_{9,t}$, requires monthly growth of October DCPC consumption, $G_{10,t} = (C_{10,t} - C_{9,t})/C_{9,t}$. However, $C_{9,t}$ does not exist because the Diary is implemented only in October.[30] Instead, we construct a daily projection of the 12-month growth rate of DCPC consumption (G) in October,

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

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

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

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 $\widehat{G}_{d,10,t}$ 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 $\widehat{G}_{d,10,t}$ and dashed blue lines are standard error bands. The red line is the *ex post* (constant) PCE estimate of G^*_{mt}. Like projections of DCPC consumption levels, G_{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 projections (2017-2020).

Although promising, the PCE growth projections are less accurate than DCPC level projections. Convergence is slower for growth rates, taking at least half or more of the month before the estimate is reasonably close. Accurate estimates of PCE growth by the end of October still would provide 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 average difference between DCPC and PCE point estimates end-of-month

[30] Limited DCPC data are available for September 29-30 each year from the phase in of Diary wave, so in principle $G_{1,mt}$ could be constructed but the short, noisy, and non-representative two-day September DCPC sample makes the exercise unacceptably imprecise.

growth rates (see figure legends), $G^*_{mt} - G_{mt}$, is relatively small: $-.028$ for four years, and .012 excluding the 2020 outlier. However, the gap is sometimes as large as 5 percentage points in absolute value. These magnitudes are relative large and limit the usefulness of DCPC projections for real-time macroeconomic forecasting and policy analysis. More development of the Diary and expansion of the sample size are needed to produce a more useful forecasts of PCE in real-time.

5.3 Exercise #3: Income Timing and Consumption

This subsection replicates two studies in the literature that estimate how the timing of income payments influences consumption behavior. In both cases, estimates of identical models using the more representative DCPC data are compared with estimates from convenience samples reported in the literature.

5.3.1 Payday Effects on Consumption

Prior studies using daily individual-level transaction data have documented an economically significant payday effect in which average consumption expenditures are greater on days when anticipated income is received (Gelman et al., 2014; Olafsson and Pagel, 2018). To test for a similar payday effect in the DCPC data, we estimate an equation similar to the literature:

$$\frac{C_{idmt}}{\bar{C}_i} = \sum_{s=-7}^{7} \beta_s I_i(Paid_{d+s,mt}) + \eta_i + \lambda_t + \lambda_{DOW} + \lambda_{WEEK} + \varepsilon_{idmt} \tag{2}$$

where $C_{idmt}/\bar{C}_i$ is the ratio of consumption spending by consumer i on day d in year t to the individual's average daily spending; $I_i(Paid_{d+s,mt})$ is an indicator variable equal to 1 if consumer i received income on day $d+s$; η_i is a consumer fixed effect; and λ are time fixed effects for the year (λ_t), day-of-the-week (λ_{DOW}), and week of month (λ_{WEEK}). Coefficient β_s measures the fraction by which individual consumption deviates from average daily spending on each day of the two weeks surrounding income paydays ($s = 0$). Despite an unbalanced panel with only three consecutive days of respondent data on consumption and income values, the DCPC has sufficient data on paydays to estimate equation 2 at the consumer level and daily frequency.[31] For comparison with the literature, we estimate equation 2) with

[31] 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.

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 thus included as an extension.

Estimated 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, estimates of $\beta_s \neq 0$ for non-bill and food spending are essentially zero, indicating the observed effect on discretionary spending is unique to paydays themselves. Total consumption spending in the DCPC increases about 60% on paydays relative to average expenditures. This estimate is qualitatively similar but smaller than the payday effect of about 70% reported in Gelman et al. (2014). As expected, the payday effect for discretionary non-bill consumption is much smaller: 23% in the DCPC and 40-56% in Gelman et al. (2014) and Olafsson and Pagel (2018), respectively. In the DCPC, the payday effect on food consumption is insignificant with a point estimate of 10%, similar to Gelman et al. (2014) in magnitude.[32] For bill payments, the payday effects more than double (109%). Unfortunately, we cannot assess the statistical significance of differences between estimates from the DCPC and literature without the other data or standard errors. However, the representativeness of the DCPC, especially relative to selected sample in Gelman et al. (2014), suggests there may be economically non-trivial quantitative selection effects (but not qualitative). The magnitude and persistence of payday effects on bill consumption suggests consumers may intentionally align their bill payments with income payments.

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 within an illiquid savings vehicle. The model predicts that agents with higher pay frequencies borrow less (and therefore repay debt less) than consumers with lower pay frequencies, which they verify with across and within consumer analysis of credit card borrowing/repayment. We use the diaries to assess whether we observe consistent behavior among a representative sample of consumers. Following Baugh and Correia (2022),

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

we collapse our data into frequency-day bins based on the respondents' survey responses and run the following specification in both dollars and in percentages of monthly income:[33]

$$Z_{fdt} = \phi' Freq_f + \lambda_{DOW} + \lambda_d + \lambda_t + \varepsilon_{fdt} \tag{3}$$

Where $Z \in$ (credit card expenditures or repayments), 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 frequency bin, with monthly pay-frequency as the omitted variable. Thus, their model predicts that there is a decreasing relation with the outcome variables and 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.

The results of equation 3 for the diaries are found in Panel A of Table 2, while the results from Baugh and Correia (2022) are found in Panel B.[34] Each column reports a separate

[33] 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.

[34] For Y^H_{fmt}, we divide the respondents' annual household income by twelve. We report 2012 USD values, while we are not able to identify if 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.

regression. The reported F value (and associated p value) correspond for a joint significance of the two indicator variables. Columns (1) - (4) report the results for the credit card borrowing dependent variable, while the rest report the debt repayment dependent variable. Consistently Baugh and Correia (2022) find a monotonically decreasing relationship between higher pay frequencies and borrowing. In general we find the same decreasing relationship with smaller magnitudes. We consistently find 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. Our results in Panel A find evidence that consumers exhibit similar time inconsistent preferences as found in Baugh and Correia (2022), though their lower magnitudes suggest the composition of such consumers are less in a representative sample.

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).[35]

In the benchmark model, the consumer maximizes utility:

$$\max_{\{C_t, A_{t+1}\}} \mathbb{E}_t \sum_{\tau=0}^{T-t} \beta^{t+\tau} U(C_{t+\tau}) \tag{4}$$

Following the authors, we combine consumers who get paid twice a month and every other week in the semi-monthly category.

[35] The benchmark model in textbooks makes implicit assumptions that abstract from the rich, granular details offered by the DCPC and complexities of daily decision making. 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.

subject to

$$A_{t+1+\tau} = (1+r)(A_{t+\tau} + Y_{t+\tau} - C_{t+\tau}) \tag{5}$$

$$A_{t+1+\tau} \geq -B_{t+\tau} \tag{6}$$

where $\beta = (1+\delta)^{-1}$ denotes the discount factor and δ the subjective rate of time preference. For simplicity and lack of data, assets earn fixed interest rate r. Income follows the standard decomposition with a permanent component, P_t, and a transitory shock π_t:

$$Y_{t+\tau} = P_{t+\tau} + \pi_{t+\tau} \tag{7}$$

$$P_{t+\tau} = P_{t-1+\tau} + \upsilon_{t+\tau} \tag{8}$$

The well-known consumption Euler equation is:

$$U'(C_t) = \beta(1+r)\mathbb{E}_t U'(C_{t+1}) \tag{9}$$

Further analysis requires specification of the utility function. Assuming linear marginal utility for analytical interpretation,[36] when $\delta = r$ consumption is a random walk:

$$C_t = C_{t-1} + e_t \tag{10}$$

where e_t is the consumption innovation. With an infinite horizon, the solution for e_t is:

$$\Delta C_t = e_t = \frac{r}{1+r}(\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{\tau=0}^{\infty} \frac{Y_{t+\tau}}{(1+r)^{\tau}} = \upsilon_t + \frac{r}{1+r}\pi_t \tag{11}$$

Consumption responds fully to permanent shocks ν_t, with a smaller response to transitory income. The above equation indicates consumers will smooth their consumption, and only change consumption in response to income shocks. This has led to a long line of literature testing if consumption responds to changed in anticipated income, as the null hypothesis derived from the PIH predicts no response.

[36] Under more realistic convex marginal utility, a second-order Taylor expansion results in an additional precautionary savings motive (Kimball, 1990; Carroll and Kimball, 1996), $\frac{(1+\gamma)}{2}\mathbb{E}_t(\Delta c_{t+1})^2$. In our empirical analysis, we use a first-order Taylor approximation which excludes the second-order term. This is primarily due to the difficulties of identifying $\mathbb{E}_t(\Delta c_{t+1})^2$. This term is likely correlated with predicted income as discussed in Carroll (1997). However, 90% of the studies examined in Havranek and Sokolova (2020) use a first-order Taylor approximation, making our results comparable to the literature which is ultimately our goal when testing the benchmark results. Thus, future research should consider measuring $\mathbb{E}_t(\Delta c_{t+1})^2$ in the DCPC.

Identification of the structural permanent and transitory income shocks is challenging with the DCPC. It does not include specific variables that robustly identify the shocks, and the time series is too short (five years) to estimate a permanent-transitory decomposition of income accurately. Instead, we propose four income models to approximate the structural specification and construct expected income:

$$Y_t = \mathbb{E}_{t-1} Y_t \tag{M0}$$
$$Y_t = \alpha + Y_{t-1} + u_t^{M1} \tag{M1}$$
$$Y_t = \alpha + Y_{t-1} + \gamma_2 (Y_{t-2} - Y_{t-3}) + u_t^{M2} \tag{M2}$$
$$Y_t = \alpha + \phi_3 t + \gamma_3 Y_{t-1} + u_t^{M3} \tag{M3}$$

M0 is perfect foresight, perhaps most plausible for daily income. M1 is a unit root process, the standard specification in macroeconomic applications. M2 is an instrumental variables approach common in microeconomic applications. M3 is an AR(1) process with a deterministic trend more suitable to short time periods.

Each income model can be converted to changes by subtracting Y_{t-1} from both sides of the equation and writing them in common form,

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

and an econometric specification can be written as

$$\Delta C_t = \beta_0 + \beta_1 \mathbb{E}_{t-1} \Delta Y_t + \beta_2 u_t + \varepsilon_t. \tag{12}$$

The PIH predicts $\beta_1 = 0$ and $\beta_2 > 0$, but it has been long documented that consumption displays "excess sensitivity" to these predicted income changes ($\beta_1 > 0$). Common explanations of excess sensitivity include binding liquidity constraints as in equation (6), and omitted precautionary saving motive derived from a second-order Taylor expansion of the above Euler equation under CRRA utility (Carroll, 1997, 2001). We test for excess sensitivity to predicted income changes in the DCPC, comparing our results to the literature.

Although these income models do not identify permanent and transitory shocks directly, the CEQ model with an AR(1) income process can be solved analytically for the implicit coefficient on income shocks (see Appendix C):

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

where ρ is the AR(1) lag coefficient and r is the real interest rate. Note that ρ quantifies the persistence of an income shock and thus can be viewed as a proxy for permanent vs. 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 $\rho = 0$, $\Omega = \frac{r}{1+r}$, which is small for low values of real interest rates. 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 of the PIH.

7 Econometric Specifications

This section describes the econometric models used to estimate the benchmark PIH model with S/DCPC data. The unique nature of the S/DCPC unbalanced longitudinal panels (overlapping diary waves) prevents direct estimation of the econometric models with daily data at the respondent level.[37] Although daily data are representative of all consumers, only three October days of time-series observations are available for each individual consumer. The next two subsections describe the data transformations necessary to estimate the consumption models. The reminder of the section applies the consumption and income models to S/DCPC data.

7.1 Synthetic Cohorts (agent aggregation)

To obtain continuous daily time series with sufficient observations at the individual level, we use the S/DCPC data to 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:

$$\overline{C}_{kdmt} = \frac{\sum_{i=1}^{I_{kdt}} w_{idt}^{D} \cdot C_{idmt}}{\sum_{i=1}^{I_{kdt}} w_{idt}^{D}} , \tag{13}$$

which forms a balanced longitudinal panel with continuous time series observations.

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

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

time periods). Our baseline estimation uses $K = 14$ (seven ages and two biological genders) with five years of October observations for 70 total 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).[38] Other cohort definitions are used and described later.

Rejection of the PIH can be explained theoretically by credit constraints, which the empirical literature often confirms. To replicate this finding, we construct cohorts based on credit constraints defined in the literature by net worth (Zeldes, 1989) and net liquidity (Kaplan et al., 2014). We follow Aguiar et al. (2024). Consumers are classified as 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 absolute value is greater than 16.5% of monthly household income.[39,40] Consumers are unconstrained (U) if they do not meet the constrained requirements.

Classification of consumers as credit constrained can be construction two ways. Constraint criteria can be applied to consumers for each time period (denoted time varying). Alternatively, the criteria can be applied to consumers over a longer period of time (denoted time invariant), in which case individual consumers are constrained if they meet the qualifications in any one of the five diary years. The time-invariant classification yields cohort bins with at least one consumer in each each diary day. Appendix D reports results for time-varying constrained cohorts.

7.2 Frequencies (time aggregation)

Using synthetic cohorts instead of respondent-level data offers multiple choices of data frequencies for estimation. Continuous time series of synthetic cohorts form a balanced longitudinal panel with data for all 31 days in October each year. However, implementing the Diary only in October each year leaves an 11-month gap in the panel's time structure, which limits the construction of changes in consumption and expected income that are central to

[38] 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.

[39] 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.

[40] Credit card debt is taken from the consumer's reported September value, and thus there is a mistiming between the liquid asset and liquid debt. However, we choose this specification to follow the liquidity definition of Aguiar et al. (2024) as closely as possible.

the benchmark PIH model.

Given this continuous-discrete (daily data, one month per year) structure of the DCPC time series panel, two frequency observations are most efficacious: daily and annual. Let Z_{dmt} denote a DCPC flow variable on day $d = \{1, 2, \ldots, 31\}$ of month $m = \{1, 2, \ldots, 12\}$ in year $t = \{2016, 2017, \ldots, 2020\}$, where subscript k is suppressed for simplicity. Thus *daily* data, $Z_{d,10,t}$, are well-defined for October 1-31 in years 2016-2020. The October panel segments can be concatenated across years and treated as pseudo-continuous, except for October 1 each year. *Annual* data are defined as time-aggregated sum of activity in October,[41]

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

Although $Z_{10,t}$ do not represent activity for the entire year t, the change $\Delta Z_{10,t} = Z_{10,t} - Z_{10,t-1}$ represents the change over 12-months (one year, or annual), which holds constant any monthly seasonal factors.[42] More generally, daily (d) changes and 12-month (m) annual changes are written as

$$\begin{aligned} \Delta_d^\tau Z_{dmt} &= (Z_{dmt} - Z_{d-\tau,mt}), \qquad 1 < d \leq 31 \\ \Delta_m^\tau Z_{mt} &= (Z_{mt} - Z_{m,t-1}), \qquad m = 10, \end{aligned}$$

respectively, where $\tau = \{1, 12\}$ denotes the length of difference in frequencies denoted by subscripts d, m.

7.3 Estimation Methodology

Following the income and consumption specifications derived in section 6, we estimate annual and daily econometric PIH models, respectively:

$$\Delta_m^{12} C_{k,10,t} = \beta_0 + \beta_1 \widehat{\Delta_m^{12} Y_{k,10,t}^H} + \beta_2 u_{k,10,t} + \varepsilon_{k,10,t} \tag{14}$$

$$\Delta_d^1 C_{kd,10,t} = \beta_0 + \beta_1 \widehat{\Delta_d^1 Y^R}_{kd,10,t} + \beta_2 u_{kd,10,t} + \varepsilon_{kd,10,t} \tag{15}$$

Where Y^R is utilized in the daily regressions as Y^H does not vary by day. We also calculate $Y_{k,10,t}^O = Y_{k,10,t}^H - \sum_{d=1}^{31} Y_{kd,10,t}^R$ and estimate (14) allowing for separate coefficients $\beta_1^{R,O}, \beta_2^{R,O}$.

[41] For the annual analysis, we use average monthly household income ($Y_{it}^H/12$) to match the frequency of consumption.

[42] In fact, the Federal Reserve chose to field the DCPC in October because it is a month with minimal seasonal factors in aggregate consumption and income data.

We assume $C_t = C_t^n$, nondurable goods and services in the diary data from section 4.1. In both equations, actual income changes

$$\begin{aligned} \Delta_m^{12} Y_{k,10,t}^H &= \left[\widehat{\Delta_m^{12} Y_{k,10,t}^H} + u_{k,10,t}\right] \\ \Delta_d^1 Y_{kd,10,t}^R &= \left[\widehat{\Delta_d^1 Y_{kd,10,t}^R} + u_{kd,10,t}\right] \end{aligned}$$

are sums of predicted (term with a caret) and unexpected ($u_{k,10,t} = f(\pi_{kmt}, \upsilon_{kmt})$) components of annual (household) and daily (respondent) income changes. A crucial assumption of these econometric models is successful estimation of predicted income changes, which depend the underlying model of income (next subsection). All PIH consumption and income models are estimated using OLS in two stages. The income models are estimated in the first stage and their predicted values calculated for use in the second stage equations (14) and (15).[43] The consumption and income models are estimated twice using data in two types of units. Estimates with data in dollar values (uppercase C, Y) yield a measure of the *MPC* under linear marginal utility from equation (10). Estimates with data in logs (lowercase c, y), which converts variable changes to growth rates, yield a measure of *elasticity* resulting from convex marginal utility. The PIH implies $\beta_1 = 0$ and $\beta_2 > 0$. Evidence in the literature overwhelmingly rejects the $\beta_1 = 0$ hypothesis, showing excessive sensitivity of consumption to predicted income, (Jappelli and Pistaferri, 2010), but credit or liquidity constraints at least partly explain the rejection (Havranek and Sokolova, 2020).

The comparison of annual and daily estimates is novel because the benchmark PIH model typically is estimated only with lower frequency data (annual, quarterly, or monthly). Even studies using high-frequency data often will time-aggregate transactions to monthly or lower frequencies for testing benchmark models (Ganong and Noel, 2019; Gelman, 2021). Estimation of the daily model offers greater precision due to many more observations, but other benefits as well. Mechanically, we can test whether the PIH predictions hold at the higher frequencies and account for time aggregation (Crawley, 2020). Economically, daily consumption decisions are influenced by factors that are hidden in low-frequency data. Examples include heterogeneous and discrete income pay periods that produce payday effects (Gelman et al., 2014; Olafsson and Pagel, 2018), bill payment effects (Gilyard, 2023), and other details of personal financial management.

[43] The second-stage standard errors have to be corrected for the use predicted values of income change from the first stage. The second-stage standard errors are bootstrapped with 1000 replications.

7.4 Income Models

Successful estimation of equations (14) and (15) requires accurately identifying the unobserved components of income changes, $\Delta_m^{12} Y_{k,10,t}^H$ and $\Delta_d^1 Y_{kd,10,t}^R$. Two strategies are common in the literature. One is to model the income process explicitly, which risks misspecification errors. The other is to use observed income changes that are plausibly identified as anticipated or unexpected, which avoids misspecification but offers less structural interpretation.[44] Because the S/DCPC do not have data or events that plausibly identify anticipated income changes and synthetic cohorts mask consumer-specific events, we estimate separate income models for each cohort.

To guard against and assess potential effects of misspecification errors on benchmark PIH model estimates, we estimate the four income models introduced in section 6 at the annual and daily frequency. Model M0 uses actual income changes under the assumption all income changes are expected. M1 applies a unit root to annual household income and daily household income.[45] Although simple and parsimonious, the stochastic trend model is not precisely estimated over short time periods and may not be appropriate at the micro level, especially with finite life cycles. M2 instruments current income changes with the second lag of income changes, which is popular in the applied micro literature (Deaton et al., 1992; Jappelli and Pistaferri, 2017) as it is correlated with the endogenous variable but not the error term. Although this specification may be optimal with many observations, the annual model is limited to 28 observations and it is unclear how well this specification fits synthetic cohort data.

Because the DCPC data may not be well-suited for either the M1 or M2 model, we propose a practical reduced-form model that may fit the available data best. The fourth model (M3) is an AR(1) specification in *levels* with fixed-effects:

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

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

where lagged income is subtracted from both sides of the equations to obtain a first-difference. In (M3$^{\text{t}}$), η_{AGE} are life-cycle age fixed effects only (exclude biological genders), t is a linear time trend, and their interaction is motivated by Appendix Figure D1 (time-series graphs

[44] 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).

[45] Note that for M1, we run equation (14) without the constant term β_0 given M1 is regressed only on the constant α.

of income by age).[46] Although the time-period is short and samples sizes small, incomes exhibit heterogeneous trends that roughly conform with standard life-cycle expectations. Income trends upward more for younger ages, stagnates for the middle ages, and is flat or slightly decreasing for older age cohorts.

Modeling daily income is more complex due to idiosyncratic features that are evident only at high frequency. To capture this complexity parsimoniously in (M3$^{\text{d}}$), λ_t and λ_d are interacted time and day fixed effects (year-by-day) and η_k are cohort fixed effects. $\vartheta_{kd,10,t}$ are within-cohort shares of variables (superscript j) that predict daily income, such as education, income rank within household, paycheck frequency, and income type.[47] These variables capture differences in paycheck timing across consumers and days.

AR(1) income models (M3$^{\text{t}}$) and (M3$^{\text{d}}$) fit the data best and relatively well in absolute terms. Figure 5 plots actual (solid lines) and predicted (dashed lines) annual (left panel) and daily (right panel) aggregate U.S. income using models (M3$^{\text{t}}$) and (M3$^{\text{d}}$), where the first row is the predicted income converted to levels and the second row in differences. Naturally, annual aggregate (across consumers) income is much smoother due to time-aggregation (monthly sum) and low seasonality (October). Consequently, the fit of the other annual income models is not significantly lower. Appendix D reports the first-stage regression results for the (M3$^{\text{t}}$) and (M3$^{\text{d}}$) specifications. The annual income prediction reports a low adjusted R^2 of .01 (.01) in levels (logs), while the M2 model reports slightly higher values of .19 (.13) and the M3 model reports values of .23 (.16). As noted earlier, daily income is more volatile—even when aggregated across consumers. For this reason, the other daily income models fit the data much worse. Both M1 and M2 models do not fit the daily income dynamics well, reporting an adjusted $R^2 \leq .01$ for both models in levels (and logs). M3 fits the daily income data significantly better with a reported adjusted R^2 of .51 (.60).

8 Estimation Results

Table 3 reports estimates of the benchmark PIH model with income models (M1-M3). Panel A contains annual estimates of equation (14), and Panel B contains daily estimates of equation (15). All models are estimated with data in levels (*MPC* sub-panels) and in logs

[46] When estimating the annual consumption models with $\beta_1^{R,O}, \beta_2^{R,O}$, we use equation M3$^{\text{t}}$ and also include $\Delta_m^{12} Y_{k,10,t}^R$ as a predictor for $\Delta_m^{12} Y_{k,10,t}^O$ and vice versa.

[47] Every respondent reports if they receive any of the ten types of income discussed in the appendix, regardless if they're observed receiving income during their diary period. Additionally, every respondent reports the frequency at which they receive income: weekly, every two weeks, twice a month, quarterly, yearly, other one-time basis, other regular basis, and other on an irregular basis.

(*Elasticities* sub-panels). In each sub-panel, the first row reports the estimated responses of consumption to changes in anticipated income (β_1), and the second row responses to changes in unanticipated income (β_2) in equations (14), and (15). The latter are $\hat{u}$, residuals from first-stage income regressions that proxy for income shocks but do not distinguish transitory and permanent shocks and may reflect model-specification error.

Estimates of the benchmark PIH model with DCPC consumption data shown in Table 3 are broadly consistent with the literature (Havranek and Sokolova, 2020). To see, consider the first three columns in Table 3 with estimates from each income process, M1-M3. In the literature, the mean estimate of β_1 (MPC) is about .40 for all data and .24 with micro data. Estimates are usually statistically significant, indicating excess sensitivity of consumption to (expected) income and rejection of the PIH model. The estimate for income model M1 (macro unit root) is close to .40 while the M2 (micro lagged income) is implausibly negative. For income model M3, however, the annual MPC (.27) is remarkably close to the literature and significant.

Annual estimates of β_2 range from .13 - .55 for MPCs and elasticities, with large standard errors. It is harder to compare these results to the literature because $\hat{u}$ combines permanent and transitory components.[48] However, the coefficient should be closer to 1.0 if permanent shocks dominate and closer to 0 if transitory shocks dominate. To explore this issue further, the third row of MPC sub-panels reports analytical responses of consumption to income shocks implied by the PIH for model M3. Calibrated values of $\Omega = r(1+r-\rho)^{-1}$ are small, and smaller than the insignificant β_2 (0.158) suggesting the data contain more transitory income shocks.[49] Importantly, we use Y^H for our annual income and Y^R for daily. While Y^H does not vary daily, we include regressions of consumption changes on respondent income and rest of household income Y^O, where $Y_t^H = Y_t^R + Y_t^O$ in Appendix Table D2 for income models M0 - M3 at the annual frequency. We find similar coefficients on both income types, and cannot reject differences in coefficients.

Turning to high frequency, Panel B in Table 3 reports estimates of the benchmark PIH model with daily data, the first such application (to our knowledge). Overall, the estimates with daily data are quite similar to those with annual data. However, the daily estimates

[48] See Carroll et al. (2017) who provide a review of estimates of transitory shocks, and Crawley and Theloudis (2024) who offer a literature review 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 around .20 when accounting for heterogeneity.

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

Table 3: Benchmark Consumption Estimates

	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	0.190*	0.418	-0.038	0.270*	-0.001	0.403*	0.153	-0.093
	(0.114)	(2.550)	(0.415)	(0.141)	(0.072)	(0.236)	(0.281)	(0.197)
β_2		0.190*	0.158	0.131	-0.120	0.575***	-0.066	0.047
		(0.111)	(0.169)	(0.169)	(0.359)	(0.208)	(0.541)	(0.388)
Ω			0.005***					
			(0.001)					
Elasticities								
β_1	0.554*	1.304	0.203	0.666**	0.076	1.002**	0.751	-0.214
	(0.326)	(43.669)	(2.267)	(0.336)	(0.248)	(0.439)	(0.706)	(0.472)
β_2		0.554*	0.354	0.487	-0.181	1.428**	-0.150	0.202
		(0.322)	(0.409)	(0.469)	(0.991)	(0.688)	(1.028)	(0.864)
Panel B: Daily								
MPCs								
β_1	0.014*	-0.152	-0.974	0.023**	0.022*	0.058**	0.041**	0.034
	(0.008)	(0.461)	(27.118)	(0.011)	(0.011)	(0.023)	(0.017)	(0.021)
β_2		0.014**	0.015**	0.003	0.013	0.062	0.010	-0.019
		(0.007)	(0.007)	(0.010)	(0.020)	(0.045)	(0.031)	(0.043)
Elasticities								
β_1	0.026***	-0.463	-0.002	0.029***	0.022***	0.037***	0.012	0.030***
	(0.003)	(29.778)	(0.545)	(0.004)	(0.005)	(0.008)	(0.007)	(0.006)
β_2		0.026***	0.027***	0.019***	0.017*	0.024	0.007	0.021
		(0.003)	(0.003)	(0.005)	(0.010)	(0.016)	(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. Grouping M0 - M1 denote income model used. " K = " grouping denotes the cohorts used. C denotes the cohort constraint specification, where C is constrained and U is unconstrained. The results of regressing the changes in consumption on the first stage residuals are included at the bottom of each sub-panel, labeled $\hat{u}_{kmt}$. Ω reports the MPC implied by the Permanent-Income Hypothesis given the first stage AR(1) coefficient (ρ), calibrated to a 5-year average of real interest rates (DGS10 from FRED), $\Omega = \frac{r}{1+r-\rho}$. Standard errors are bootstrapped (1000 replications).
[2] Note that $\beta_1^{M0} = \beta_2^{M1}$ as all income variation is treated as expected in M0, and unexpected in M1. If we consider average consumption as μ in $\Delta C_t = \mu + v_t$, it can be easily shown by setting this equal to the consumption equation with M1 that $\beta_1^{M1} = \mu/\alpha$. That is, β_1^{M1} is the fraction of average consumption to average income. In the diaries, $\mu = 59.33, \alpha^{M1} = 141.83$ which results in β_1^{M1}.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

have relatively lower magnitudes and standard errors, and are more consistent across cohort specifications. The daily β_1 MPC (elasticity) in Model M3 is .023 (0.029) and significant. The β_2 estimates are all positive and similar magnitude to those for Models M1 and M2, but insignificant except for M3.[50]

Interestingly, the M3 daily MPC estimate is about an order of magnitude smaller than the annual estimate (0.023 versus 0.270) based on October data each year. This is likely not a coincidence and may be due to differences in the timing of consumption and income. At high frequencies income is discrete dependent on pay frequency while consumption is (essentially) continuous daily leading to a misalignment of consumption and income. To test if this misalignment is the driving difference in magnitudes, we create a daily panel of average consumption and income across respondents with the same pay frequencies: Weekly, Bi-Weekly, Semi-Monthly, and Monthly. This will allow us to see how MPCs vary by paycheck frequency. Additionally, for weekly consumers, we then aggregate their consumption and income to the weekly frequency:

$$\overline{C}_{f_w,w,10,t} = \sum_{d}^{D_w} \overline{C}_{f_w,d,10,t} \ , \ \overline{Y}^R_{f_w,w,10,t} = \sum_{d}^{D_w} \overline{Y}^R_{f_w,d,10,t}$$

Where $\overline{C}_{f_w}, \overline{Y}_{f_w}$ denote average weekly consumption and income across consumers with weekly income frequency, f_w. We then estimate (15) with income model M3$^{\text{d}}$ to examine how the MPCs change when consumption and income are measured at the same frequency, and therefore synchronous.[51] Note this calculation of creating synchronous consumption and income is only feasible with weekly paychecks, as lower frequencies would not allow for enough observations. Results can be found in Table 4, where columns denote frequency of paycheck and column groupings denote frequency of data. The first-stage results can be found in Appendix Table D5, with R^2 ranging from .48 to .81. In column one, we aggregate weekly earner's consumption and income to the weekly frequency, so that consumption and income are synchronous in terms of timing. The magnitude on expected income grows in

[50] Daily applications of testing consumption smoothing may be insightful given the 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 makes daily consumption decisions, it may be important to account for this by estimating the models at a daily frequency.

[51] 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 D5 for first-stage results.

size when using consumption and income that are synchronous frequencies, and is lower than the annual aggregate result from Table 3, albeit insignificant.[52] This suggests that the misalignment between daily consumption and pay frequency is driving the magnitudes differences in annual and daily estimates.

In the remaining columns, we estimate MPCs by weekly, bi-weekly, semi-monthly, and monthly paycheck earners at the daily level (here, the timing of income and consumption will be asynchronous). We include the benchmark daily results from Table 3 in column 2 for comparison. While the results are mostly insignificant (besides bi-weekly), we see the coefficients grow with pay frequency length, until monthly where the magnitudes diminish. If the misalignment between consumption and income is the cause of smaller MPCs, we'd expect the *opposite*: MPCs should grow as the alignment between to consumption and income become closer to matching (that is, weekly would have higher MPCs compared to monthly).

Table 4: Paycheck Frequency Regressions

	Synchronous C, Y		Asynchronous C, Y				
Data Frequency:	Annual	Weekly	Daily				
				Subsamples by Income Frequency			
Respondent Sample:	Full Sample	Weekly Subsample	Full Sample	Weekly	Bi-Weekly	Semi-Monthly	Monthly
MPCs							
β_1	0.270*	0.219	0.023**	0.000	0.030**	0.057	0.032
	(0.141)	(0.358)	(0.011)	(0.034)	(0.012)	(0.074)	(0.024)
β_2	0.131	-1.338	0.003	-0.021	0.039	0.060	0.019
	(0.169)	(3.949)	(0.010)	(0.065)	(0.030)	(0.092)	(0.027)

[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 (from Table 3) and weekly respectively, where weekly is estimated for only those consumers who have weekly paycheck frequencies. We refer to these and Synchronous C,Y as consumption and income occur simultaneously. 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 3 reports the daily estimates from Table 3. Columns 4 - 7 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 2, 4-7).
[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors or bootstrapped (1000 replications).

Given we found the magnitude of MPCs are larger when consumption and income are synchronous, we suspect additional unaccounted factors at play. A growing MPC with longer pay frequency may suggest impatience within the pay cycle, consumers may be overspending when income arrives which is exacerbated by longer pay frequencies. This corresponds to Parsons and Van Wesep (2013), who finds that consumers with present-bias consumer more soon after the paycheck arrives, and less prior to the next paycheck (in which the pattern

[52] The high standard errors are likely due to the limited number of possible observations with this method, as aggregating by week allows for 20 observations (five years of four weeks).

grows with pay frequency length). However, without more statistical precision no definite conclusions can be made from the results.

Returning to Table 3, overall results for β_1 and β_2 are approximately consistent with the prior literature but do not unequivocally reject the benchmark PIH model. Model M3 produces statistically and economically significant estimates of β_1, but the estimates in Models M1 and M2 are unstable, mostly insignificant, and often negative; the M1 daily elasticity is very negative and significant. All models produce positive and plausible estimates of β_2, many of which are statistically significant; these results are consistent with the benchmark PIH model. Taken together, the results favor M3 as the preferred model based on its closer adherence to results in the literature. The efficacy of the M1 and M2 income models is less clear, and they both fit the income data less well than the M3 model. In general, the elasticity estimates are higher than MPC, which may be due to factors not accounted discussed in Havranek and Sokolova (2020) such as consumption risk and non-separable utility in consumption and leisure.

For income model M3 only, the remaining columns of Table 3 (five through eight) report estimates of the benchmark PIH model for subsamples of consumers defined by their likelihood of being credit constrained (C) or unconstrained (U).[53] Consistent with the literature, many specifications of the PIH model are more likely to be rejected for credit constrained consumers than for unconstrained consumers. Estimates for unconstrained consumers are generally close to zero and not statistically significant (besides daily MPC based on liquidity constraint), suggesting the PIH model cannot be rejected, whereas constrained consumers have larger and more often significant MPC estimates as predicted by theory. Evidence of rejection for constrained consumers is strong for net worth, with significant MPCs of .40 (annual) and .06 (daily), but weak and inconsistent for net liquidity. Havranek and Sokolova (2020) find that the excess sensitivity measures are .12 lower on average, which is in line with our MPC results. When credit constraint categories are time-varying each year, the annual results are less consistent and sometimes contradictory across definitions (see Appendix Table D1).

[53] 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.

9 Sample Selection Effects

This section investigates and quantifies potential sample selection effects on estimates of consumption behavior that arises from the use non-representative convenience samples similar to those used in the literature. Although data from convenience samples can be weighted to approximate U.S. demographics from the Current Population Survey (CPS), *ex post* stratification methods do not guarantee elimination of sample selection effects. Such effects may arise from unobserved economic behavior or from the failure to use influential observed economic behavior in the construction of weights used to draw random samples. For each exercise, the difference between estimates from the more representative DCPC data and from the convenience samples in the literature quantifies the extent of sample selection effects.

Table 5: Subsample Regressions (Daily)

	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	0.089	0.009	0.032***	0.059	0.059***	0.070	0.058	0.070***
	(0.068)	(0.006)	(0.011)	(0.041)	(0.020)	(0.137)	(0.038)	(0.022)
β_2	0.037	-0.010	-0.179**	0.012	-0.016	-0.089	-0.011	0.073**
	(0.077)	(0.017)	(0.071)	(0.017)	(0.039)	(0.189)	(0.029)	(0.031)
Elasticities								
β_1	0.057***	0.018*	0.032***	0.028**	0.032***	0.026*	0.017	0.028***
	(0.016)	(0.009)	(0.007)	(0.013)	(0.000)	(0.015)	(0.019)	(0.002)
β_2	0.019**	0.025*	-0.006	-0.007	0.030***	0.002	-0.023	0.006
	(0.009)	(0.013)	(0.007)	(0.020)	(0.005)	(0.008)	(0.047)	(0.004)

[1] Table presents daily consumption equations across subsamples. K = A(2)Subsample(2). Column groupings denote subsamples. 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 subsamples we utilize are based on data availability and subsamples used in previous literature. From the subsamples identified in Table 1, we use mobile payments users, visa adopters, and cash users.[54] Additionally, we include consumers who revolve credit card debt due to their higher discount rates estimated in Fulford and Schuh (2024, 2023) and interpreted as impatience. Ideally we would include PFM users and bank account users, but these measurements are not available for the entire analyzed sample. We include four

[54] Mobile payment users are those that used a mobile app to make a payment in the last 12 months. Cash users are defined by those who make more than 50% of their monthly retail payments in cash.

cohorts in each analysis: the two subsample cohorts, and two age cohorts. We then estimate the consumption equations separately for each subsample of interest. For the analysis, we utilize the daily data to allow for more observations throughout time for consumers.

Results are presented in Table 5. Column groupings denote the subsamples of interest, while columns labeled "No" are the estimates for those not a part of the subsample, and "Yes" are. The MPCs and elasticities in β_1 show clear differences between the subsamples, though sometimes inconsistent between MPCs and Elasticities. The PIH cannot be rejected for mobile payment users and credit card convenience users, compared to their counterparts who show generally larger, more precise estimates. Visa adopters show larger but insignificant MPCs, and elasticities are essentially the same. Those who are not primarily cash users show more precise MPCs and elasticities, though the theoretical reason for any difference is not clear. β_2 estimates show similar trends between subsamples as β_1, with some estimates being implausibly negative. These estimates show there may be large differences between subsamples. Even when weighting is applied to match CPS demographics, the underlying behavior of agents may influence inference on consumption and income dynamics.

10 Policy Implications and Future Opportunities

Although the DCPC continued to provide valuable new representative, publicly available data on individual-level consumption and income in 2016-2020, it still has limitations relative to large, proprietary, transactions data sets—especially data frequency and number of respondents. However, the DCPC has another crucial advantage: it can be expanded and improved. Rather than accepting the "accidental" success of the DCPC as is, the payment diary instrument is a blueprint for the intentional development and implementation of a more sophisticated data construction instrument that moves closer to a fully integrated set of household financial statements.[55] Given the relative success and promise documented here, government policy makers and even private-sector agents may find it profitable to fund future development of the payment diary instrument.

Development of the payment diary would benefit from three improvements to data construction. First, the measurement instruments (survey and diary) need better identification of key theoretical concepts (consumption, income, emergency saving, etc.), expanded coverage of balance sheet items (especially more forms of liquidity and longer term assets and liabilities), and upgraded use of "real-time" transaction interviews each night of data en-

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

try. Second, data collection needs more respondents (especially for geographic coverage), greater frequency (at least quarterly for macroeconomic analyses), and perhaps longer diary periods for individual consumers. Switching to a household sampling unit and expanding the sampling frame (especially higher income households) would be major improvements as well. Finally, expanding the professional staff devoted to data production is needed for data: management, design, and delivery; documentation and instructions; user bibliographies; and cleaning and imputation procedures based on economic theory.

Research using the DCPC data for analysis of consumption and income has been limited thus far, but three directions for future research are promising. First, the diary instrument could be implemented around special upcoming topics, such as randomized tax rebates, policy regime shifts, and semi-predictable natural disasters or health pandemics. If combined with incisive real-time interviews tailored to elicit consumer decision making, these projects could yield important new insights. Second, the DCPC data can be merged with other data in creative ways, such as credit-bureau files (Cole et al., 2018) and private-sector data breaches (Rodriguez and Schuh 2021), or jointly with access to existing transactions data bases, such as financial institution customers. Finally, if the Atlanta Fed made the data available to the public in real-time (rather than with a one-year lag), researchers could use them for forecasting and business cycle analysis.

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

11 Conclusion

This study has demonstrated the capability of the DCPC in measuring accurate consumption and income behavior as a high-frequency data set. The proficiency of the payment diaries as a transaction data source was shown through three primary findings. First, extending the work of Schuh (2018) this study displayed the DCPC continues to captures core U.S.

consumption and income estimates, comparable to standard aggregate measures such as the PCE consumption and BEA DPI. Second, the accuracy and rapidness of the real-time data analysis showed the diary's representative estimates are realized quickly throughout October, finding the daily dynamics of consumption converging to aggregate monthly statistics with precision and timeliness. Third, we exhibited that the DCPC shows potential in estimating consumption and income behavior by replicating common results found within the consumption literature. Together, these findings highlight the capacity of the DCPC as a high-frequency data source in measuring daily consumption behavior.

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

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

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Technical Appendix

Appendix A Data Construction Details

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.

Figure 1: 5-year Consumption and Income Averages

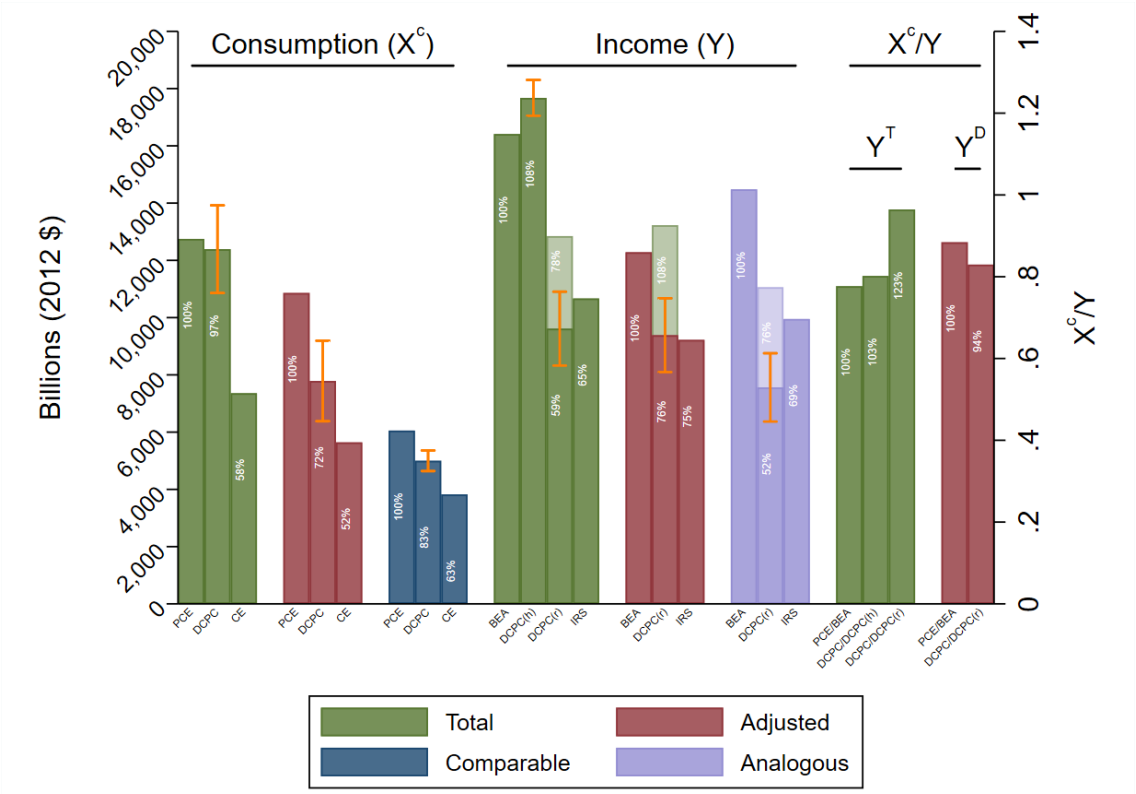


Figure shows the five-year consumption (DCPC, PCE, and CE) and income (DCPC, BEA, IRS) corresponding to Appendix tables B1, B2, and B3. The x-axis are different categories of expenditures, while the y-axis is 2012 dollar values (left) and fraction of income (right). Percentages reported are all indexed to PCE for consumption and BEA for income values of each category. Consumption categories: "Total" are expenditures, "Adjusted" remove unique categories, and "Comparable" are the most comparable categories. Income categories: "Total" is total gross income, "Adjusted" removes unique categories and is net income, and "Analogous" are similar income categories, which is net for DCPC and gross for the other datasets. Orange range plots are the 95% confidence intervals for DCPC estimates. DCPC(r) is respondent income, while DCPC(h) is household income. Transparent bar under total DCPC(r) estimates gross respondent income using the ratio of total to adjustable BEA income. The transparent green bar under adjusted DCPC(r) reports the estimated after-tax household income using the BEA ratio. The transparent analogous income bar reports estimated gross respondent income using the BEA ratio. X^c/Y reports the total and adjusted consumption aggregates divided by their respective income categories, whose values correspond to the second y axis. X^c/Y for DCPC/DCPC(r) uses the estimated gross respondent income. Y^T and Y^D denote total and disposable income respectively.

Figure 2: Daily Consumption Expenditures and Income

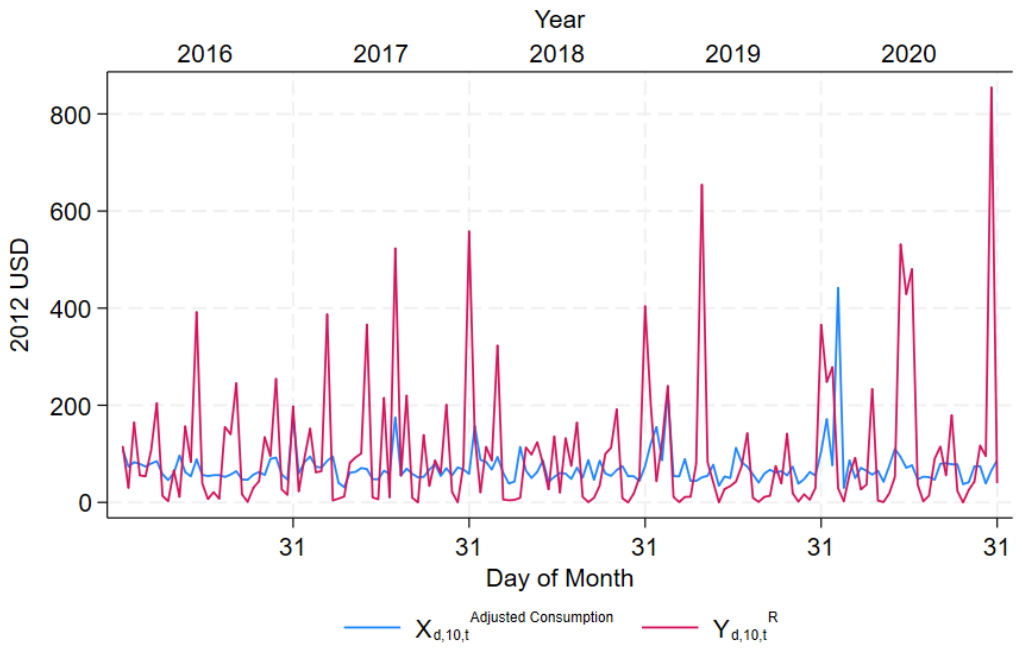


Figure 2 shows the aggregate daily plots of adjusted DCPC consumption and respondent income. Years are concatenated.

Figure 3: Daily Estimates and Annual Forecasts: 2018

(a) Daily Estimate of Monthly Payments

(b) Forecasting Annual DCPC Growth

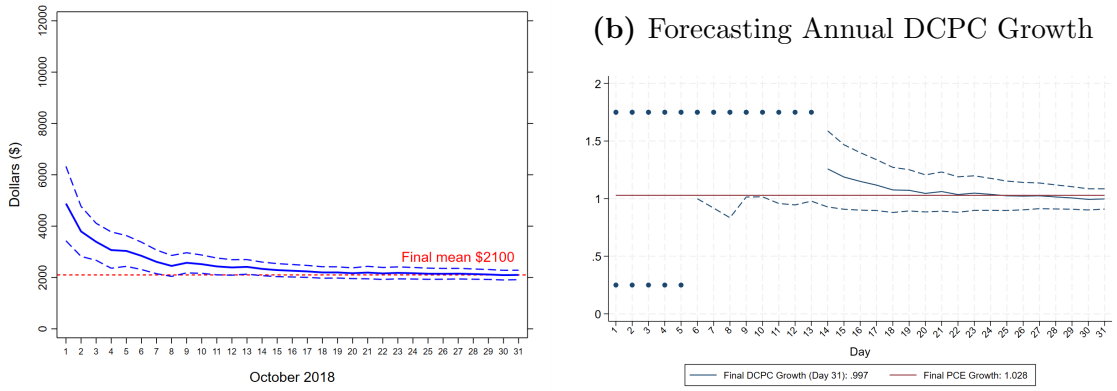


Figure 3 reports the daily estimates of annual DCPC growth for 2018 (right panel) and the daily estimates of monthly payments per consumer for 2018 (left panel). The solid blue line in the right panel represents G_{dmt} for each day of the diary, while the red line shows PCE growth G^*_{mt}. In the left panel, dashed lines indicate 95% confidence intervals, and the dotted red line is the final mean. Scatter points cap estimates above 1.25 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).

Figure 4: Consumption Response to Income Payments

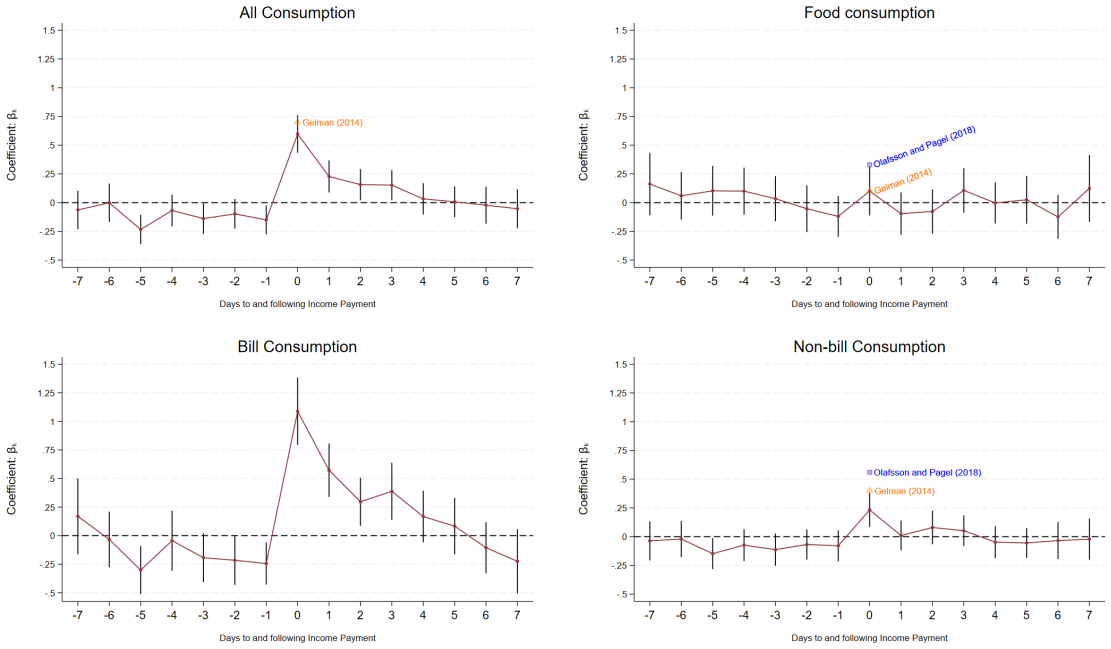


Figure 4 reports the β_s coefficients from equation 2 over the four consumption categories. Negative days denote days before income payment (-7 through -1), while positive days denote days after income payment (1 through 7). paydays. Black lines denote 95% confidence intervals. Results from Gelman et 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 Table 2.

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

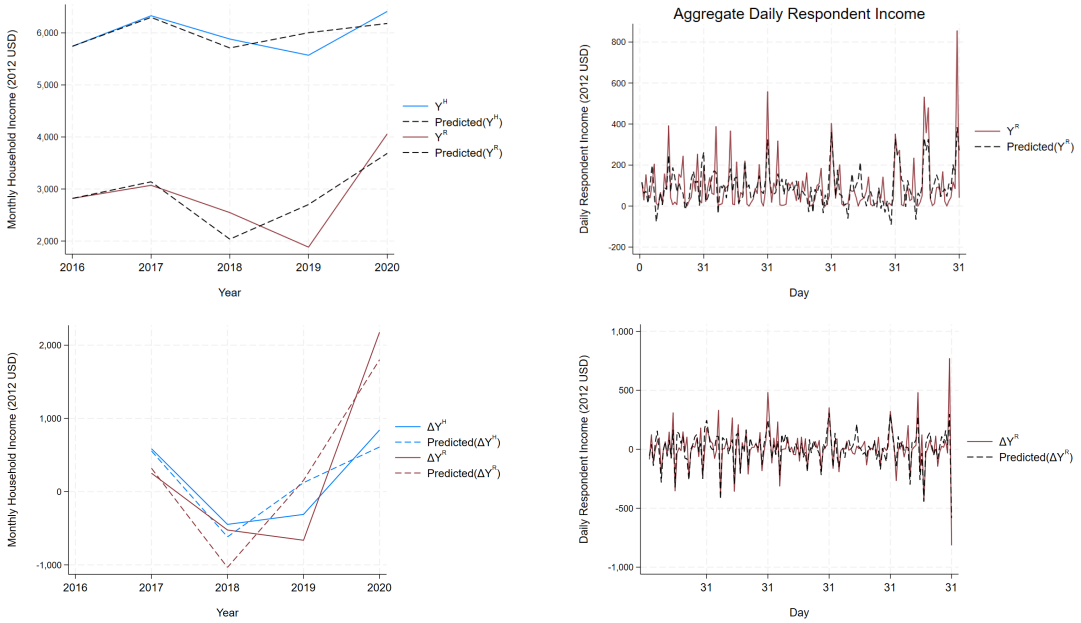


Figure 5 reports monthly income in the first panel and daily income in the second panel over all respondents. The blue line report Y^H, while the red line reports Y^r. The black line in both graphs are the predicted values of each income type at each frequency using a similar specification to M3^t without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

A.2 Data Structure

Figure A1: Diary Wave Implementation

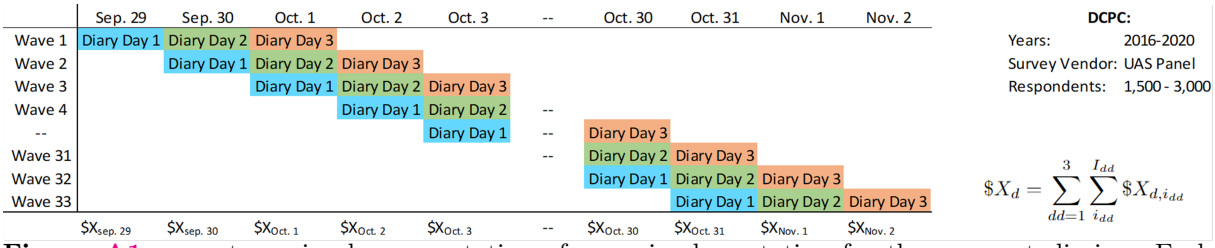


Figure A1 presents a visual representation of wave implementation for the payment diaries. Each wave contains an approximately equal number of respondents who are randomly assigned to each wave. Each wave contains three days where respondents record their daily transactions. The first wave begins September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

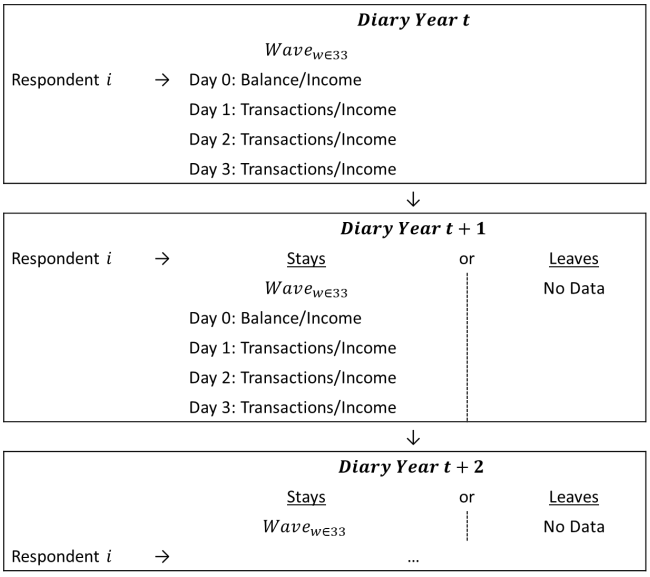


Figure A2 presents a visual representation of the panel structure of the payment diaries. Respondents from the SCPC are offered to take the DCPC. Any respondent i who agrees to participate in diary year t is randomly assigned to one of 33 waves (see figure A1) On the initial diary day 0, account balances 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 A10: Changes to the DCPC

Sponsor:	Federal Reserve Banks of Boston, Atlanta, and San Francisco						
Content Summary:	Payments, income, payment instruments, account balances, instrument carried/available, cash balances, use of instruments (frequency, amount), choice reasons						
Measurement Period:	Daily (three consecutive, randomly assigned)						
Target population:	Age 18 and above, non-institutional population						
	2012	2015	2016	2017	2018	2019	2020
Reporting period	October	Oct, Nov, Dec	October	October	October	October	October
Days in October reported	1st - 31st	16th - 31st	1st - 31st	1st - 31st	1st - 31st	1st - 31st	1st - 31st
Vendor	RAND Corporation	University of Southern California	University of Southern California	University of Southern California	University of Southern California	University of Southern California	University of Southern California
Sampling Frame	American Life Panel (ALP)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)	Understanding America Study (UAS)
Outsourced Sampling Frame	-	Growth from Knowledge (GFK)	-	-	-	-	-
Total Respondents	2,468	Total: 1,392 UAS: 1,076 GFK: 316	2,848	2,793	2,873	3,016	1,537
- In October	-	UAS: 238 GFK: 0	-	-	-	-	-
Merchant Categories	Merchant (45)	Merchant (9) Submerchant (34) Purpose (8) Subpurpose (42)	Merchant (9) Submerchant (44) Purpose (8) Subpurpose (44)	Payee (8) Merchant (21) Purpose (41)	Payee (8) Merch (21) Pay Categories (60)	Payee (8) Merch (21) Pay Categories (60)	Payee (8) Merch (21) Pay Categories (60)

Figure A3: Evolution of Payment Categories in the DCPC

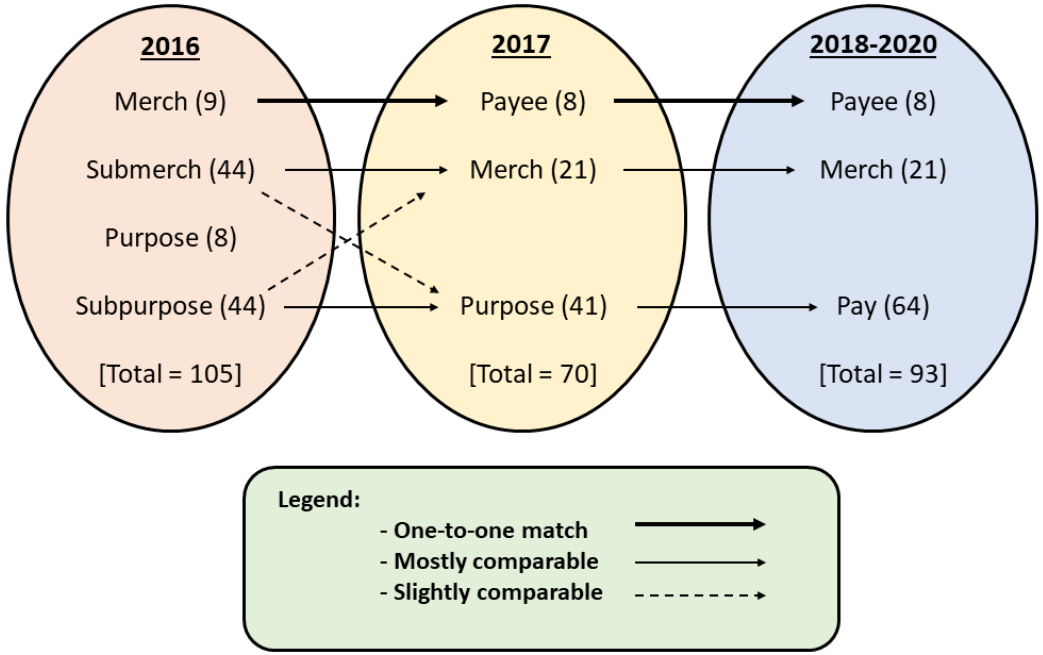


Figure A3 offers a simple overview of changes to DCPC payment categories over the years. In 2012, there were 45 possible merchant categories in which expenditures could be categorized. In 2015, merchant was simplified into 9 categories, and submerch categories were added to add more details to the merchant 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. Total income compares the estimates before any adjustments. Total is broken down into comparable and noncomparable categories. Note these comparisons are before any adjustments. Comparable category in this table reports the comparisons of identified recorded income found in the DCPC and the same income types in the other data set.[56] The DCPC tends to match 59% and 90% of BEA and IRS results comparably. However, this comparison is before deducting taxes or supplements to wages and salaries, and therefore this comparison misses important differences between within the income types. After removing taxes and other differences between the data sets, adjusted income reports the disposable income with common income definitions between the DCPC and BEA/IRS.

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

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

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

Table B3: IRS and DCPC Income Estimates

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

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

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
Analogous Income	7,562	6,876	1.1	.52	.47
Noncomparable Income	2,054	2,052	1	1.06	1.06
Adjusted Income	9,386	8,732	1.07	.76	.71

Table 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

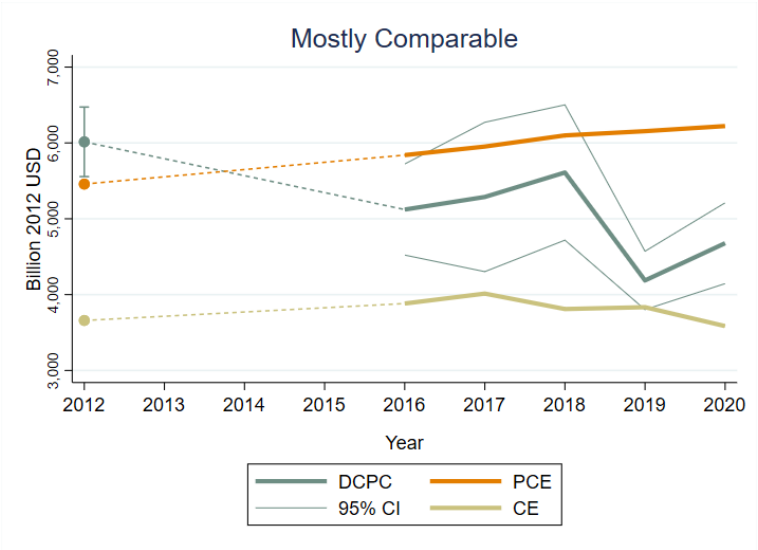


Figure B1 shows the annual estimates of comparable consumption across DCPC, PCE, and CE. 2012 estimates are reported by circles for comparison, with bars indicating confidence intervals in 2012. Dashed lines are to indicate missing values from 2013-2015. Thick solid lines are point estimates, while thin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

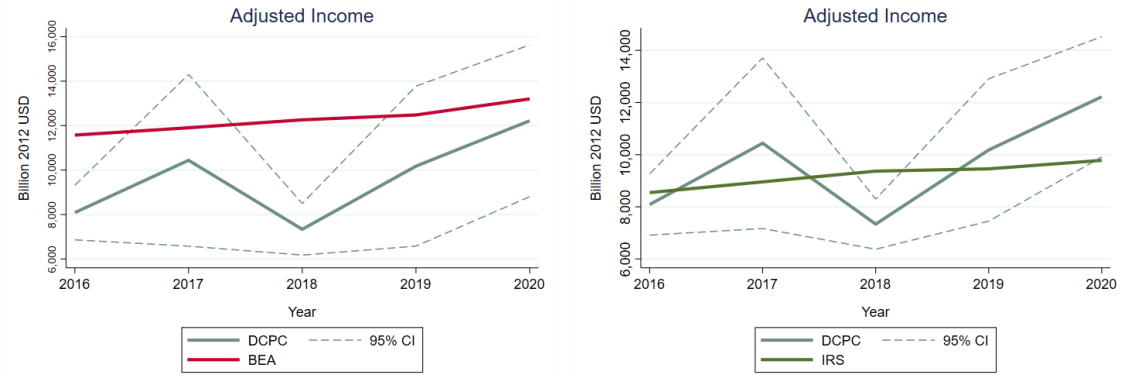


Figure B2 shows the annual estimates of adjusted income across DCPC, BEA, and IRS. Figure B2a compares DCPC and BEA adjusted income, while figure B2b compares DCPC and IRS income. 95% confidence intervals are reported for DCPC by dashed lines. All estimates are reported in billions 2012 USD.

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

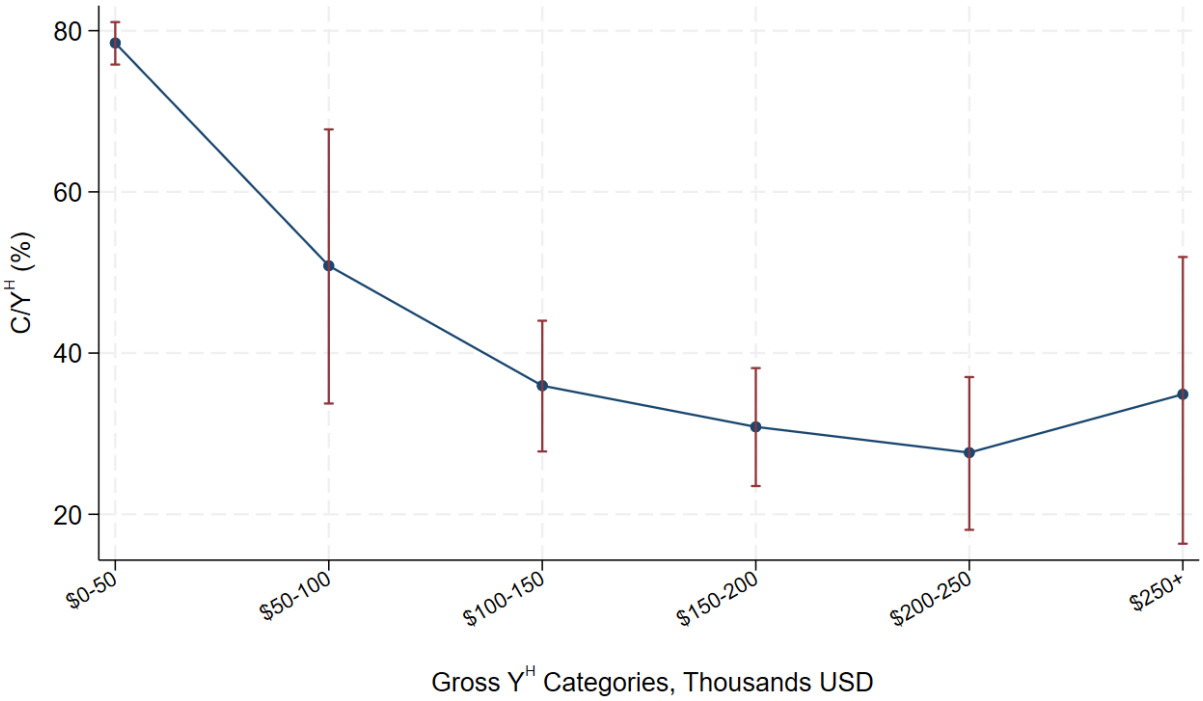


Figure reports consumption expenditures divided by income in the 2016 - 2020 DCPC. Consumption is estimated by using the average adjusted consumption categories (annualized) divided by average household income within each household income category.

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

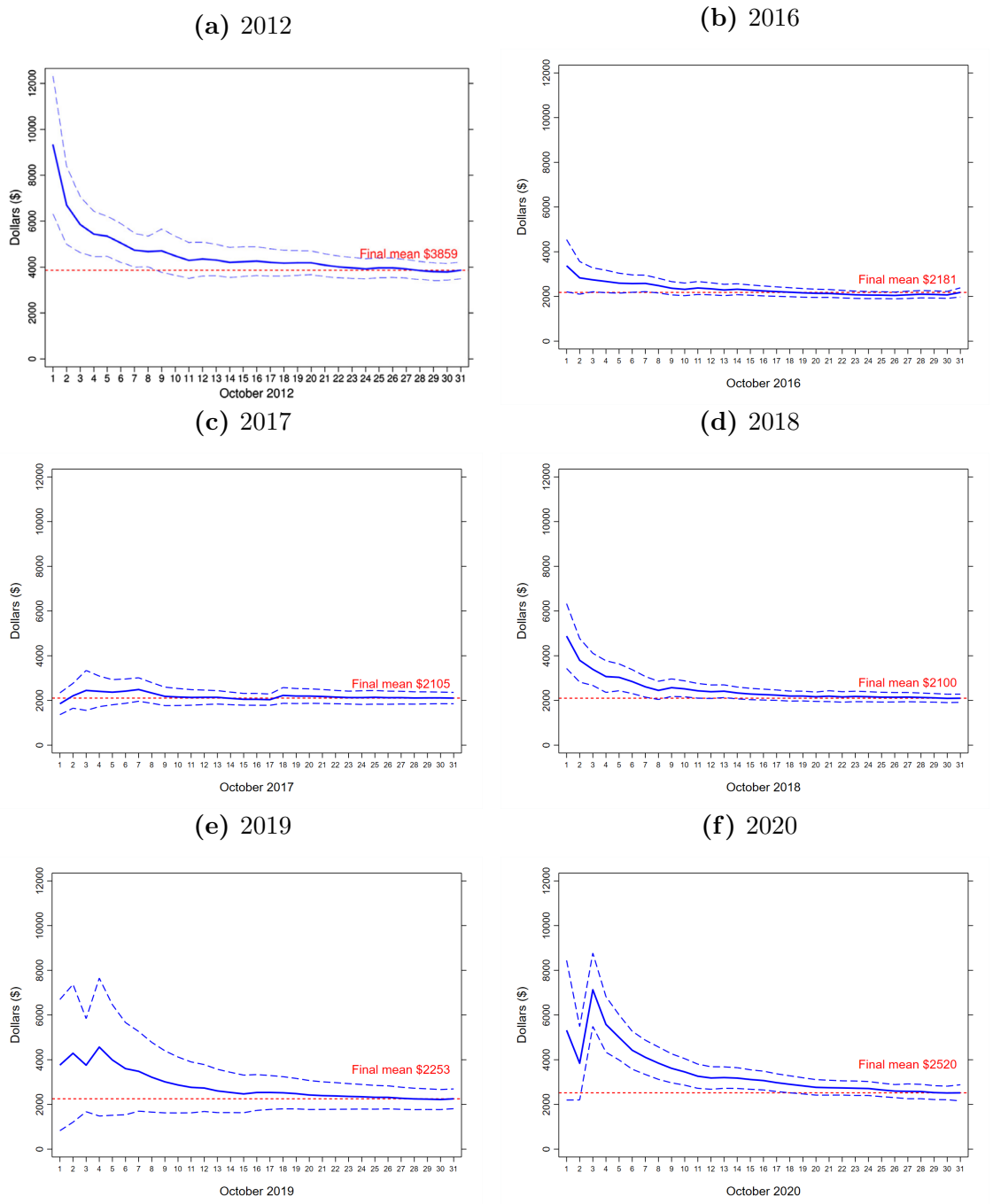


Figure B4 reports the results of the daily estimates of monthly payments per consumer, as discussed in section 5.2.1. Dashed lines indicate 95% confidence intervals, and dotted red lines are the final mean. Subfigure B4a is taken directly from Schuh (2018), while subfigures B4b - B4f are calculated from 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 (see equation 1). The estimation procedure from Schuh (2018) is used for calculating standard errors.

Figure B5: Forecasting Annual DCPC Growth

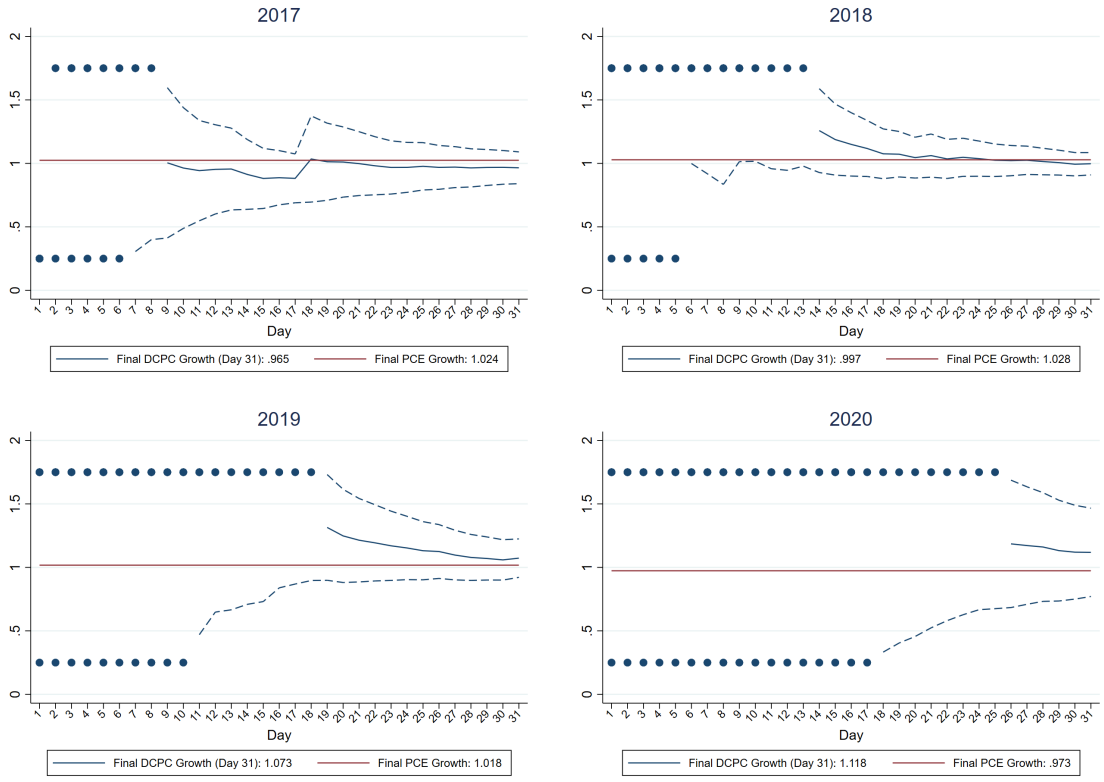


Figure B5 reports the daily estimates of annual DCPC growth. The solid blue line reports G_{dmt} for each day of the diary. The red line reports PCE growth G^*_{mt}. The legend reports end-of-month growth estimates for DCPC and the PCE growth rate. Scatter points cap estimates above 1.25 and below .25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

Appendix C Theory Derivation

C.1 Implied MPC and Elasticity of an Income Shock

Defining the income-generating process can shed light on the consumption response to unanticipated income changes implied by the model. Deaton et al. (1992) and Jappelli and Pistaferri (2017) both show the implied MPC of an income innovation when income is defined as an ARMA(p,q) process, as in Flavin (1981). We briefly describe how we apply this characterization to our data.[57]

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

$$Y_t = \sum_{a=1}^{p} \rho_a Y_{t-a} + \sum_{b=0}^{q} \phi_b u_{t-b} \tag{16}$$

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

Which can be written as follows:

$$Y_t = u_t + \sum_{s=1}^{\infty} \psi_s u_{t-s}$$

$$\text{Where} \tag{17}$$

$$\psi_s = \phi_s + \sum_{j=1}^{s} \rho_j \psi_{s-j}$$

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

$$\mathbb{E}_t Y_{t+s} - \mathbb{E}_{t-1} Y_{t+s} = \psi_s u_{it}$$

$$\Delta c_t = \frac{r}{1+r} \sum_{s=0}^{\infty} \frac{(\mathbb{E}_t Y_{t+s} - \mathbb{E}_{t-1} Y_{t+s})}{(1+r)^s} = \frac{r}{1+r} \left[\sum_{s=0}^{\infty} \frac{\psi_s}{(1+r)^s} \right] u_t \tag{18}$$

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

$$\frac{r}{1+r} \left[\sum_{s=0}^{\infty} (1+r)^{-s} \psi_s \right] u_t = \frac{r}{1+r} \left[\frac{1 + \sum_{s=1}^{q} (\frac{1}{1+r})^s \phi_s}{1 - \sum_{j=1}^{p} (\frac{1}{1+r})^j \rho_j} \right] u_t \tag{19}$$

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

$$\frac{r}{1+r} \frac{1 + \frac{1}{1+r}\phi_1}{1 - \frac{1}{1+r}\rho_1} \cdot u_t = \frac{r}{1+r} \frac{1+r+\phi_1}{1+r-\rho_1} \cdot u_t \tag{20}$$

In our specification, we model income as a simple AR(1) process. Therefore, $\phi_1 = 0$ in equation 20 and thus:

$$\left(\frac{r}{1+r} \frac{1+r}{1+r-\rho} \right) \cdot u_t = \Omega \cdot u_t \tag{21}$$

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

[58] 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 get an estimate of the type of income changes apparent in the diaries. When estimating the AR(1) process, we control for year and age fixed effects, and their interaction. Once ρ is obtained from the regression, we use the delta method to compute standard errors reported in the table.

Appendix D Additional Econometric Results

D.1 Additional Results

Figure D1: Income Profiles by Age Cohorts

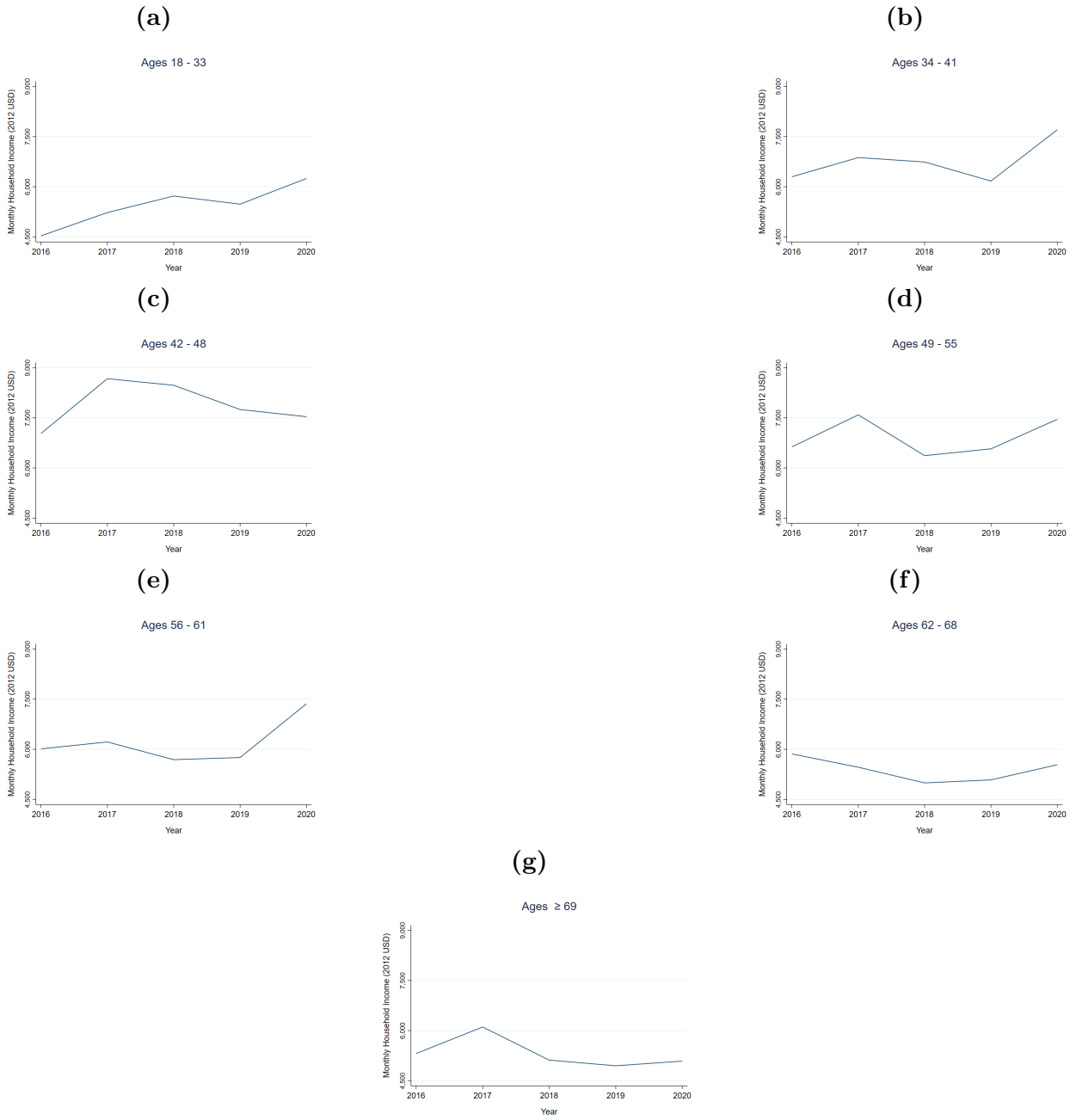


Figure D1 plots the time series of monthly household income for each age cohort from 2016 through 2020. All values are in 2012 USD values.

Table D1: Time-Varying Constraints

	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
	(0.104)	(0.079)	(0.262)	(0.299)
β_2	-0.010	0.118	0.316	-0.481
	(0.373)	(0.239)	(0.406)	(0.423)
Elasticities				
β_1	0.373	0.006	0.761	-0.686
	(0.344)	(0.242)	(0.681)	(0.855)
β_2	0.082	0.340	0.810	-0.746
	(1.023)	(0.874)	(1.066)	(0.980)
Panel B: Daily				
MPCs				
β_1	0.002	0.025***	0.032**	0.042*
	(0.033)	(0.003)	(0.013)	(0.022)
β_2	0.021	0.017	0.019	-0.005
	(0.018)	(0.014)	(0.022)	(0.025)
Elasticities				
β_1	0.026***	0.041***	0.012	0.032***
	(0.008)	(0.007)	(0.008)	(0.002)
β_2	0.011	0.018	0.004	0.020***
	(0.009)	(0.024)	(0.025)	(0.006)

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

Table D2: Separate Components of Y^H

	K=A(7)G(2)			
	M0	M1	M2	M3
Annual				
MPCs				
β_1^R	0.186	0.188	-0.208	0.278*
	(0.113)	(0.310)	(8.839)	(0.155)
β_1^O	0.175	-	-0.311	0.254
	(0.123)	(-)	(15.256)	(0.162)
β_2^R		0.186*	0.266	0.118
		(0.111)	(0.188)	(0.182)
β_2^O		0.175	0.368*	0.114
		(0.123)	(0.212)	(0.219)

[1] Table reports the annual MPC estimates when including respondent income Y^R and other household income Y^{Oth} 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. $\beta_1^{R,Oth.}$ cannot be identified simultaneously in M1: thus one is excluded. Standard errors are bootstrapped (1000 replications).
[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.2 First Stage Results

Table D3: First Stage Results: A(7) G(2) Annual

	$\widehat{\Delta Y}^H$			$\widehat{\Delta y}^H$		
	(1) M1	(2) M2	(3) M3	(4) M1	(5) M2	(6) M3
α	142*	286*	-313,922	.0228*	.0468**	-35.1
	(73.1)	(136)	(564,030)	(.0122)	(.0211)	(96.6)
$\widehat{\Delta_m^{12} Y}^H_{km,t-2}$		-.429**				
		(.153)				
$\widehat{Y}^H_{km,t-1}$			-.503***			
			(.142)			
$\widehat{\Delta_m^{12} y}^H_{km,t-2}$					-.376**	
					(.17)	
$\widehat{y}^H_{km,t-1}$						-.404***
						(.132)
$\eta_{age} \times t$						
18 - 33 $\times$ t			157			.0191
			(279)			(.0479)
34 - 41 $\times$ t			242***			.0364***
			(36.2)			(.00432)
42 - 48 $\times$ t			-543*			-.0707*
			(282)			(.0342)
49 - 55 $\times$ t			9.81			.00395
			(204)			(.0307)
56 - 61 $\times$ t			346			.0593
			(272)			(.0386)
62 - 68 $\times$ t			167***			.0377***
			(46.9)			(.00678)
$\geq$ 69 $\times$ t			-231***			-.0362***
			(65.5)			(.00669)
η_{age}						
34 - 41			-170,039			-34.8
			(571,612)			(97.3)
42 - 48			1,413,509*			181
			(794,635)			(118)
49 - 55			297,623			30.7
			(713,253)			(117)
56 - 61			-381,920			-81.1
			(794,917)			(125)
62 - 68			-20,516			-37.5
			(577,077)			(98.2)
$\geq$ 69			782,089			112
			(585,374)			(98.1)
N	56.00	28.00	56.00	56.00	28.00	56.00
$Adj.R^2$	0.01	0.19	0.23	0.01	0.13	0.16

[1] Reports the first stage results of M1, M2, and M3 for cohorts A(7) G(2). B is the backwards operator.
[2] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D4: First Stage Results: A(7) G(2) Daily

	$\widehat{\Delta Y}^R$			$\widehat{\Delta y}^R$		
	(1) M1	(2) M2	(3) M3	(4) M1	(5) M2	(6) M3
α	5.462**	7.140**	-84.848**	0.053**	0.056	-2.935**
	(2.419)	(3.169)	(39.423)	(0.019)	(0.035)	(1.360)
$B^2\ \widehat{\Delta_d^1 Y}^r_{kdmt}$		-0.037**				
		(0.015)				
BY^r_{kdmt}			-0.971***			
			(0.038)			
$B^2\ \widehat{\Delta_d^1 y}^r_{kdmt}$					-0.077**	
					(0.034)	
By^r_{kdmt}						-0.971***
						(0.024)
$\vartheta^{(IncomeRank)}_{kdmt}$			-21.196			-0.241
			(54.856)			(0.743)
$\vartheta^{(Bachelors\ degree)}_{kdmt}$			175.334**			0.496
			(76.834)			(1.042)
$\vartheta^{(Masters\ degree)}_{kdmt}$			96.077			1.321
			(77.403)			(1.234)
$\vartheta^{(Professional\ degree)}_{kdmt}$			301.793			1.259
			(207.225)			(2.926)
$\vartheta^{(Doctorate\ degree)}_{kdmt}$			571.491			-0.492
			(442.946)			(2.363)
$\vartheta^{f_{Y^r}=Weekly}_{kdmt}$			-15.118			2.304***
			(52.723)			(0.860)
$\vartheta^{f_{Y^r}=Two\ Weeks}_{kdmt}$			34.063			-0.546
			(53.412)			(0.778)
$\vartheta^{f_{Y^r}=Twice\ a\ Month}_{kdmt}$			150.100			0.813
			(108.105)			(1.265)
$\vartheta^{f_{Y^r}=Quarterly}_{kdmt}$			-37.009			2.258
			(119.426)			(1.735)
$\vartheta^{f_{Y^r}=Annual}_{kdmt}$			114.331			2.177
			(108.595)			(1.814)
$\vartheta^{f_{Y^r}=Other1}_{kdmt}$			-76.569			-4.688*
			(108.046)			(2.727)
$\vartheta^{f_{Y^r}=Other2}_{kdmt}$			-344.860**			0.465
			(154.572)			(3.447)
$\vartheta^{f_{Y^r}=Other3}_{kdmt}$			-14.219			-0.502
			(70.557)			(1.514)
$\vartheta^{Y^r\in Self}_{kdmt}$			17.862			2.622*
			(98.310)			(1.403)
$\vartheta^{Y^r\in Social\ Security}_{kdmt}$			-14.182			1.268
			(48.426)			(1.156)
$\vartheta^{Y^r\in Employer\ Retirement}_{kdmt}$			24.684			2.090*
			(88.462)			(1.073)
$\vartheta^{Y^r\in Savings\ Retirement}_{kdmt}$			-72.333			-0.853
			(90.036)			(1.563)
$\vartheta^{Y^r\in Interest,Dividend}_{kdmt}$			86.423			-0.951
			(79.206)			(1.267)
$\vartheta^{Y^r\in Rent}_{kdmt}$			0.320			1.084
			(141.854)			(1.576)
$\vartheta^{Y^r\in Government\ Assistance}_{kdmt}$			-17.841			-1.129
			(53.241)			(0.955)
$\vartheta^{Y^r\in Alimony}_{kdmt}$			-367.729			13.734*
			(313.566)			(7.663)
$\vartheta^{Y^r\in Child\ Support}_{kdmt}$			-24.644			0.333
			(113.841)			(2.474)
N	2100.00	1960.00	2100.00	2100.00	1960.00	2100.00
$Adj.R^2$	0.00	0.00	0.51	0.00	0.01	0.60

[1] Reports the first stage results of M1, M2, and M3 for cohorts A(7) G(2). B is the backwards operator. All interactions and cohort fixed effects are dropped from the table for display purposes. ϑ^Z_{kdmt} reports cohort shares of variable Z (takes a value between 0 and 1). ϑ^Z_{kdmt} reports count of respondents within the cohort.

Table D5: 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	150.000	120.000	150.000	120.000	15.000
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).