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

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Abstract

The 2012 (first) U.S. Diary of Consumer Payment Choice (DCPC) unexpectedly yielded daily data on transaction-level consumption that closely tracks aggregate U.S. data (Schuh, 2018). This paper extends the analysis through 2020. Innovations to the survey instrument improved consumption data precision and added after-tax income receipts that closely track aggregate U.S. data even better. Proprietary transactions data sets have many more consumers and observations, but payment diaries can produce comparable consumption and income data with three relative advantages: 1) representative of U.S. consumers; 2) publicly available; and 3) flexible data measurement opportunities. Representativeness allows the Diary data to accurately predict aggregate government data and forecast real-time macroeconomic developments. The Diary data exhibit comparable micro consumption and income dynamics to those in large-scale, proprietary transactions data. We leverage the DCPC's representativeness to quantify selection effects for consumers who adopt personal financial management (PFM) methods.

JEL Codes: E21, D12, D14

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1 Introduction

Research on consumer payment choices shows that tracking individual payments yields an unexpected, unintended benefit of being able to derive high-quality measures of consumption expenditures from dollar values authorized by payment instruments. Bagnall *et al* (2016) first reported that aggregate payments from consumer diaries in advanced economies are on the order of magnitude of national consumption. Schuh (2018) extended this finding by studying the 2012 (first) U.S. Diary of Consumer Payment Choice (DCPC) in more careful detail and reported two surprising results. First, aggregate DCPC payments identified as consumption expenditures using government data definitions are remarkably close to aggregate personal consumption expenditures (PCE) in the national income accounts—and notably closer than estimates from the Consumer Expenditure Survey. As a result, daily DCPC aggregate consumption data in October, 2012, offered accurate real-time forecasts of the level of monthly PCE before official government data were released. Second, aggregate DCPC total payments are remarkably close to aggregate disposable personal income (DPI) in the national income accounts.

Although intriguing and encouraging, the 2012 DCPC results begged several questions. Were the 2012 results a fluke or would they hold up with additional years of data? Was the limited information used to identify consumption expenditures separately from non-consumption expenditures accurate, or would better identification of consumption categories in subsequent year alter the correspondence of DCPC and PCE consumer expenditures? Would the correspondence of total DCPC payments to aggregate DPI be confirmed by direct collection of income receipts, and how would received income compare with reported household income? And, perhaps most importantly, are individual-level DCPC data sufficiently accurate and nationally representative, thus trustworthy to evaluate consumption and income dynamics at the consumer and U.S. levels?

This paper answers these important questions and provides new evidence on potential sample selection effects in convenience samples. We use data for 2016-2020 from the DCPC, which was revised and improved after 2012, for two validation exercises: 1) assess how better identification of consumption expenditures affected the relationship of DCPC to PCE and CE data; and 2) examine whether direct measurement of daily consumer income receipts (henceforth, "recorded

income") matches aggregate DPI data and respondents' self-reported household income. Validated consumption and income data are then used to update and expand the real-time analysis of Schuh (2018) that shows prediction power in daily DCPC data for monthly PCE data (levels and growth rates). Encouraging validation and prediction results then motivate estimation of basic consumption models and comparison with the literature. Because the DCPC is perhaps the most nationally representative transactions data set (Baker and Kueng, 2022), we use adoption and use of personal financial management methods by some consumers to test for sample-selection effects that may be relevant for convenience samples of transactions data.

After 2012, DCPC aggregate consumption and income data continued to match official U.S. data better than alternatives. The Diary survey instrument was revised to improve classification of expenditures, especially bill payments, and more precisely distinguish consumption from non-consumption expenditures. While the revisions increased the accuracy of identification of consumption expenditures, they also resulted in more payments being excluded from consumption expenditures after 2012. As a result, DCPC aggregate consumption from 2016-2020 was somewhat lower relative to PCE than in 2012, but it still accounted for 81% of comparable PCE consumption categories and was still 28% higher than CE consumer expenditures. The Diary survey instrument also was expanded to *record* all types of after-tax income received by individual consumers rather than relying on the indirect measure of total expenditures or self-reported annual household income. Income payments in several categories were recorded daily along with the frequency of received income (weekly, biweekly, monthly, etc.). A new finding is that DCPC aggregate recorded income from 2016-2020 matches 98% of DPI and is 15% higher than IRS aggregate income when adjusted for differences between income measurements. These results provide additional evidence that payment diaries continue to supply excellent and accurate consumption and income estimates that are representative of official U.S. data.

After 2012, daily DCPC aggregate consumption data also continued to provide forecasting power for monthly PCE data that would be of value to the private sector if available in real time. From 2016-2020, the time series of daily DCPC aggregate consumption data reveals increasingly accurate estimates of the level and growth rate of monthly PCE. In most years, by the middle of October (15th day) the daily DCPC projection of monthly PCE is within a standard error of the final

government estimate, which isn't published until well after the end of October. This analysis exemplifies the real-time value of the payment diary data for macroeconomic analysis, and reinforces value of identifying representative consumption behavior at the daily frequency.

Having demonstrated the accuracy and value of the DCPC aggregate data, we use them to estimate consumption and income dynamics and compare them to analogous results from proprietary transactions data reported in the literature. Implementing a synthetic panel structure, the results imply that monthly-aggregated consumption elasticity with respect to income estimates are between .15 - .17, which is similar but lower than Baker (2018) and other elasticities found in the consumption literature. Notably, when measuring daily consumption responses to income for the panel, daily elasticity estimates are between .04 -.07, indicating that consumption elasticity decreases at higher frequencies. When examining average consumption responses of consumers on paydays relative to days surrounding income payments (as in Gelman et al. (2014) and Olafsson and Pagel (2018)), we find that there is a significant consumption increase on paydays, which persist for multiple days afterwards. This excess consumption response on paydays diminishes when looking at non-bill consumption such as in Gelman et al. (2014), though still present and greater than on days surrounding the income payment. These analyses show that the payment diaries have potential in capturing the consumption and income dynamics found in other studies.

Employing the unique payment measurements found in the DCPC, we compare convenience samples with a representative control and find distinguishing variation in behavior and characteristics of these convenience samples. We find PFM adopters tend to be younger, have higher levels of education, and higher income than respondents who do not use PFM services. When employing a logit regression to study determinants of PFM adoption, we find evidence that consumer preferences play a role while indicators of financial distress do not. We then estimate consumption elasticities across the PFM subsamples, where the results suggest that PFM adopters have lower elasticities than those without a PFM. As an additional extension, we also estimate consumption elasticities by credit card subsamples, including credit card adopters and revolvers who have carried credit card debt month to month. Initial estimates show mixed findings on differences in elasticities for these users.

Although payment diaries like the DCPC were not intended and designed to be a rich source of mi-

cro transactions-level data for analysis of individual consumption and income dynamics, this paper provides additional evidence of their value for such endeavors. Consumption and income data derived from the DCPC are comparable in measure and scope to that of proprietary transactions data sets which typically have many more observations and longer, continuous time periods. However, the DCPC offers three relative advantages: 1) representative of U.S. consumers; 2) public availability; and 3) creative, flexible data measurement opportunities. This paper only demonstrates the first two relative advantages, but future research could exploit the third. Given building evidence of the potential value offered by payment diaries for consumption, saving, and personal financial management data and research, efforts to expand the sample and frequency of the DCPC may be a public policy worth considering.

2 Literature Review

2.1 Consumption and Income

A large body of literature studies the implications on consumption of the Life-Cycle/Permanent income hypothesis, as reviewed in Jappelli and Pistaferri (2010). These models predict consumption should not change to anticipated income, and there should be little response to unexpected transitory income shocks. The reaction of consumption to permanent shocks depends on the degree of persistence. However, a number of studies find that there exists excess response of consumption to anticipated income (Lusardi (1996), Hsieh (2003), Stephens Jr (2003)), and transitory shocks (Johnson et al. (2006),Blundell et al. (2008), Carroll et al. (2017), Parker (2017)) beyond the prediction of the benchmark model, and large responses to permanent shocks (Baker (2018)).[1] There are numerous theories which explain the excess sensitivity to consumption[2], including liquidity constraints (Zeldes (1989)) and the wealthy hand-to-mouth (Kaplan et al. (2014)), precautionary savings and buffer-stock behavior (Carroll (1997)), and behavioral characteristics of consumers (Attanasio et al. (2020), Laibson et al. (2021)) to name a few. We do not attempt to the explain excess responses of consumption, but instead examine if the excess sensitivity exists in the DCPC as found in these studies.

[1] See Jappelli and Pistaferri (2010) for a comprehensive review.

[2] See Kaplan and Violante (2022) for an investigation of modeling strategies for matching MPCs found in empirical data.

Due to the rise of comprehensive transaction records, a natural use of the high-frequency data is to examine consumption behavior of households and individuals. Two important features of many high-frequency transaction data exhibit compared to aggregate data are daily transactions, and detailed heterogeneity of agents. Studies which utilize transaction data have used these advantages to study possible explanations for deviations in standard life-cycle/permanent income models. This includes studying how consumption changes to anticipated or unanticipated income (Baker (2018), Kueng (2018), Baugh et al. (2021), Agarwal et al. (2007), Olafsson and Pagel (2019)) or consumption responds to regular/irregular income near income payment days (Gelman et al. (2014), Olafsson and Pagel (2018)).

Often, these papers find a consumption response to income payments, over household income and liquidity. Baker (2018) examines consumption elasticities during the great depression along household debt and liquidity. By matching individuals to their employers, Baker (2018) identifies exogenous changes to household income and finds that elasticities are higher for those with more debt, which is related to liquidity constraints. When estimating consumption elasticities in Section 7.1, we compare our results to Baker (2018). Examining consumption on paydays, Gelman et al. (2014) and Olafsson and Pagel (2018) examine multiple categories of consumption spending and find an increase in many of these categories. Gelman et al. (2014) finds that recurring spending accounts for a large, significant portion of the payday response, in which those with lower liquidity exhibit the highest response. Additionally, the authors find that fast food and coffee shops pending exhibits almost no payday response. Olafsson and Pagel (2018) find that there is a significant payday response across all spending categories, levels of liquidity, and over household income. When estimating the daily consumption response on days in which respondents receive income in Section 7.2, we compare our results to these authors.

Papers which have access to data consumer debt also examine how consumers pay back their debt or consume relative to their liabilities (Baugh and Correia (2022), Hundtofte et al. (2019), Agarwal et al. (2021)). Given that many of these data sets contain long periods of many different types of consumers, there has been additional progress in understanding why consumption responses to income payments deviate from standard consumption theory. Gelman (2021) uses transaction data in a buffer-stock framework to explain the variance of MPC heterogeneity from observable and un-

observable characteristics of consumers. Kuchler and Pagel (2021) find that financial sophistication and impatience are associated with consumers committing to paying debts. Gathergood and Olafsson (2022) examine the co-holding puzzle of consumers holding both liquid savings and consumer debt and find evidence of mental accounting. The important insights found from these studies have all used transaction data in furthering the consumption literature. Using a personal financial management application, Carlin et al. (2022) study how easier access to the software affected user welfare. The authors show that when mobile access to the spyware became available, when before it was only accessible through an online browser, the frequency of non-sufficient fund fees decreased. The results indicate that increased access to technology leads to welfare improvements.

Using the payment diaries, we replicate consumption elasticities as in Baker (2018) as well as consumption responses to paydays following Gelman et al. (2014) and Olafsson and Pagel (2018).

2.2 Transaction Data Sources

There has been an emerging literature which uses transaction data to study expenditure behavior. These data sources contain high-frequency transaction decisions which are often accompanied by additional consumer finances and demographics. These features of the data allow for a detailed analysis of expenditures not possible with aggregate data. Transaction data is usually derived from financial records of consumers and personal financial management software. Financial records are often provided by financial institutions such as banks (Ganong and Noel (2019)) and credit card firms (Gathergood et al. (2021)), while personal financial management information is provided by financial aggregation software (Baker (2018)). Other forms of transaction data may come from retail scanner data, as in Klee (2008). However, recent studies have been using data from financial institutions and aggregators due to their ability to collect a rich amount of diverse consumption, financial, and demographic information on consumers.

Baker and Kueng (2022) offers a comprehensive review of the literature which uses transaction data, including their sources, uses, and benefits. The use of transaction data has seen an increase within the last decade in part due to their massive sample sizes which are often accompanied by detailed demographic and balance sheet positions of households. Transaction data can collect all payments for a panel of individuals, allowing for thousands to millions of observations in a data set.

This combined with balance sheet characteristics along many demographics of individuals allows for a comprehensive analysis of consumption decisions and behaviors which cannot be found in many other data sources. Because this data is collected directly from the transactions of individuals, there is a high quality of accuracy in observations which may not be found in recollection based survey data. These benefits enable analyses of consumption along demographic and financial heterogeneity in testing consumption behavior, which is not possible with other data sources.

2.3 Measuring Transactions with Payment Diaries

It has been recently discovered that a new source of high-frequency data from payment diaries can measure consumption. While the DCPC originally is intended to track the daily payments of respondents, Schuh (2018) shows that the DCPC can successfully measure consumption representative of U.S. spending, and effectively tracks PCE and CE consumption. Since the DCPC tracks all payments made by respondents during the diary, merchant categories in the DCPC can identify consumption for each transaction. Schuh (2018) shows that after categorizing payments into consumption categories, the 2012 DCPC consumption estimates are 17% higher than comparable consumption categories to the PCE estimates. Because of the high accuracy of the diaries in tracking consumption, combined with rich demographic and financial information, the DCPC offers a promising alternative in studying consumption behavior. This paper continues the analysis of the DCPC performance of estimating consumption for the additional years of the diaries, and finds the DCPC continues to compare to the PCE and CE consumption estimates. Additionally, this study finds that income estimates of the DCPC successfully measure representative recorded income relative to BEA Personal Income and IRS aggregate income estimates.

Due to the structure of payment diaries, the DCPC offers trade-offs in data availability compared to other transaction data sources. The DCPC is implemented by the Federal Reserve Banks of Atlanta, Boston, and San Francisco annually where respondents are chosen to be representative of U.S. demographics. This feature combined with sampling weights ensures researchers that payment decisions by respondents are representative of national behavior as a whole. Further, because the diary is sponsored by the Fed, data sets are publicly available to researchers, which allows for replication of results. Finally, because the diaries primarily track payment behavior, the DCPC

offers payment information which are often not found in other data sources. For example, all types of payment instruments are possible for respondents to record, including cash and check amounts. When combined with its partner survey, the SCPC[3], the diaries can identify respondents by payment preferences. The most significant limitation of the diaries is its sample size. Because respondents are invited to take the diary for three days, and the relatively short time period, there exists far fewer observations in the DCPC compared to other transaction data. Additionally, because the diaries are a newer source of payment data, the number of years available for analysis are limited. However, because of the benefits discussed, the DCPC offers a unique opportunity to be studied jointly with other data to understand nationally representative consumer behavior.

3 Consumer Payments Data

Data on consumer payment choices emerged in the wake of the Transformation of Payments from paper to electronic media that unfolded around the turn of the 21st century. An early motivation was the long-awaited decline of paper check use in the United States documented in Federal Reserve Board (2002) and analyzed in Schuh and Stavins (2010). Researchers in monetary economics, along with payments practitioners and analysts, recognized a need to understand where the Transformation would lead and discover the optimal electronic payment system in terms of social welfare. These needs were initially blocked by a dearth of data on how consumers—the ultimate end-users of the payment system—made payment choices, especially cash (physical currency). Such data are crucial to discovering and providing the types of electronic payment services would maximize consumer utility. One important response was the development by industrial countries of surveys that asked consumer respondents to *recall* their adoption and use of financial accounts and means of payments (instruments). A second response extended recall-based surveys by developing diaries that asked consumer respondents to *record* their payment transactions. The literature on survey methodology documents the superior quality of recording-based measurement instruments, and the optimality of relatively short consumer diaries of one week or less.

[3] The Survey of Consumer Payment Choice (SCPC) is a survey conducted annually by the Fed. Respondents from the survey are asked to participate in the DCPC, allowing for data sets to be combined.

3.1 U.S. Survey and Diary Instruments

U.S. efforts to develop public consumer payments data were originated by researchers at the Federal Reserve Bank of Boston in 2003.[4] Motivated by a successful internal trial survey with a convenience sample of employees (Benton *et al* 2005), the Boston Fed launched the official Survey of Consumer Payment Choice (SCPC) in 2008. It has been implemented annually ever since; the Federal Reserve Bank of Atlanta took over management in 2018.[5] The SCPC is an approximately 30-minute online questionnaire that asks respondents to recall two main types of information about their payments: 1) adoption of bank accounts, payment instruments, and other payment-related services; and 2) use of payment instruments measured as the number (volume) of payments made in a typical month with each type of payment instrument.[6]

The success and value of the SCPC, particularly in documenting the resilience of consumer use of cash, motivated the addition of the Diary of Consumer Payment Choice (DCPC) in 2012.[7] Initially, the goal of the Diary was to validate the measurement of recall-based survey data on the number of payments by asking respondents to record each payment and cash management activity every day for three consecutive days. Respondents spend approximately 15-30 minutes per day completing an online questionnaire about their daily activity, plus a brief survey the night before their Diary begins. After analyzing the 2012 data for a couple years discovering its value, the DCPC has been implemented annually since 2015. Over time it became clear the Diary had greater value for several reasons. First, it collected the dollar value of each payment (not in the SCPC), which offers additional insights to payment choices but also reflects consumer expenditures in some cases. Second, by also collecting the dollar values of asset balances (cash and checking account holdings) and their management (deposits and withdrawals), the Diary data provide an exact accounting of financial flows. Third, the Diary also collects unique, nearly real-time information about each payment (time and date, payment instrument, merchant or payee type and name), the conditions impacting the consumer's transaction (cash on hand, payment instruments available at the time,

[4] The private sector had already been conducting proprietary consumer payment surveys. Examples include Dove Consulting, etc....

[5] For more information about the Survey and Diary, see https://www.atlantafed.org/banking-and-payments/consumer-payments.

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

[7] For more details about the DCPC, see Greene et al. (2018), Schuh (2018), and (Greene and Stavins (2021)).

etc.), and consumer attitudes about the transaction (actual versus preferred instrument, planned versus unplanned expenditure, etc.).

The SCPC and DCPC are implemented jointly in a manner analogous to the Consumer Expenditure (CE) survey and diary.[8] In September, the selected respondents complete the SCPC and indicate their willingness to participate in the subsequent DCPC. Typically, more than 95 percent of Survey respondents agree to participate in the Diary during a randomly selected three-day period between September 29 and November 2. The night before their Diary period begins, respondents complete a brief online survey to update information they provided in their Survey that year, which may have occurred up to nearly two months before the Diary. Respondents in the SCPC and DCPC can be linked by their unique identifiers so that all data from both instruments can be used to analyze each respondent.

3.2 Sampling Frames

The consumer payment Survey and Diary are implemented with random samples drawn sampling frames populated by ongoing participants in a longitudinal internet survey panel. From 2008-2015, the primary sampling frame was RAND's American Life Panel (ALP). Although innovative and valuable, the ALP at that time was a convenience sampling frame cobbled together over time with arbitrary methods of recruiting survey panelists. For this reason, the ALP frame was not representative sample of U.S. consumers, although random samples drawn from it were post-stratified to make each sample closer to being representative.

From 2015-present, the primary sampling frame has been the Understanding America Study (UAS) panel, which was developed by the former managers of the ALP. The UAS was designed to produce a sampling frame that reflects cutting-edge panelist recruitment techniques for modern survey panels.[9] Thus, random samples of consumers from UAS are expected to be as representative of U.S. consumers as is possible for survey conducted without the benefit of government administrative records for the entire population. The UAS also includes day-of-the-week, daily, and annual and individual post-stratification weights that use the Current Population Survey (CPS) to match any

[8] For more information about the CE, see https://www.bls.gov/cex/.
[9] Documentation forthcoming...

discrepancies arising from the variation of annual recruitment differences.[10]. The quality of the representative samples and sampling weights in the SCPC and DCPC were evident even in the ALP in 2012 (Schuh, 2018), but should be even better in the UAS.

Adjustment cost occurred due to the transition from the ALP to the UAS that affected the size and quality of the 2015 samples. The UAS began its first panel in 2015 so it had recruited only a relatively small sample that was not at an optimal composition for representing all U.S. consumers. As a result, the SCPC and DCPC were implemented in separate samples drawn from the ALP and UAS in 2015 only. Because the ALP and UAS respondents could not be matched longitudinally, only the 2015 UAS sample can be matched to the 2016 sample. Unfortunately, the 2015 UAS sample is less than half the size of 2016, which limits its use in the subsequent analysis.[11]

3.3 Sample Selection and Design

Upon completion of the SCPC, the respondents who agree to participate in the DCPC are randomly assigned to a consecutive three-day period starting on September 29. Each day thereafter, a new three-day wave of respondents is assigned until October 31. The last wave ends November 2. This process of randomly assigning diarists over the month of October ensures that there are representative transactions being recorded each day of October during the diary. Each day contains overlapping days with an approximately equal share of respondents on each diary day (1, 2, and 3); September 29-30 and Nov 1-2 are not representative. While respondents begin keeping track of transaction on the first diary day, there is an initial diary day (diary day 0) in which respondents complete an online survey, updating their information from the SCPC and recording account balances and income payments. On these initial diary days, no transaction data is recorded from respondents and thus cannot be used when calculating consumption and income

[10] Day-of-the-week and daily weights are available for only the October dates, and not for the dates in September and November. Individual weights are not time dependent, and are available for each respondent in the SCPC and DCPC.

[11] Due to a smaller size of the UAS panel, additional third-party vendors were used in 2015. Respondents came from UAS, Growth from Knowledge (GFK), and Qualtrics. Because the response rate for the Qualtrics subsample was low and issues with the quality of the data, these observations are excluded from the Fed's public data set. Because of these limitations, it was not possible to implement the DCPC in the full month of October so the diary dates ranged from October 13 through December 17th. For more details about the challenges of the 2015 sampling frame, see Angrisani et al. (2018).

measurements.[12]

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

3.4 Innovations since 2012

Since the 2012 diary, six more years have been included in the DCPC (2015 - 2020). The DCPC has undergone multiple changes during this time as summarized by Table A9 of Appendix A. At its core the DCPC remains the same by tracking consumer transactions over three consecutive diary days randomly assigned in the month of October.

In recent years, merchant categories have been improved to allow for increased identification of recipients and purposes of payments made by respondents. In the 2012 diary, there were 45 merchant categories used to identify the merchant type for which the payment was received. In 2015 forward, additional categories were added to track the purpose of the payment. These categories changed each year from 2015 to 2018, but since 2018 have remained the same. Categorization of each merchant category and purpose category can be found in Appendix A, Table A7. 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

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

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. Some of these income do not have type of income identified, as they may be from other sources not defined by the income types listed above or money from other sources. Therefore, there exists income identified by income type and unidentified income which cannot be categorized. When calculating aggregate income, this unidentified income is reported separately from the identified income types.

4 Data Construction

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

4.1 Consumption Data

4.1.1 Identification

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

relationships.[13] For this reason, payments include both official consumption expenditures, C, and numerous expenditures:

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

where C^u are unclassified consumer expenditures (e.g., underground economy or illegal activity, which can appear in payment diaries), I^c is investment purchases of consumer durable goods or other assets (e.g., art) excluded from official consumption, ΔD^- is debt-reduction payments (e.g, mortgage or credit card), $A2A$ are asset-to-asset transfers, and $P2P$ are person-to-person transfers (e.g., gifts or bequests to others; $P2P^+$ is income). Broadly speaking, the first term in braces represents comprehensive consumption and the second term in braces represents changes to net worth (i.e., part of saving).

Identification of consumption occurs by separating C from non-consumption payments $X - C$ using the structure of the diary survey. Each payment expenditure includes information about the payee, or "merchant," who received the payment from the consumer. The merchant is identified not specifically, like Whole Foods in Boston MA, but rather by an industry category, like Grocery Stores. The industry categories were constructed based loosely on several input criteria: NAICS codes, official consumer expenditure categories (PCE and Consumer Expenditure Survey), and the goals and needs of payments research. Merchant industry categories are further refined using variables with information about the reason and purpose for the payment. These purpose variables identify narrower categories as to the type of payment made to the merchant when merchant categories are board (such as loan repayments to financial service providers). Consumption expenditures are defined by this information to match theoretical concepts and classified into consumption categories $j = \{1, \ldots, J_t^c\}$ for comparison with PCE and CE estimates. Time variation in J_t^c reflects the fact that the consumption classification scheme varied over time as improvements were made to increase precision of consumption identification. A crucial improvement to the 2012 Diary was the ability to identify and separate portions of ΔD^- in later years that had to be included in C by Schuh (2018). For more (gory) details about this meticulous process, see Appendix A and Tables A2-A8

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

The rich and unique structure of the DCPC requires unavoidably detailed notation and derivations. Let C_{ikjdmt} denote consumption expenditures for respondent (consumer) $i = \{1, \ldots, N_t\}$ in demographic cohort $k = \{1, \ldots, K\}$ and consumption category j. Cohorts are defined by age, gender, race, and education, and $K = 24$. It is unnecessary to carry both i and k subscripts because each individual is uniquely assigned to a demographic cohort, so only the relevant identifier is included. Discrete time periods are represented by day of the month, $d = \{1, \ldots, D_m\}$, month of the year (September and October), $m = \{9, 10\}$, and year, $t = \{2012, \ldots, 2020\}$.[14]

4.1.2 Aggregation

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

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

Unweighted total consumption for individual i is

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

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

However, any aggregation across respondents or days requires the inclusion of representative sampling weights. Let the representative sampling weights for individual data be denoted w_{it}^S for the Survey and w_{idt}^D for the Diary.[15] The daily Diary sampling weights aggregate to the number of

[14] 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.

[15] Actual sampling weights for Diary are available for two frequencies, $\tilde{d} = \{d, \overline{d}\}$, corresponding to daily and average day-of-the-week, respectively. The latter are used because they have lower variance given the relatively small samples.

respondents included in the Diary, N_{mt} for the whole month as follows:

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

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

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

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

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

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

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

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

Annual aggregate U.S. consumption is estimated as

$$C_t = \overline{C}_{10,t} \cdot P_t \cdot 30.42 \cdot 12$$

because October has more days (31) than the average month of the year (30.42).[16] Analogous

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

procedures are used to estimate aggregate U.S. income and other DCPC data.

4.1.3 Synthetic Cohorts

Another type of aggregation that yields benefits for the construction of longitudinal panels is the grouping of individual consumers i into cohorts k. Thus, cohort-level consumption is

$$C_{kdmt} = \sum_{i \in k} w_{idt}^{D} \cdot C_{idmt}$$

Cohorts are defined by demographic information that is likely important for understanding heterogeneity in consumption behavior. The demographics used to define cohorts are age, gender, race, and education, which have a total of $K = 24$ unique demographic categories.[17] Because the cohorts aggregate over multiple individual consumers, there is less mismatch between consumption and income frequencies, hence fewer days with zero income. When examining consumption elasticities of convenience samples in Section 8, cohorts of convenience samples are also included.

4.2 Income Data

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

[17] Sex is categorized by male and female. Race: white and non-white. Education: no college or any amount of college. Age: <35, 35-55, >55.

In addition, the DCPC *records* all types of income received each day by the respondent (individual consumer), Y_{ijdmt}, and the frequency at which income payments are received. Here, subscript $j = \{1, \ldots, J_t^y\}$ denotes *income* categories. Time variation in J_t^y likewise reflects the fact that categories of actual received income varied over time as improvements were made to diary survey. The main improvement was the inclusion of received income, which was not available in the analysis of the 2012 DCPC by Schuh (2018). Income categories are found in Table A1; employment income is the most common. As discussed in section 3.4, some recorded income types are unidentifiable due to some recorded income having having no recorded type.

Like most other transactions-level data sets, income payments are discrete and thus less frequent than consumption, which is essentially continuous (daily). As a result, a significant number of respondents do not receive any income on a given day. However, the SCPC asks respondents about the frequency of the primary form of income, and the DCPC asks respondents who receive income about its type and frequency. On the initial diary day 0, respondents are asked the last date they received some form of income prior to diary day 0. On their last day of the diary (diary day 3), respondents are also asked the next date they expect to receive an income payment. This allows us to identify how close the respondent is to their next and last income payment, even if respondents aren't identified receiving income during the diary days. We utilize these variables in Section 7.2 to measure how respondents' consumption differs on days leading up to and following income payments. In this analysis, the panel examines respondent i consumption on day d in diary year t and therefore the synthetic panel is not utilized.

4.3 Longitudinal Panels

4.3.1 Structure

The unique features of the DCPC pose significant challenges for the construction of a longitudinal panel that enables proper analysis of the joint consumption and income dynamics. Two main design factors are important. First, the time series of the Diary is discontinuous. The daily DCPC is administered only in seven of the nine years from 2012-2020, and only one month of those years, except for two days of partial data in the preceding and subsequent months. Second, the time series of individual respondents also is discontinuous in that it only includes three of 31 days of the

month.

For these reasons, the DCPC longitudinal panel is unbalanced within months and across years. The problem is less severe within one month because respondents rotate randomly according to the sampling design, few exit and none enter during a wave, and all respondents in the public data completed each of the three diary days. This makes the DCPC longitudinal panel for one month (year) less susceptible to selection effects that might bias estimated coefficients. However, using DCPC data for only one month (year) significantly reduces the number of observations relative to a panel that pools multiple Diary years. Pooling across years is more problematic due to unexplained entry and exit of respondents. The Diary sampling design strives to recruit the same respondents every year but only some respondents return each year, so selection effects can be significant across years. See Figure A2 of the Appendix for a visual representation of the respondent's decision to stay in the dairy.

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

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

4.3.2 Changes and Growth

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

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

where τ denotes the length of difference over periods in the frequency; this number is suppressed when $\tau = 1$. The annual change is based on monthly data and defined as

$$\Delta_t^\tau = Z_{imt} - Z_{i,m,t-1}$$

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

4.4 Data Cleaning and Robustness

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

5 Aggregate U.S. Consumption and Income Statistics

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

5.1 Consumption Expenditures

As explained in Schuh (2018) and Appendix A, PCE data include many data sources and are a more comprehensive estimate (broader coverage) of consumption expenditures than either the DCPC or CE data. Furthermore, the three consumption sources have somewhat different classification schemes for expenditures. For these reasons, the comparison includes two smaller aggregate measures of consumption. One measure is *Adjusted Consumption*, which excludes consumer expenditure categories not included in all three data sources.[18] A second measure is *Mostly Comparable Consumption*, which limits the analysis to expenditure categories that are most similar among the three data sources and generally follows the official BLS correspondence between CE and PCE.[19] Mostly Comparable categories The DCPC consumer expenditures are matched as best as possible to the PCE and CE categories using merchant categories (see Tables A7 and A8).

Aggregate DCPC consumer expenditures are somewhat lower in 2016-2020 than 2012 due to better identification in the questionnaires, but the DCPC expenditures continue to match PCE better than do CE data, as shown in Figure 1.[20] Before any adjustments, the DCPC matched 97% of

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

[19] See the BLS correspondence between CE and PCE. Non-comparable categories mainly are related to medical payments, insurance payments, vehicle related purchases, tuition payments, professional services, and other miscellaneous categories which are difficult to directly compare. For details on the exact categorization, see Table A7.

[20] Data in the figure are in constant $2012. The bars show five-year averages of PCE, DCPC, and CE consumption estimates corresponding to Table B1 of the Appendix, which reports a detailed comparison of consumption categories j defined in section 4.1.

PCE total expenditures from 2016-2020, while the CE only matched 58% of PCE consumption. However, Adjusted DCPC consumption is only 72 percent of PCE, down from 92 percent in 2012, but still higher than CE (52 percent). In Mostly Comparable categories, the DCPC and CE both match more of PCE on average (81% and 63%, respectively), but the DCPC continues to be notably closer than CE. Year-to-year estimates of DCPC and CE aggregate consumption fluctuate as shares of PCE non-trivially, as shown in the Appendix.

Figure 1: 5-year Consumption Averages

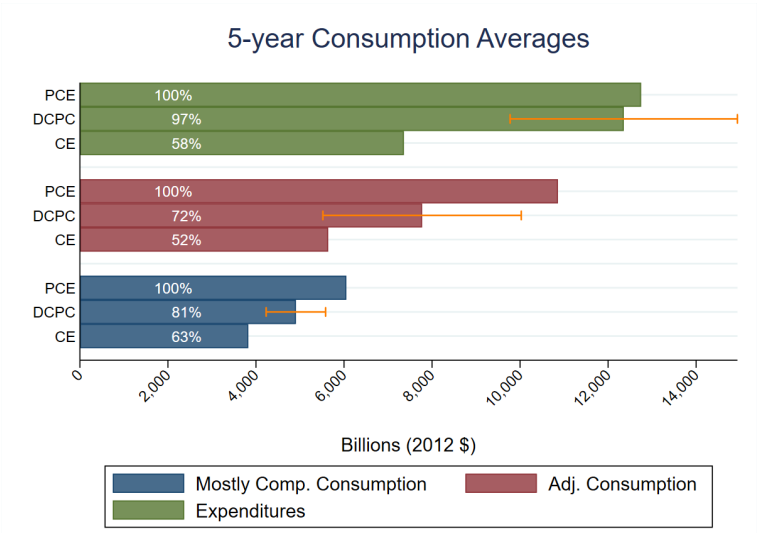


Figure 1 shows the five-year consumption averages for the DCPC, PCE, and CE corresponding to table B1. The y-axis are different categories of expenditures, while the x-axis is dollar values. Percentages reported are all indexed to PCE values of each consumption category and therefore PCE is always 100%.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

5.2 Recorded Income

The income estimates calculated from section 4 are compared to BEA and IRS income to measure how well DCPC results compare to aggregate statistics. Out of the three data sets, BEA income is the more comprehensive income measures as it encompasses current income received by individuals from all sources. IRS income estimates includes only sources of taxable income, and therefore excludes many of the income types found in BEA personal income.[21] Therefore, there exist significant differences between BEA and IRS income that may not make the two strictly comparable. Because of this difference, income results for the DCPC are calculated to match IRS and BEA

[21] Therefore, there exists a gap between IRS and Personal Income estimates as described in Ledbetter (2004)

income separately in order to make the most accurate comparison.

Figure 2: Income Averages

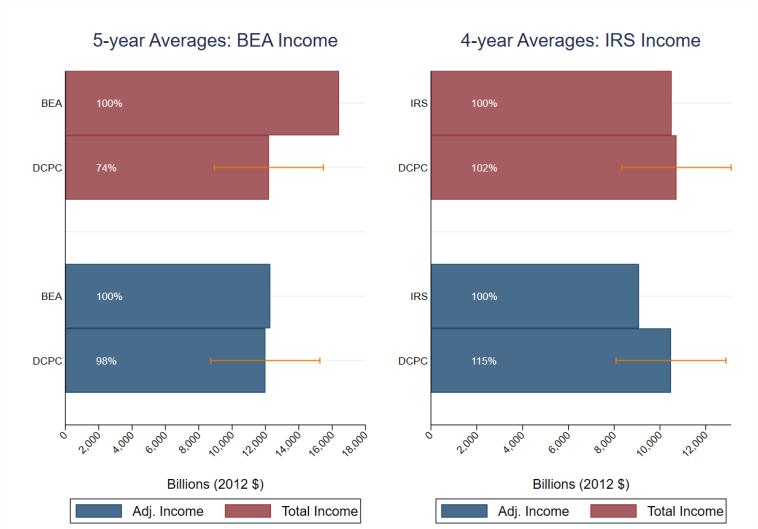


Figure 2 shows the four and five year income averages of the DCPC compared to BEA and IRS income, corresponding to tables B2 and B3. The y-axis are different categories of income, while the x-axis is dollar values. Percentages reported are all indexed to either BEA or IRS category values. Orange range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

Figure 2 reports the 4 and 5 year income averages of the DCPC compared to BEA and IRS income. Appendix Table B2 reports the 5 year average income estimates of the BEA and DCPC from 2016-2020, while Table B3 reports the 4 year average income estimates of IRS and DCPC from 2016- 2019.[22] For both comparisons, total income and adjusted disposable income are included, and percentage values included are indexed to either BEA or IRS income.

Total income reports the aggregated income statistics from all data sets with no adjustments. Even before any adjustments for comparability, it can be seen from Figure 2 that DCPC income matches a significant portion of both BEA and IRS income. Because there exists differences in types of income measured between the DCPC and other data, total income is categorized by comparable and noncomparable income in Appendix Table B2. Comparable income categories in the DCPC are identified recorded income in the DCPC as discussed in section 3.4 which are also found in the other income data, while noncomparable categories are unidentified recorded income that types which cannot be categorized, as well as identified income types which are not found in the other

[22] As the time of this paper, 2020 estimates of IRS income were not available. Therefore, the 2016-2019 four year averages are used, and income results from the 2020 DCPC is not included in the IRS comparison.

data sets. For BEA and IRS income, noncomparable income includes income that is not within the DCPC. For a full list of income types in each category, see Tables A2 and A3. Total income is adjusted to remove taxes and other income categories unique to each data set, which is reported by adjusted income.[23] Additionally, an estimate of employee contributions to retirement (from the IRS) is removed from BEA income, as income reported in DCPC is after employee contributions. Adjusted income should be interpreted as the closest comparison of disposable income between the data sets. When examining the 4 and 5 year averages from the income results, the DCPC matches 98% of adjusted BEA disposable income, and is 15% greater than adjusted IRS disposable income. Annual estimates of adjusted income between the DCPC/BEA and DCPC/IRS are found in Figure B2 of the Appendix.

Given these results of consumption and income, this study concludes that the DCPC captures a significant portion of representative U.S. consumption and income behavior. Therefore, the DCPC shows potential to study the nature of U.S. consumption and income. The daily frequency of the the DCPC data offers opportunities to study consumption decisions jointly with recorded income of individuals at a high-frequency, representative of U.S. consumption and income. Due to the success of the DCPC, Section 6 investigates the real-time data capabilities of the DCPC.

6 Real-Time Data Analysis and Forecasting

6.1 Daily Estimates of Monthly Payments per Consumer

To examine how quickly October DCPC estimates reach their monthly average, we examine the daily estimate of monthly consumption per consumer using the following equation from Schuh (2018):

$$\bar{C}_{dmt} = \sum_{s=1}^{d} (\frac{31}{d}) \bar{C}_{sm,t} \tag{1}$$

Where $\bar{C}$ is the monthly consumption per consumer during October ($m = 10$) on day of the month d in year t. Therefore, the equation estimates the 31-day projection of average daily payments derived

[23] Because income reported in the BEA is pre-tax income, unique categories from each data set are removed after the comparison of comparable categories.

from the cumulative sum of payments since October 1st, divided by the number of days. Results can be found in Figure 3. The results presented in the figure utilize the Fed scripts for cleaning outliers. Examining the daily estimates of monthly consumption per consumer gives insight to the timeliness of the DCPC throughout the month. The 2012 results are included from Schuh (2018) for comparison. In 2012, the estimates are significantly higher towards the beginning of the month, and the final mean is within the 95% confidence intervals after about 10 days into the month. The final mean is significantly higher than 2016-2020, likely due to the additional identification and exclusion possible in the proceeding diaries as discussed in section 3.4. In 2016-2017, it can be seen that the final mean is within the 95% confidence intervals sooner in October than in 2012, and stays stable throughout the month. In 2018-2020, the daily estimates of monthly consumption per consumer is higher in the beginning of the month before converging to its monthly mean, a similar pattern to the 2012 results. While the confidence intervals are wide for 2019, the point estimates approach the monthly mean between 9 to 17 days into October. These results suggest that the precision of the DCPC is realized relatively quickly within the diary period for all sample periods.

6.2 Forecasting October PCE with Daily Consumption Growth

Next, this section investigates how well daily consumption growth can forecast the change in PCE from September to October. To forecast October PCE from September PCE, the following formula is used:

$$\hat{C}^*_{dmt} = C^*_{m-1,t} \cdot G_{dmt} \tag{2}$$

$$G_{dmt} = \left[\frac{\sum_{s=d-2}^{d} C_{sm,t}}{\sum_{q=(D_{m-1,t})-2}^{D_{m-1,t}} C_{qm-1,t}} \right]^{\frac{D_t}{d}} \quad if\ d \geq 3 \tag{3}$$

Where t is the month, d is the calendar day within the month ($d = \{1, \ldots, D_t\}$, $D_t \in \{28, 30, 31\}$), and t is the year ($y \in \{2016, 2017, ..., 2020\}$). C^* is PCE consumption, while C is DCPC consumption. G_{dmt} is calculated by taking ratio of a 3-day moving average during each day of the October diary to the 3-day average consumption estimates in September.[24] This ratio is then raised to

[24] While the DCPC contains September dates, these dates are to ensure each respondent has three days during the diary. Therefore, the estimates are not weighted. Additionally, September 28th does not include any payment information, as this was the initial day for respondents in which demographic information was collected. The third to last day in October consumption estimate is used in place of September 28th.

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

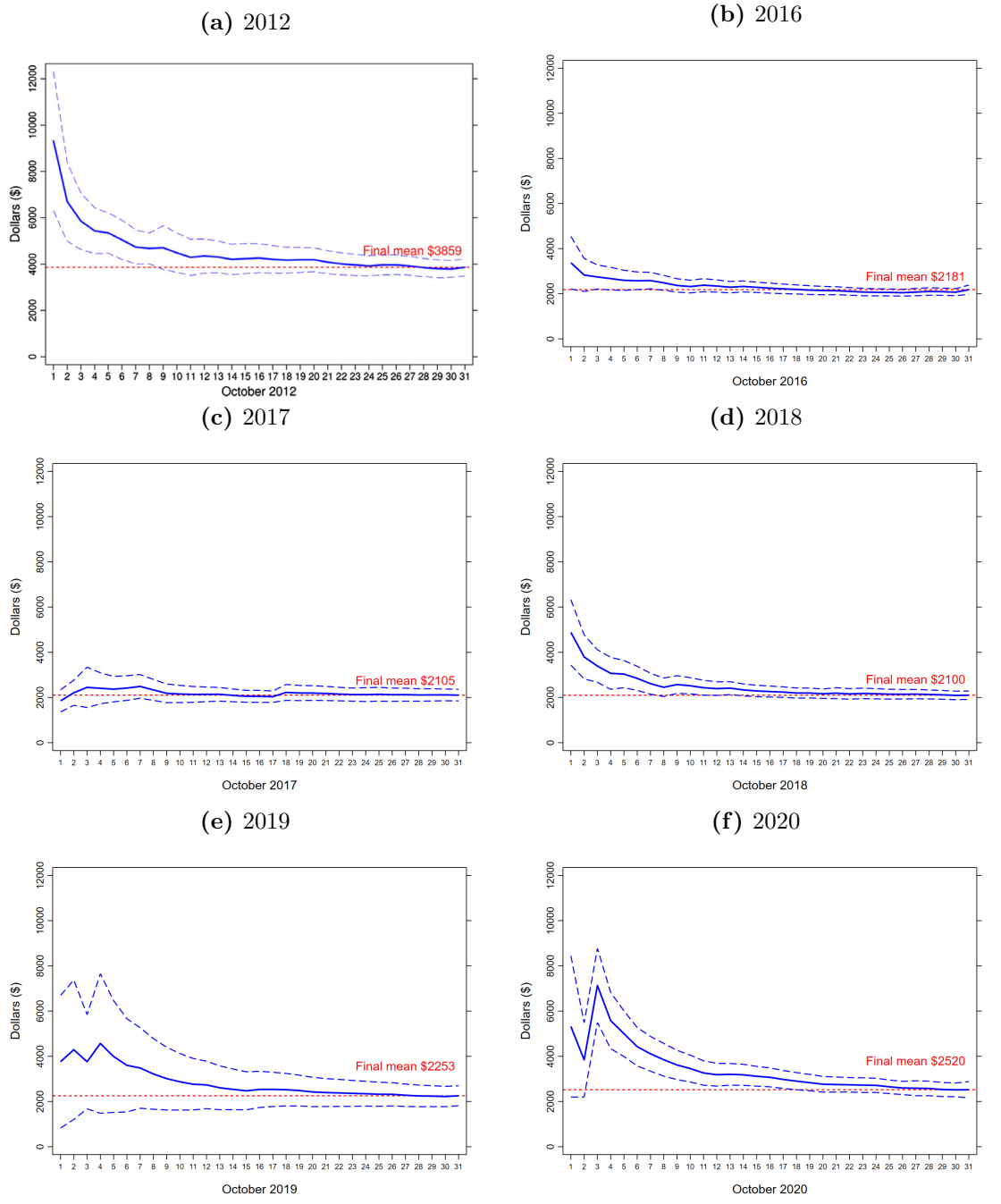


Figure 3 reports the results of the daily estimates of monthly payments per consumer, as discussed in section 6.1. Dashed lines indicate 95% confidence intervals, and dotted red lines are the final mean. Subfigure 3a is taken directly from Schuh (2018), while subfigures 3b - 3f are calculated from the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

the power of $\frac{D_t}{d}$ to project the monthly growth rate of September to October DCPC. Therefore, G_{dmt} is a daily estimate of the monthly DCPC growth rate in a given year t. Multiplying G_{dmt} by September PCE ($C^*_{m-1,t}$) derives the forecast of October PCE, which can be compared to the official October PCE publications to examine how well the payment diaries measure consumption growth. Figure B3 of the appendix provides a graphical representation of the methods described in equations 2 and 3.

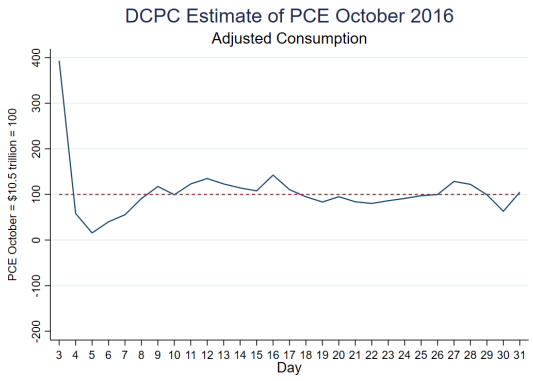
The daily forecast estimation of October PCE using the diaries[25] can be found in Figure 4. The blue line shows the daily DCPC forecast of October PCE estimates, which have been indexed to the PCE estimate of that year. As of this draft, confidence intervals for the diary forecasts have yet to be calculated. The red dashed line indicates the October PCE estimates indexed to 100 for convenience. In 2018 and 2019, DCPC estimates towards the beginning of the month are very large and have been capped for display purposes, indicated by the dashed blue lines. From the figure, it can be seen that throughout most years there is a large beginning of the month increase in consumption which causes the DCPC forecast to be higher, while converging to the PCE October estimate after approximately 8 to 10 days into October for each year. The 2020 forecast begins with a very small forecast, mainly due to large end-of-month September consumption values causing the moving averages ratio to be low. This is persistent throughout the month, and does not reach the PCE estimate by the end of October, though approaches it by the end of the month. The results show that the daily three-day moving average growth from September in DCPC consumption can capture the September to October PCE growth with relatively high accuracy throughout most of the years, and is capable of doing so very quickly in early October.

This section has analyzed the dynamics of consumption estimates within the DCPC by examining the daily estimates of spending per consumer as well as the forecasting capability of the DCPC using daily projections. From both exercises it can be seen that the DCPC projections reach their average quickly within the diary, showing the timeliness of DCPC estimates. Since the paper has now shown both the representativeness and the real-time data capabilities of the DCPC, the next section will investigate consumption and income dynamics using the payment diaries by replicating studies within the consumption literature.

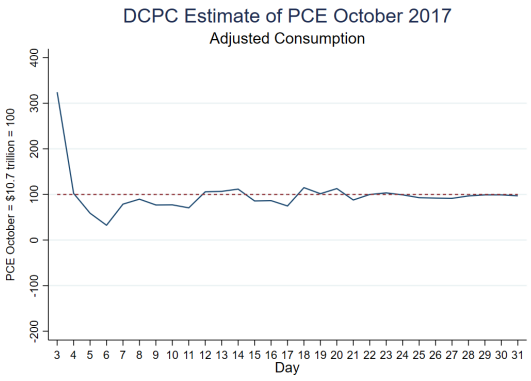
[25] Results were seasonally adjusted by regressing daily DCPC aggregate consumption on day-of-week and week-of-month indicator variables. Observations were cleaned using Fed scripts.

Figure 4: Forecasting October PCE from Septebmer PCE Using DCPC Growth

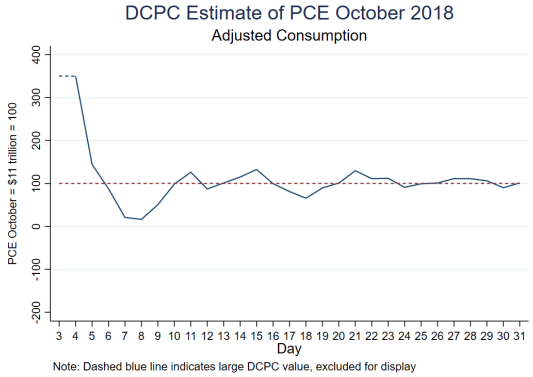
(a) 2016



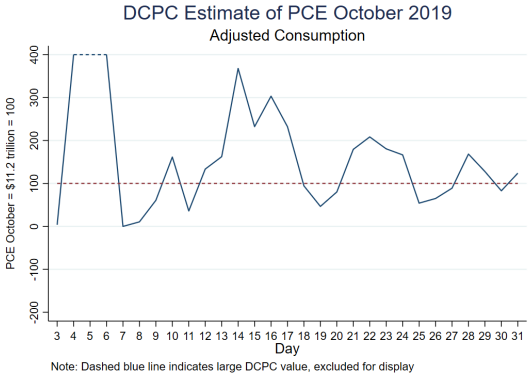
(b) 2017



(c) 2018



(d) 2019



(e) 2020

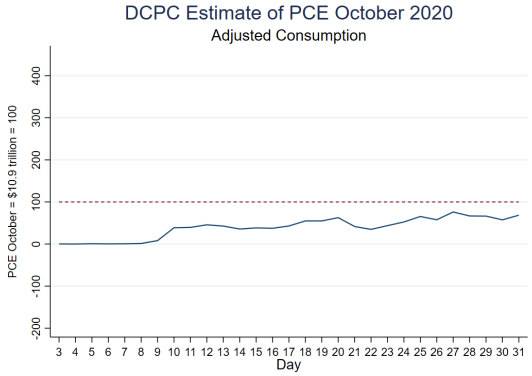


Figure 4 reports the results of the daily estimates of PCE October, as discussed in subsection 5. Estimates are indexed to PCE October of each year, where DCPC estimates are denoted by the blue line and the October PCE value is denoted by the red dashed line. Index values are reported on the y-axis title for each subgraph. Values are seasonally adjusted for day of the week and week of the month variation. Dashed blue lines indicate a large DCPC estimate that exceeds y-axis graph range, and has been limited graphically due to display purposes.

7 Replication of the Literature

We now turn to analyzing consumption and income dynamics at daily and monthly frequencies by replicating results found within the consumption literature using similar forms of transactions-level data. The goal is to replicate key results for aggregate and individual dynamics of consumption and income. We focus in on a few of the studies the DCPC can best replicate.

7.1 Consumption Elasticities

Our goal is to examine if the DCPC can replicate the consumption and income dynamics patterns found throughout the literature discussed as discussed in Section 2.1, utilizing the diary's panel structure. Ideally, we would like to identify anticipated income, as well as transitory and permanent shocks to income for each individual respondent. According to the benchmark Life-Cycle/Permanent income hypothesis models, consumption should not change when there are expected changes in income, as it is already anticipated by the individual. This is also true for transitory shocks; that is, MPC out of transitory shocks should be 0. Only with permanent income shocks should there be a positive MPC, which depends on the degree of persistence of the shock. However, the literature often finds excess responses to income changes than hypothesized by the benchmark models due to a variety of factors as previously discussed in Section 2.

In longer panel data, the identification of the types of changes in income is usually achieved by a statistical decomposition of income shocks using covariance restrictions on consumption and income. However, given the structure of the payment diaries there exists limitation in modeling the income process. First, for each respondent we only observe three days of consumption and income in a given year. This severely limits the time dimension needed to identify the transitory and permanent components of income for a given individual. To help resolve this issue, we create synthetic cohorts to identify monthly estimates of consumption and income for each cohort. However, there is also only five years of data available to the analysis, therefore limiting the time dimension even for the synthetic cohorts. If more years were available, we could identify income shocks through conventional methods, such as an instrumental variable procedure and lagged income to model the income process, but the lack of years severely restricts this option. Therefore, the ability to

identify these shocks are limited. In the diaries, we can identify both household income (Y^H) and recorded income (Y^R). However, Y^H is reported as ranges in the public data set before 2017 and only continuous afterwards which limits the years usable for the analysis. Recorded income is either identified (Y^I) or unidentified (Y^U) as previously discussed (where $Y^R = Y^I + Y^U$). Therefore, changes to Y^R for an individual give a snapshot of the income received during their three diary days. Given only three diary days are available per respondent (as well as random assignment to waves within the diaries), there are very cases in which a respondent is identified receiving income payments for multiple diary years. By aggregating Y^R across cohorts, this allows us to identify changes in cohort income per year, but restricts our ability to identify anticipated vs. unexpected shocks.

Given these obstacles, we provide our initial attempt to identify the response of consumption to changes in recorded income utilizing synthetic cohorts. By aggregating consumption and income across cohorts, we are able to track changes in consumption and income for all individuals who share the same demographic characteristics. Following Baker (2018), we use the following regression:

$$\Delta_t^1 c_{kmt} = \beta_0 + \beta_1 \Delta_t^1 y_{kmt} + \varepsilon_{kmt} \tag{4}$$

where y is the natural log of recorded income for cohort k in October (m) of year t, and c is the natural log of total consumption expenditures. Therefore, we measure the elasticity of consumption as in Lusardi (1996), Hsieh (2003), and Baker (2018), who report estimates between 0-.5 when measuring income responses to different types of changes in income.[26] We compare our results to Baker (2018), who uses transaction data for consumption and income at the quarterly frequency. While Baker (2018) primarily focuses on how debt and liquidity are related to income shocks (using instruments for exogenous changes in income), we compare our results to Baker's Table 7, column 1 in which excludes liquidity and debt measurements and the instrument is not utilized.

[26] Hsieh (2003) uses the dividend payment of the Alaskan Dividend Fund with the CE to examine consumption response to income, and finds an estimate of approximately 0%. However, dividends are normalized by family income which is prone to measurement error. Kueng (2018) replicates this finding and shows when the dividends are normalized to total expenditures, elasticities are approximately .12-.14

Moving forward, we acknowledge the identification strategy used is less than ideal due to the data limitations of the diaries in identifying types of changes in income. We run regression 4 by recorded income types (Y^R, Y^I, Y^U) as an initial attempt to examine which type of income drives the elasticity results. First, we run the regression with only Y^R, which corresponds to Panel A of the elasticity tables. Then, we run the regressions with both Y^I and Y^U as separate variables in the same regression, allowing for separate coefficients on each income type.[27] Differing coefficients on Y^R, Y^I, Y^U may help us understand which types of shocks are more experienced by income type. For example, if the coefficient on unidentified income Y^U results in small, insignificant values when Y^I does not, then this may imply unidentified income is greater composed of unexpected income changes. In future analyses, we plan increase our identification of expected and unexpected income by methods such as examining income by frequency, disaggregating consumption elasticities further by income categories in Y^I, and connecting Y^H to Y^R.

When examining the daily changes in consumption and income for each cohort, a similar specification is used:

$$\Delta_d^1 c_{kdmt} = \beta_0 + \beta_1 \Delta_d^1 y_{kdmt} + \varepsilon_{kdmt} \tag{5}$$

Where consumption and income is the daily total of each cohort, differenced across each day of the month in a given year. To the best of our knowledge, there is no paper that examines daily elasticities of consumption and income with this specification. We include it here to measure the temporal effects of aggregating across different time periods.

Results from regression 4 can be found in Table 1. Each panel is a separate regression. Panel A reports the results with only y^R, while Panel B reports the results when y^I and y^U income types are included as independent variables in one equation.[28] Panel A shows a consumption elasticity of approximately .15 for the synthetic cohorts at the monthly aggregated level, and .17 when

[27] While most cohorts have either identified or unidentified recorded income in a given diary year, some cohorts may have 0 in either identified or unidentified. We replaced these 0 observations with .01 when taking logs in order to not exclude them from the analysis.

[28] Note that two outliers were removed from the regressions, specifically the two lowest changes in log consumption which contrasted the overall trend.

Table 1: Synthetic Cohorts: Annual Changes

	(1)	(2)
Panel A		
$\Delta_t y^R_{kmt}$	0.150***	0.168**
	(0.054)	(0.065)
Panel B		
$\Delta_t y^I_{kmt}$	0.133***	0.165***
	(0.037)	(0.045)
$\Delta_t y^U_{kmt}$	-0.033	-0.039
	(0.030)	(0.038)
Obs.	94	94
Year Fixed Effects	X	X
Cohort Fixed Effects		X

[1] Standard errors in parentheses.
[2] Cohorts: Age (<35, 35-55, $55>$), Edu (No College, Any College), Race (White, Non-White), Gender (Male, Female). All columns include year fixed effects. Cohort fixed effects included when noted. Dependent variable is change in log consumption. Each panel is a different regression. Panel A is including all recorded income, while Panel B is including identified and unidentified income separately in the same regression.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

including cohort fixed effects to account for unobserved heterogeneity that may bias the estimates. Compared to Baker (2018) who finds an elasticity of .3 when aggregating consumption and income to the quarterly level, this number is smaller and on the lower end of the literature. However, the positive significant results imply that DCPC income is capturing some degree of persistent shocks, or is finding a deviation from the prediction of the benchmark consumption models. When running the regression with both y^I and y^U to identify how each recorded income type is influencing Y^R in Panel B, y^I shows a significant positive elasticity between .13 - .17, while y^U is insignificant between -.03 to -.04. Interestingly, Panel B that y^I shows that identified income exhibits a consumption response, while y^U does not. This could be that identified income is composed of more permanent shocks, though would be expected to be higher if this accounted for a large share of the income change. y^I therefore may likely be finding excess consumption responses to anticipated income or transitory shocks as often found by the empirical literature. On the other hand, y^U is small, insignificant, and negative. This implies that consumption does exhibit large responses to the changes these income changes. Because we cannot identify what these income payments are in the diaries, the benchmark consumption models imply these may be income changes which are completely anticipated, or are unexpected but transitory in nature.

Table 2: Synthetic Cohorts: Daily Changes

	(1)	(2)
Panel A		
$\Delta_d y^R_{kdmt}$	0.072***	0.072***
	(0.010)	(0.010)
Panel B		
$\Delta_d y^I_{kdmt}$	0.043***	0.043***
	(0.010)	(0.010)
$\Delta_d y^U_{kdmt}$	0.039***	0.039***
	(0.012)	(0.012)
Obs.	3,291	3,291
Year Fixed Effects	X	X
Cohort Fixed Effects		X

[1] Standard errors in parentheses.
[2] Cohorts: Age (<35, 35-55, $55>$), Edu (No College, Any College), Race (White, Non-White), Gender (Male, Female). All columns include year fixed effects. Cohort fixed effects included when noted. Dependent variable is change in log consumption. Each panel is a different regression. Panel A is including all recorded income, while Panel B is including identified and unidentified income separately in the same regression.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we move on to examining the consumption elasticities of the synthetic cohorts at the daily frequency. Table 2 reports the regression results from equation 5, where consumption and income is aggregated and differenced daily for cohorts. When examining y^R, consumption elasticities are .07, which is about half of the coefficient estimate in Table 1 for all types of recorded income. This finding is essentially the same when including cohort fixed effects implying time-invariant, unobservable characteristics do not impact consumption responses to income at the daily level. This result of lower consumption elasticities at higher daily frequencies suggests that the lower consumption elasticities found in Table 1 compared to the literature are partially due to the level of aggregation. Baker (2018) and Gelman et al. (2014) notes a similar finding in that MPC tends to increase at longer horizons when comparing their results to other studies. As in Table 1, there exists a significant positive consumption elasticity, indicating that the income in the DCPC is likely picking up on the excess consumption response to income found within the literature. When examining y^I and y^U jointly in Panel B, the consumption elasticity of both income types is approximately .04. This is similar to Panel A though slightly lower. Notably, Y^U is not positive and significant unlike in Table 1. This difference implies that when income is differenced daily within the month, the changes to Y^U are also deviations from the Life-Cycle/Permanent Income hypothesis either by

anticipated or unexpected transitory shocks.

Together, Tables 1 and 2 suggest that the DCPC shows potential in capturing the consumption and income dynamics similar to those found within the literature. The elasticities of Table 1 are lower than other studies, while Table 2 shows that the dynamics hold at the daily level, and further imply the lower estimates from the monthly aggregation may be in part due to level of aggregation (monthly) where other studies examine quarterly or annual horizons. However, the positive significant results imply that the response of consumption to changes in income are likely capturing deviations from the benchmark models. The surprising finding of a small, negative relation between consumption and unidentified income at the monthly aggregation may suggest these unidentified income payments may contain more unexpected temporary income shocks due to their value and significance, but requires further analysis to understand these results.

7.2 Daily Consumption Response to Income

Given the high-frequency nature of the DCPC, it is possible to study how individual respondents change their relative daily consumption on days they receive income, and if this differs from the days before and after their payday. The prior analysis identification of income was constrained by the fact that many respondents do not receive income payments during the diary, and thus synthetic cohorts were constructed to be able to study consumption and income in a panel. However, as discussed in Section 4.2, the DCPC asks respondents during their initial diary day the last date in which they received some form of income, and during their final diary day the next date in which they expect to receive income. Therefore, these variables allow us to identify the next/last anticipated income payments outside of the diary. Using these variables along with identifying when respondents are paid in the diary, it is possible to identify how consumption differs by the number of days until the next and since the last income payment across respondents. Because the payment diaries track respondents' next and last income days for all respondents, we are able to utilize a higher number of consumers than was possible in the elasticity analysis of Section 7.1, as almost all respondents report their next/last income date. For each respondent, we calculate how many days until their next income payment, and their last income payment. When a respondent is identified as receiving income during the diary, we record this day as a "payday" and recalculate the number

of days until/since their next and last income relative to this payday.[29] We then compare each consumer's average consumption by how many days until and since their last income payment. For this analysis, only identifiable income categories are used to identify paydays to match the definition of regular payments used by these authors. Though identified may not necessarily always be regular for the respondent, excluding unidentified income will help better isolate these regular income payments. In future plans, we will continue to identify more regular from irregular income payments.

Indeed, prior studies that utilize transaction data have documented a payday effect on consumption at the daily level. Using transaction data, Gelman et al. (2014) and Olafsson and Pagel (2018) show that average consumption is greater on paydays. We utilize the following equation, similar to the ones used by the aforementioned authors:

$$\frac{C_{idt}}{\bar{C}_i} = \sum_{s=-7}^{7} \beta_s I_i(Paid_{d+s,t}) + \eta_i + Z_{dmt} + \varepsilon_{idt} \tag{6}$$

Where $\frac{C_{idt}}{\bar{C}_i}$ is the ratio of consumption spending by consumer i on day d in year t to the individual's average daily spending, $I_i(\cdot)$ is an indicator variable equal to 1 if the consumer received an income payment at time $d+s$, η_i are consumer fixed effects, and Z_{dmt} is a vector of time fixed effects. For time fixed effects, Gelman et al. (2014) includes day of week effects while Olafsson and Pagel (2018) includes day of week, week of month, and month of year effects. The coefficient β_s measures the fraction by which individual consumption deviates from average daily spending in the days surrounding income payments.

Following the authors discussed above, this study follows equation 6 where the dependent variables analyzed are total consumption, nonrecurring spending, and restaurant/ fast food spending. We also include recurring spending as a comparison to non-recurring spending. Fast food and restaurant spending is chosen to measure discretionary, nondurable consumption. Nonrecurring spending is identified as consumption excluding billed spending, while recurring spending is only consumption

[29] The last and next income day variables are asked for respondents correspond to income payments outside of the diary, not within. Therefore, we are not able to use this variable to identify anticipated income payments within the diary.

for bill payments. Day-of-week, week-of-month, and year time fixed effects are included in the specification under Z_{dmt}.

Table 3: Consumption Response to Income Payments

	(1) All Consumption	(2) Bill Consumption	(3) Non-bill Consumption	(4) Food Consumption
Income Day	0.597***	1.088***	0.233***	0.240***
	(0.083)	(0.150)	(0.076)	(0.089)
Observations	30,182	21,136	29,191	26,855

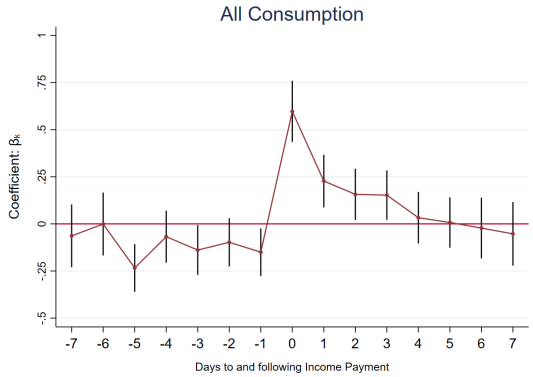
Table 3 reports the regression results from equation 6. Dependent variable denoted by columns. The dependent variable is the ratio of spending within the consumption category to the average daily spending on the payday. Includes dummy variables for date of income payments, and days for leading to and following income days. Controls for day of week effects and week of month effects. Errors are clustered by respondent. * p<0.1, ** p<0.05, and *** p<0.01.

Table 3 reports the spending response of consumption in each category for each category type (β_0 from equation 6). Only the payday effect is included in the table, while a graph of all values of β_s are shown in Figure 5 for all consumption, bill consumption, non-bill consumption, and food consumption. As shown by the table, there exists a statistically positive payday effect for total consumption, indicating that a respondent's consumption increases by approximately 60% on paydays. This is similar to Gelman et al. (2014) who finds a payday effect of about 70%. As shown by Subfigure 5a, consumption stays at or below average on the days leading up to the payday, and increases significantly on the payday. The consumption remains above average for three days after the payday, before diminishing to its average. Therefore, consumption exhibits a significant and persistent payday effect. For non-bill consumption, which accounts for non-recurring spending, there exists a payday effect on paydays and diminishes the day after. Importantly, the magnitude of the effect is smaller than all consumption, suggesting that the consumers are timing their bills with their income days for bill payments, and accounts for a significant portion of the excess spending response to income found in all consumption. Finally, for food consumption the results suggest that there is also a payday response of consumption to income.

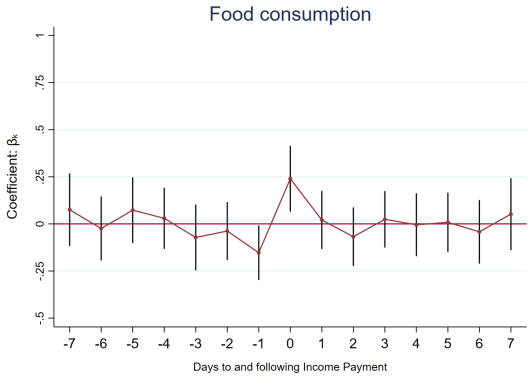
The results presented find a significant payday response which are similar to the finding of Gelman et al. (2014) and Olafsson and Pagel (2018). Similar to Gelman et al. (2014), this study finds that the coincident timing of regular income and regular spending accounts for most of the excess payday response of consumption. While this conclusion is similar to the Gelman et al. (2014), the results reported in this study suggest that there is a higher payday effect for spending on food. Additionally, the results found here find significant payday responses as in Olafsson and Pagel

Figure 5: Consumption Response to Income Payments

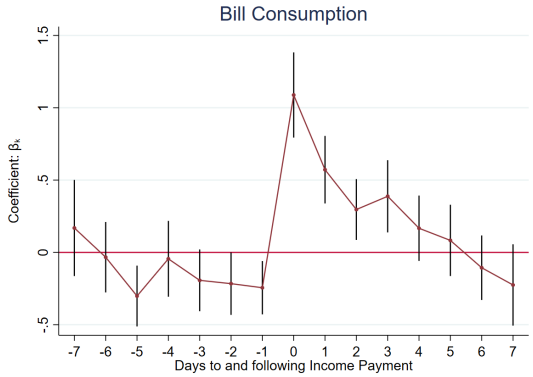
(a) All Consumption



(b) Food Expenditures



(c) Bill Consumption



(d) Non-bill Consumption

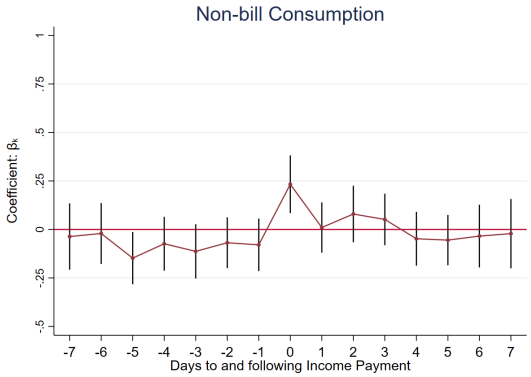


Figure 5 reports the β_s coefficients from equation 6 over the four consumption categories. Negative days denote days before income payment (-7 through -1), while positive days denote days after income payment (1 through 7). Day 0 corresponds to estimates reported in Table 3. Black lines denote 95% confidence intervals.

(2018), though the magnitudes are smaller here. These differences may be due to the different demographics among the data sets, or other unknown factors not explored. Regardless, the DCPC is still capable of finding the core conclusion that consumption does exhibit an excess response on paydays relative to non-paydays, which is found in both papers.

8 Personal Financial Management

Given its relative strength in representing U.S. consumers, the DCPC data offer a unique opportunity to compare and contrast consumption and income dynamics between different types of consumers. Although much larger in terms of observations and time periods, some proprietary transactions-level data sets are convenience samples that are less representative whereas the SCPC

and DCPC can identify potential sample selection effects in a statistically robust manner. One important application is personal financial management (PFM), which is central to some prominent analyses in the literature (Section 2) and covered by the payment Survey and Diary as well. Payment choices are a key part of PFM, so the unique focus of the SCPC and DCPC also provides additional information not found as often or completely in other data sources. This section leverages the advantage and unique focus of the SCPC and DCPC data to extend the literature that analyzes the effects of PFM and payment choice on consumption and income dynamics.

8.1 PFM Data

In 2015-2016 only, the SCPC asked respondents if they had a PFM service or app for budgeting and monitoring account balances as defined by the Survey. To reply in the affirmative, respondents could choose one or more of the following: Mint.com, You Need a Budget, Moneystream.com, moneyStrands, BudgetSimple, MoneyWiz, GoodBudget, or Other.[30] Although respondents who use any form of PFM other than those listed could have chosen "Other," it is possible some respondents use another method of PFM that might not be triggered by question recall or even recognized by the respondent as being "PFM." For example, a consumer who uses a spreadsheet to develop a budget and actively manages it using online or mobile banking features judiciously could reasonably be defined as "doing PFM." Thus, the SCPC data may understate actual PFM behavior. The 2016 DCPC had a typical number of respondents (2,848). In 2015, the UAS sampling frame was small and less representative, so the 2015 DCPC had less than half as many respondents (1,392) but is still included in the adoption analysis. PFM responses to the SCPC are merged with the DCPC. Because there are proportionately fewer longitudinal matches of respondents between 2015 and 2016, dynamic adoption analyses are not conducted here and 2015 is excluded from dynamic consumption analyses.

In 2016, only 6.1% of respondents had adopted PFM services, although this percentage may have increased since then. Table 4 reports the demographic composition of all 2016 DCPC respondents (first column) and demographics by PFM adoption (columns two and three). The last column reports the percentage-point differences between PFM and non-PFM respondents (*statistical sig-*

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

nificance forthcoming). PFM adopters exhibit several economically significant differences. PFM adopters tend to be younger (especially 25-34 year old), better educated (college or higher), and higher income ($100,000 or more). Adoption is monotonically increasing across income categories but drops notably at $200,000, perhaps because the highest income households can afford better to outsource PFM services. Interestingly, white consumers are relatively less likely to adopt PFM whereas non-white consumers relatively more likely. Women are slightly more likely to adopt PFM but the difference is relatively modest.

The results in Table 4 reflect the demographic characteristics of presumably *all* PFM users, so they should not be expected to match the demographics in a transactions-level data set obtained from just one PFM service. For example, the PFM data sets of Gelman et al. (2014) and Baker (2018) show similar compositions in younger individuals. The sample from Baker (2018) shows a younger population than the PFM DCPC sample, while Gelman et al. (2014) sample has lower education attainments. Gelman et al. (2014), Olafsson and Pagel (2018), and Baker (2018) sources show higher shares of male as than the DCPC as well. While these data sets are examined over different years, and for Olafsson and Pagel (2018) the population of Iceland, there seems to be a common trend among of younger households using PFM, while the DCPC sample shows a lower share of males and higher education.

8.2 Adoption of PFM

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

$$\text{Prob}(A_{it} = 1) = f(DEMOG_{it}, Z_{it}) + \varepsilon_{it} \tag{7}$$

separately for 2015 and 2016. $DEMOG$ is the vector of basic demographic characteristics motivated by Table 4 and supplemented with additional demographics, and Z_{it} is a vector of explanatory variables that may explain PFM adoption. Lacking a "deep" theory of PFM, we populate Z_{it} with a set of variables available in the SCPC or DCPC with some intuitive logic and possibly predetermined assuming adoption occurred in the year of estimation. Of course, a limit of this

Table 4: Demographic Comparisons of the 2016 DCPC: PFM

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

Table 4 presents selected demographics comparisons of the DCPC. The first three columns are percentages. The first column reports demographic compositions for the entire sample. The second column reports the demographic compositions for only PFM users, while the third column reports the compositions for respondents without PFM services. The last column reports the percentage point difference between PFM users and respondents without PFM services.

static analysis is that adoption measured in year t may not reflect the actual year PFM was first adopted (or perhaps re-adopted after discarding).[31] Unfortunately, neither the SCPC or DCPC collects data on the intensive margin of PFM use, so we cannot estimate a two-step Heckman selection model.

Beyond demographics, we see two core motives for consumer adoption of a PFM service : financial conditions and personal preferences. Some consumers (and households) may need better financial management because they are experiencing financial distress (conditional on income). Distress variables are: credit card revolver, self-reported FICO score; and experienced (during the past 12 months) checking overdraft, payday loan, or a significant event causing "financial distress."[32] Other consumers may want PFM services because they enjoy financial planning or have a comparative advantage in it, and thus have a higher propensity to adopt PFM even if they are not experiencing financial distress. Preference variables are: adoption of automatic bill payment; checked records while completing the (recall-based) SCPC; and the degree of responsibility in shopping, bill payment, saving/investment, or other financial matters. Of course, the distress and preference variables may be correlated.

Table 5 reports the estimated average marginal effects in 2015 and 2016 for the logit regression in equation (7), with estimates of $DEMOG$ listed in the first vertical panel and estimates of Z_{it} continued in the second vertical panel. The simplified versions of demographic variables from Table 4 are statistically significant predictors of PFM adoption: younger, better educated, higher income, and non-white consumers are more likely to be adopters. In fact, even the lowest income consumers within a household are less likely to adopt conditional on household income. In contrast to income, the *lowest* wealth households are more likely to be adopters. Estimates for marital status and household size are mixed, modest, and less precise.

The results generally suggest that consumer preferences help explain PFM adoption somewhat but financial distress does not help at all, surprisingly. Consumers who have have adopted automatic bill payments are significantly more likely to be PFM adopters; those who have most of the saving/investment responsibility or checked their records when filling out the Survey have positive and

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

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

occasionally significant positive coefficients. In contrast, the coefficients on all variables reflecting financial distress, hence the consumer's need for better PFM, are statistically insignificant. Even revolving credit card debt is not associated with higher PFM adoption. Perhaps these variables are not the right measures of financial distress, or maybe financial distress simply does not causal PFM adoption.

Table 5: Marginal Effects from PFM Logit

	(1) 2015	(2) 2016		(1) 2015	(2) 2016
Age	-0.002***	-0.001***	Most Bill Resp	0.019	-0.034*
	(0.001)	(0.000)		(0.027)	(0.019)
Non-White	-0.003	0.033**	Most Shopping Resp	0.018	0.014
	(0.020)	(0.015)		(0.018)	(0.012)
Education (Base: Any College)					
High school or less	-0.058***	-0.045***	Most Saving/Invest Resp	0.042*	0.004
	(0.015)	(0.010)		(0.025)	(0.014)
Higher Education	0.047	0.026	Most Other Financial Resp	-0.032	0.021
	(0.029)	(0.016)		(0.033)	(0.016)
Married	-0.028	0.021*	Ever Automatic Bill	0.044***	0.043***
	(0.020)	(0.012)		(0.017)	(0.011)
Household Size	0.012*	-0.003	Payday loan last 12 months	0.026	-0.002
	(0.006)	(0.004)		(0.062)	(0.024)
H.H Income: $50,000 and up	0.030*	0.024**	Financial Distress last 12 months	0.002	-0.006
	(0.016)	(0.012)		(0.027)	(0.016)
Income Rank: Lowest	-0.004	-0.033***	Overdraft Last 12 Months	0.012	-0.002
	(0.019)	(0.010)		(0.018)	(0.012)
Net Worth (Base: $0 - Median)			FICO score (Base: 750 and up)		
Less than $0	0.032	0.031*	Below 600 - 749	-0.006	-0.015
	(0.025)	(0.017)		(0.021)	(0.011)
Median - 75th Perc.	0.011	-0.009	Unknown to Respondent	-0.050**	0.007
	(0.020)	(0.013)		(0.021)	(0.019)
Above 75th Perc.	0.011	0.006	Checked Records	0.019	0.025**
	(0.022)	(0.014)		(0.020)	(0.012)
			Revolver	-0.002	0.011
				(0.017)	(0.010)
Obs.	1,216	3,151			

[1] Table 5 presents the marginal effects from the logit regression, where the dependent variable is PFM adoption. All results from the table are from one regression, and are separated by panel columns for space. Columns (1) and (2) denote a separate regression with subsamples of respondents form 2015 and 2016 respectively. Standard error in parentheses. Base next to categorical variables denote omitted variables. Age and household size are continuous, while all other variables are categorical. Median Net Worth: $ 49,000.

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

8.3 PFM and Consumption Dynamics

Tables 4 and 5 of the previous analysis have shown that PFM users exhibit both demographic and preference dissimilarities from non-PFM users, suggesting potential differences in consumer behavior within these individuals. In order to examine if there are any differences in consumption behavior between PFM and non-PFM users, we repeat the analyses from Section 7 on the PFM and non-PFM samples. To begin, we first conduct the consumption elasticity analysis using the methods from Section 7.1 to examine differences in elasticities between PFM and non-PFM users. The synthetic panel approach is utilized, with additional cohorts for PFM and non-PFM users. We estimate the elasticities at the monthly frequency to these cohorts, using y^R in one regression, and y^I and y^U separately in one regression. While the SCPC was used to identify PFM users in 2015 for examining demographics and adoption of PFM, the 2015 DCPC is excluded from this paper and thus we match PFM users in the DCPC using the 2016 SCPC only. Additionally, the SCPC does not identify PFM users after 2016. We identify the 2016 PFM users in the sample and record them as PFM users 2017 forward in the diaries. While it is possible that these respondents may not use PFM services in these future years, we are interested in measuring consumption differences between individuals who have a higher propensity to engage in detailed budgeting behavior. Therefore, since these users can be identified as engaging in active financial management in 2016, we believe it is a fair assumption these users continue to monitor their finances even if they stopped PFM services. There are likely respondents in the later diaries who adopted PFM services, however we cannot identify these new adopters given the SCPC identification of PFM is only in 2016.

Table 6: Synthetic Cohorts with PFM: Annual Changes

	Only Year Fixed Effects			With Cohort Fixed Effects		
	(1) All	(2) Non-PFM	(3) PFM	(4) All	(5) Non-PFM	(6) PFM
Panel A						
$\Delta_t y^R_{kmt}$	0.075	0.160*	0.069	0.061	0.154	0.055
	(0.049)	(0.087)	(0.076)	(0.056)	(0.094)	(0.088)
Panel B						
$\Delta_t y^I_{kmt}$	0.175***	0.234***	0.153*	0.156***	0.209***	0.136
	(0.049)	(0.037)	(0.087)	(0.057)	(0.039)	(0.100)
$\Delta_t y^U_{kmt}$	-0.053	-0.178***	-0.025	-0.060	-0.190***	-0.030
	(0.050)	(0.038)	(0.087)	(0.057)	(0.038)	(0.102)
Year Fixed Effects	X	X	X	X	X	X
Cohort Fixed Effects				X	X	X

[1] Standard errors in parentheses.
[2] Cohorts: Age (< 35, 35-55, 55 >), Edu (No College, Any College), Race (White, Non-White), Gender (Male, Female), PFM (User, Non-User). All columns include year fixed effects. Cohort fixed effects included when noted. Dependent variable is change in log consumption. Each panel is a different regression. Panel A is including all recorded income, while Panel B is including identified and unidentified income separately in the same regression.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 reports the consumption elasticities for PFM users utilizing equation 4, where cohort consumption and income is aggregated to the monthly level and differenced by diary year. Each column in the table refers to different subsamples used: The entire sample of cohorts (All), non-PFM users, and PFM users. Columns (1) - (3) use year fixed effects, while columns (4) - (6) use both year and cohort fixed effects. Panel A uses y^R as the income measurement in the regressions with subsamples, while Panel B allows y^I and y^U to be separate variables in the regressions over subsamples. When examining the results of y^R in Panel A, consumption elasticities are positive, yet mostly insignificant throughout the columns. The coefficients for the entire sample are smaller than Table 1, except for non-PFM users. Importantly, non-PFM users tend to have higher coefficients than PFM users, though marginally significant in column (2) and no significance in column (5). However, when looking at Panel B, y^I shows a larger coefficients with greater significance throughout. With including year fixed-effects or both cohort/year fixed effects, the elasticities for consumption on non-PFM users are significantly higher than those with a PFM. Additionally, these coefficients are larger than when using the entire sample in columns (1) and (2). These positive significant coefficients imply that Y^I are capturing an extent of permanent income shocks, or deviations from the life-cycle hypothesis in transitory shocks or anticipated income. Given the lower elasticities

for PFM users, these results suggest that these users may be smoothing consumption to more so than their non-PFM counterparts if these changes in income are reflective of anticipated income payments or transitory income shocks. This may be related to the proxied preferences in financial management found in the PFM adoption analysis. When examining Y^U, the results are largely small and insignificant except for the non-PFM user results implying non-PFM users decrease their consumption when Y^U increases. While the result is puzzling, further analysis will be conducted into understanding this relationship.

These results suggest that there are differences consumption behavior for individuals who use PFM software. While the previously analysis suggests this difference exists at a monthly frequency, we now examine if PFM users change their relative average consumption on paydays. Replicating the analysis from Section 7.2, we run equation 6 by all respondents, and those who adopted a PFM and those that did not. Table 7 reports the coefficient of the change in average consumption on the day the respondent received an income payment, relative to the days surrounding the income payment across respondents. The dependent variable in the table uses all consumption types, and all controls from equation 6 are included. Column (1) reports the payday effect for all respondents, which corresponds directly to column (1) of Table 3, and has the same coefficient as it is the same equation. When we examine only the subsample of PFM users, the results are slightly higher than that of all respondents and those without PFM, though only significant at $p<0.1$. These results suggest there is some slight evidence that PFM users actually increase their relative consumption on paydays more than the rest of the population. However, a payday effect is still evident for respondents without PFM, though the difference in coefficients between each is not large.

Table 7: Consumption Response to Income: PFM

	(1) All Respondents	(2) PFM Users	(3) Non-PFM
Income Day	0.597***	0.662*	0.590***
	(0.083)	(0.363)	(0.085)
Observations	30,182	1,532	28,650

Table 7 reports the regression results from equation 6 across all respondents, and those who did and did not use PFM services in 2016. All consumption is used as the dependent variable. The dependent variable is the ratio of spending within the consumption category to the average daily spending on the payday. Includes dummy variables for date of income payments, and days for leading to and following income days. Controls for day of week effects and week of month effects. Errors are clustered by respondent. * p<0.1, ** p<0.05, and *** p<0.01.

The results presented in this section suggest that there exist important differences in both demographics and behavior between individuals who use PFM services and the rest of the population. There is a clear contrast in demographics, with PFM users having higher levels of income and higher education than the rest of the DCPC sample. These demographics and certain measurements of preferences for PFM both show correlations with PFM adoption when analyzed with a logit regression, while necessity variables show little predictive power. When examining monthly consumption elasticities with respect to income, PFM users seem to have lower and less significant elasticity estimates than the non-PFM counterparts. Taken together, these results imply that there may be characteristics of PFM users which enable them to engage in a higher degree of consumption smoothing. When looking at how each individual's consumption responds on paydays relative to non-paydays, the change in consumption appears to be slightly higher for PFM users, though the difference is small and the significance is weak, suggesting that the payday response is similar to those with and without a PFM.

8.4 Payment Choices and Consumption Dynamics

The consumer's choice of instrument when making a payment is not arbitrary. Payment usage is both determined by costs of the instrument, as well as various demand factors which are often correlated with consumer demographics (Stavins (2017)). Credit cards in particular provide both short-term, unsecured credit and liquidity to consumers. In the context of life-cycle behavior, credit cards can act as a mechanism for consumers to smooth their consumption within their pay cycle.

Consumers which utilize this short-term credit either pay their credit card balance in full each month (convenience users) or carry over debt month to month (revolvers) as described by Fulford and Schuh (2017). The extent to which consumers utilize credit as a consumption smoothing mechanism may depend on if the consumer revolves their credit debt. Consumers who revolve their short-term debt are more constrained by their credit limit, and thus their consumption may be more responsive when income payments are received.

To analyze how credit cards are used to smooth consumption, we utilize the SCPC in conjunction with the payments diaries to measure differences in consumption elasticities by credit card adoption and revolving credit card debt. The SCPC questionnaire asks respondents whether they use credit cards, and whether credit card holders have carried over debt from the last month or at any point the previous year. Using the synthetic panel framework discussed in Section 7.1, we first measure the consumption elasticity of credit card adopters and those who do not use credit cards. Then, for those who do use credit cards, we identify respondents which revolve their credit card debt as either those who had positive debt in the previous month or anytime within the last 12 months.

Table 8: Synthetic Cohorts with Credit Card Characteristics: Annual Changes

	All	Adoption		Revolving	
	(1)	(2)	(3)	(4)	(5)
	Base	Non C.C. Adopters	C.C Adopters	Revolvers	Non Revolvers
Panel A					
$\Delta_t y^R_{kmt}$	0.023	0.024	0.023	0.106**	-0.031
	(0.023)	(0.037)	(0.029)	(0.042)	(0.040)
Panel B					
$\Delta_t y^I_{kmt}$	0.051***	0.038	0.061**	0.063*	0.065*
	(0.019)	(0.028)	(0.025)	(0.034)	(0.036)
$\Delta_t y^U_{kmt}$	-0.033	-0.019	-0.044	0.033	-0.095**
	(0.021)	(0.030)	(0.028)	(0.042)	(0.038)
Year Fixed Effects	X	X	X	X	X
Cohort Fixed Effects	X	X	X	X	X

[1] Standard errors in parentheses.
[2] Cohorts: Age (< 35, 35-55, 55 >), Edu (No College, Any College), Race (White, Non-White), Gender (Male, Female), Credit Card Adoption (Adopters, Non-Adopters), Credit Card Debt Revolvers (Revolvers, Non Revolvers). All columns include year fixed effects. Dependent variable is change in log consumption. Each panel is a different regression. Panel A is including all recorded income, while Panel B is including identified and unidentified income separately in the same regression.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimated consumption elasticities across credit card characteristics can be found in Table 8. Co-

horts are aggregated to the monthly frequency, and differenced across diary years, as in equation 4. Each column reports regression results when estimated on different credit card subsamples. Panel A uses all y^R as one variable in the regressions on subsamples, while Panel B allows y^I and y^U to be separate variables in the regressions over samples. First, in Panel A, we see mostly small and insignificant values throughout the panel. This suggests that when including the additional credit card cohorts, there is little consumption response to income with this added variation. When looking at the sample of credit card adopters and non-credit card adopters in columns (2) and (3), the results shows no difference from each other or the entire sample in column (1). In columns (4) and (5), credit card adopters from column (3) are further broken into those who have revolved credit card debt within the last 12 months (column (4)) and those who pay off their credit card debt each month (column (5)). For revolvers, there is a higher and significant consumption elasticity than non revolvers, which perhaps indicates a form of liquidity constraint for these consumers.

For Panel B which examines y^I and y^U jointly, we see that identified income is mostly significant throughout. For credit card adopters, there is a significant consumption elasticity compared to those without credit cards, which is smaller and insignificant. This result suggests that those without credit cards are not responding to either the anticipated income changes or transitory shocks that be a part of y^I. On the subsample of credit card adopters, we see similar coefficients for both revolvers and non-revolvers. This is different than found in Panel A, where revolvers showed higher elasticities. This seems to be primarily from y^U, which is negative for for revolvers and perhaps driving the coefficient of y^R.

From these findings, there is suggestive that there may be differences in consumption behavior across credit card users. The results indicate that those who use credit cards may exhibit higher consumption elasticities than those who do not have credit cards in changes to y^I. There are mixed results for those who carry credit card debt by month: the consumption elasticity for total income suggests that revolvers exhibit higher responses to income, while the consumption elasticity for identified income implies that those who do not carry over credit debt have similar consumption responses. Further exploration is needed to definitively explain the nature of these results.

9 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 three unique and substantive benefits over other high-frequency data: 1) The payment diaries are publicly available for researchers, 2) its structure is implemented to be representative of U.S. consumers, and 3) provides detailed payment information not found in other transaction data sources. Utilizing these three distinguishing qualities, this study analyzed demographic and consumption behavior in convenience samples. The results provide suggestive evidence of characteristic differences in convenience samples which data is taken from within the transaction literature. Although these findings need to be explored further for a definitive inference, the evidence shows the potential insights the DCPC is able to provide.

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

understanding of daily consumption and income dynamics.

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Technical Appendix

Appendix A Data Construction Details

Appendix A reports the details in constructing consumption and income for the DCPC. Tables A1 - A8 report income and consumption types in the DCPC, and maps them to CE, PCE, BEA, and IRS data sets for Section 5. Table A9 offers a summary of changes to the DCPC. Figures A1 -A3 offers visual representations of the wave structure of the diaries, the panel nature of the diaries, and how merchant categories have evolved over the years, respectively.

Table A1: DCPC Income Identified Categories

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

Table A2: 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 A2 maps payment coding to income categories found in the aggregate income results in Table B3. Codes reported correspond to Table A1.

Table A3: 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 A3 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 A4: 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 A4 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 A7. Example: SM3 in Table A7 for 2016 corresponds to Pharmacy, submerch 3.

Table A5: DCPC Payment Categories: 2017

Merch (M)	Purpose (P)
1 - Grocery stores, convenience stores without gas stations, pharmacies	1 - Credit card repayment
2 - Gas stations	2 - Mortgage
3 - Sit-down restaurants and bars	3 - HELOC
4 - Fast food restaurants, coffee shops, cafeterias, food trucks	4 - Auto or car loan
5 - General merchandise stores, department stores, other stores, online shopping	5 - Installment loan
6 - General services: hair dressers, auto repair, parking lots, laundry or dry cleaning, etc.	6 - Zero-interest or no-money-down loan
7 - Arts, entertainment, recreation	7 - Payday loan
8 - Utilities not paid to the government: electricity, natural gas, water, sewer, trash, heating oil	8 - Student loan
9 - Taxis, airplanes, delivery	9 - Marketplace or peer-to-peer loan
10 - Telephone, internet, cable or satellite tv, video or music streaming services, movie theaters	10 - Loan from another person
11 - Building contractors, plumbers, electricians, HVAC, etc.	11 - Health insurance
12 - Professional services: legal, accounting, architectural services; veterinarians; photographers or photo processers	12 - Life insurance
13 - Hotels, motels, RV parks, campsites	13 - Umbrella insurance
14 - Rent for apartments, homes, or other buildings, real estate companies, property managers, etc.	14 - Vehicle insurance
15 - Mortgage companies, credit card companies, banks, insurance companies, stock brokers, IRA funds, mutual funds, credit unions, sending remittances	15 - Homeowners or renters insurance
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.	16 - Other type of insurance
17 - Charitable or religious donations	17 - Parking
18 - Hospital, doctor, dentist, nursing homes, etc.	18 - Tolls
19 - Government taxes or fees	19 - Public transit
20 - Schools, colleges, childcare centers	20 - Utilities
21 - Public transportation and tolls	21 - Federal taxes
Payee (PY)	22 - State taxes
1 - Financial services provider	23 - Local taxes
2 - Education provider	24 - Property taxes
3 - Hospital, doctor, dentist, etc.	25 - Car or vehicle taxes
4 - Government	26 - Charitable donation
5 - Nonprofit, charity, religious	27 - Offering, tithe, collection plate
6 - A person	28 - Purchase goods or services
7 - Retail store or online retailer	29 - Gift or allowance
8 - Business that primarily sells services	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 A5 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 A7. Example: M2 in table A7 for 2017 corresponds to Gas stations, merch - 2.

Table A6: 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 A6 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 A7. Example: M2 in table A7 for 2018-2020 corresponds to Gas stations, merch - 2.

Table A7: 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 A7 maps payment coding to consumption categories found in the aggregate consumption results in Table B1. Codes reported correspond to tables A4, A5, A6.
[*] M17 only included if it was also specified the payment was a purchase of a good or service.

Table A8: 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 A8 gives a description of the categorization of consumption in PCE and CE. Categories were matched based on the BLS report comparing PCE and BLS, found here.

Table A9: Changes to the DCPC

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

Figure A1: Diary Wave Implementation

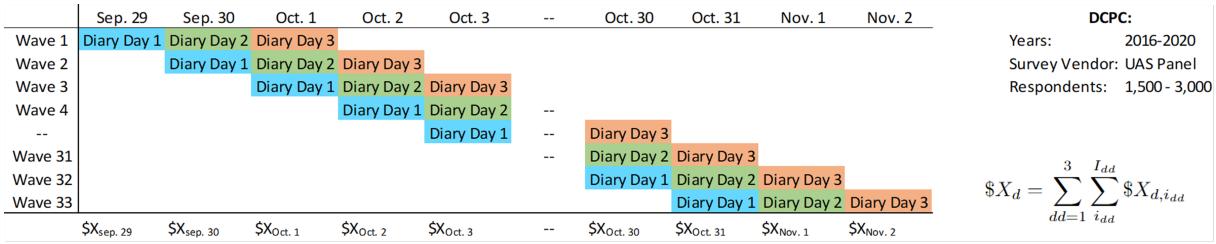


Figure A1 presents a visual representation of wave implementation for the payment diaries. Each wave contains an approximately equal number of respondents who are randomly assigned to each wave. Each wave contains three days where respondents record their daily transactions. The first wave begins September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

Figure A2: Panel Structure of the DCPC

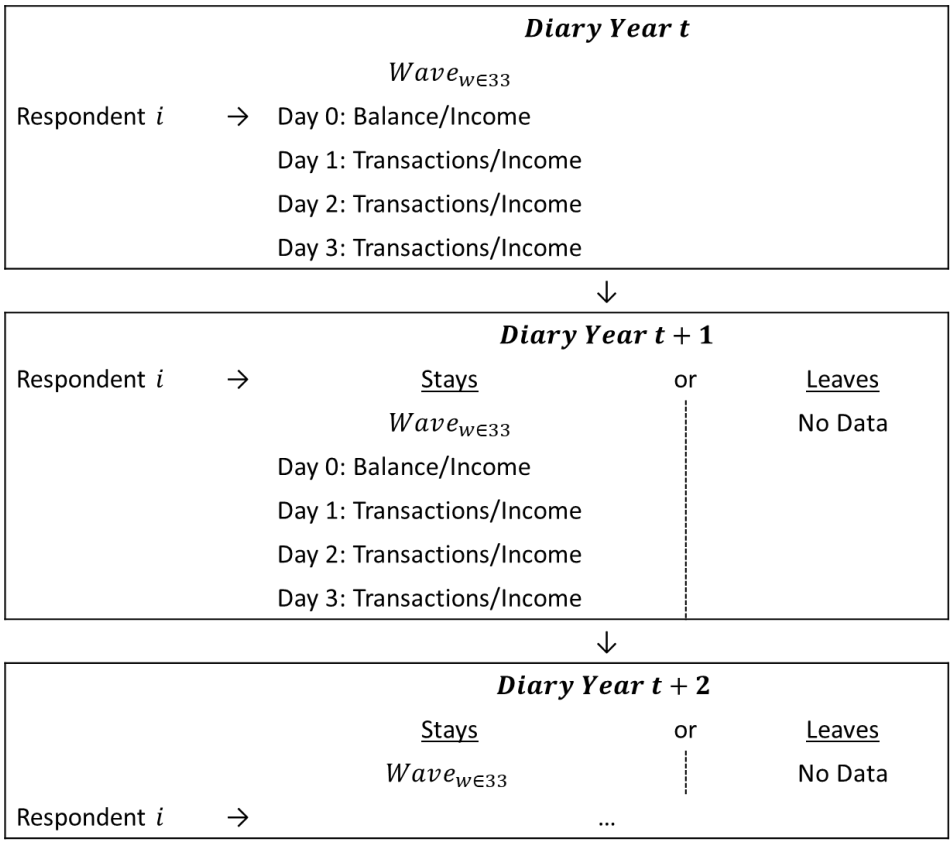


Figure A2 presents a visual representation of the panel structure of the payment diaries. Respondents from the SCPC are offered to take the DCPC. Any respondent i who agrees to participate in diary year t is randomly assigned to one of 33 waves (see figure A1) On the initial diary day 0, account balances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

Figure A3: Evolution of Payment Categories in the DCPC

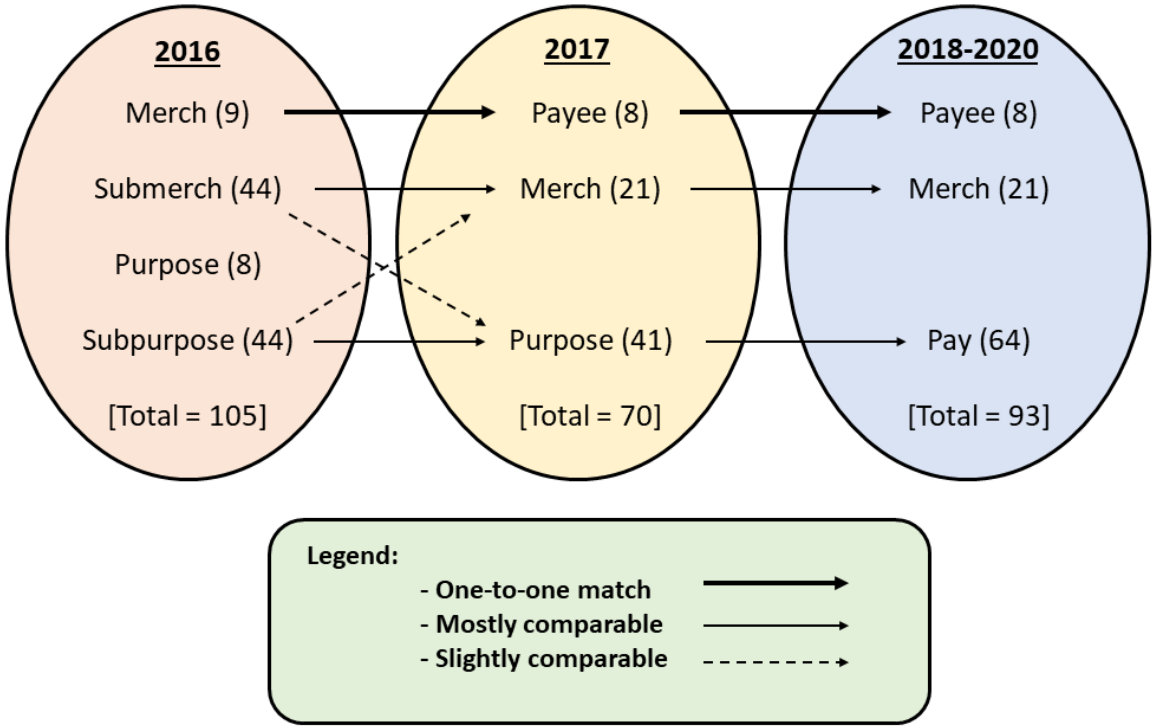


Figure A3 offers a simple overview of changes to DCPC payment categories over the years. In 2012, there were 45 possible merchant categories in which expenditures could be categorized. In 2015, merchant was simplified into 9 categories, and submerch categories were added to add more details to the merchant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

Appendix B Data Validation Details

Appendix B reports additional validation details from Sections 5 and 6. Tables presented correspond to the Figures in Section 5, and report the detailed 4 and 5 years income and consumption results. Additionally, annual time series of comparable consumption and adjusted income are included. Figure B3 provides a visual representation of the forecasting method used in Section 6.

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 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.[33] The DCPC tends to match 52% and 74% 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.[34] 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.

[33] 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.

[34] When removing taxes and supplements to wages and salaries, the DCPC comparable categories match 60% of BEA income and 78% of IRS income respectively.

Table B1: 5 Year Averages of Consumption

5 Year Averages (2012 Billions USD)	CE	PCE		DCPC	CE/PCE	DCPC/PCE
	(1)	(2)		(3)	(4)	(5)
Total Expenditures	**7,360**	**12,749**		**12,356**	**.58**	**.97**
	(138)	(151)		(798)		
-Imputed Rent	1,719	1,479		-		
	(66)	(23)				
-Non-Profit Goods and Services		409		-		
		(10)				
-Mortgage Payments, Expenses for Owned Dwellings	-	-		1,254		
				(149)		
-Taxes, Payments to Persons, Non-Classifiable	-	-		431		
				(95)		
-Loan Repayments	-	-		2,895		
				(204)		
Adjusted Consumption	**5,641**	**10,861**		**7,774**	**.52**	**.72**
	(96)	(129)		(655)		
Mostly Comparable	**3,825**	**6,089**	**6,054**	**4,907**	**.63**	**.81**
	(70)	(70)	(70)	(23)		
Food and Food Services	981	1,688	1,688	1,160	.58	.69
	(24)	(19)	(19)	(23)		
General Merchandise	447	1,087	1,087	1,208	.41	1.11
	(16)	(9)	(9)	(152)		
Housing and Utilities	1,274	1,520	1,520	1,657	.84	1.09
	(5)	(28)	(28)	(120)		
Transportation	788	915	915	368	.86	.4
	(16)	(12)	(12)	(53)		
Entertainment and Recreation	174	367	367	275	.48	.75
	(4)	(3)	(3)	(62)		
Pharmaceuticals	140	477	477	15	.29	.03
	(39)	(13)	(13)	(8)		
Other*	20	36	-	224	.57	NA
	(2)	(1)		(58)		
Mostly Noncomparable	**1,816**	**4,772**	**4,807**	**2,867**	**.38**	**.6**
	(117)	(79)	(79)	(610)		
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**	**12,208**	**.74**
	(313)	(1,618)	
Comparable	**14,480**	**7,573**	**.52**
	(294)	(647)	
Wages and Salaries	8,233	4,944	.6
	(135)	(626)	
Proprietor's Income	1,472	402	.27
	(51)	(84)	
Retirement, Interest, and Dividends	2,585	780	.3
	(43)	(79)	
Rental Income	623	182	.29
	(6)	(61)	
Social Security	912	1,132	1.24
	(18)	(303)	
Government Assistance	655	133	.2
	(96)	(32)	
Noncomparable	**1,932**	**4,635**	**2.4**
	(21)	(1,220)	
Unidentifiable Income	-	4,610	
		(1,223)	
Other	1,932	24	
	(21)	(3)	
Less:			
Taxes	1,949	192	
	(19)	(26)	
Employee Contributions to Retirement	298		
	(6)		
Supplements to Wages and Salaries	1,882		
	(22)		
Alimony and Child Support	-	24	
		(3)	
Adjusted Income	**12,284**	**11,991**	**.98**
	(277)	(1,635)	

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

Table B3: IRS and DCPC Income Estimates

4 Year Income Averages of DCPC and IRS Income (2012 Billions USD)	**IRS** (1)	**DCPC** (2)	**DCPC/IRS** (3)
Total Income	**10,511**	**10,719**	**1.02**
	(213)	(820)	
Comparable	**9,836**	**7,286**	**.74**
	(166)	(748)	
Wages and Salaries	7,165	4,677	.65
	(111)	(732)	
Proprietors' Income	937	412	.44
	(10)	(108)	
Interest and Dividends	386	88	.23
	(23)	(58)	
Retirement Income	963	683	.71
	(20)	(87)	
Rental Income	54	125	2.3
	(2)	(29)	
Social Security	299	1,187	3.98
	(11)	(385)	
Government Assistance	22	113	5.23
	(1.15)	(31)	
Alimony	10	1.21	.12
	(.14)	(1.03)	
Noncomparable	**675**	**3,433**	**5.09**
	(61)	(284)	
Unidentifiable Income	-	3,408	
		(283)	
Other	675	25	
	(61)	(3)	
Less:			
Taxes	1,428	213	
	(26)	(20)	
Child Support	-	25	
		(3)	
Adjusted Income	**9,082**	**10,481**	**1.15**
	(209)	(806)	

Table B3 reports the aggregate 4-year average estimates of IRS and DCPC income results. 4-year averages (2016-2019) are used because as the time of this paper, 2020 IRS income estimates are not available. Total income is all income types from both data sets with no adjustments. Total income is the sum of comparable and noncomparable income. Comparable income is any income type that is identifiable in the DCPC, and is match to IRS income types with similar categories. Noncomparable income is multiple categories in the IRS which do not match any definitions from DCPC, while noncomparable categories in DCPC is income whose type is not identifiable, or child support (under other). Taxes and child support are removed to create adjusted income. May not sum directly due to rounding. Estimates are in 2012 billions USD, standard errors are reported in parentheses. Last column reports the ratio of DCPC income to IRS income.

Figure B1: Annual Comparable Expenditures

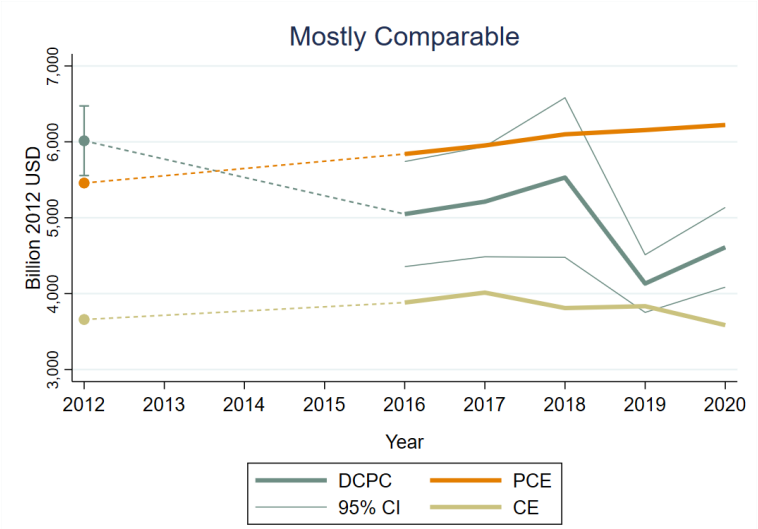


Figure B1 shows the annual estimates of comparable consumption across DCPC, PCE, and CE. 2012 estimates are reported by circles for comparison, with bars indicating confidence intervals in 2012. Dashed lines are to indicate missing values from 2013-2015. Thick solid lines are point estimates, while thin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

Figure B2: Annual Adjusted Income

(a) DCPC and BEA Income

(b) DCPC and IRS Income

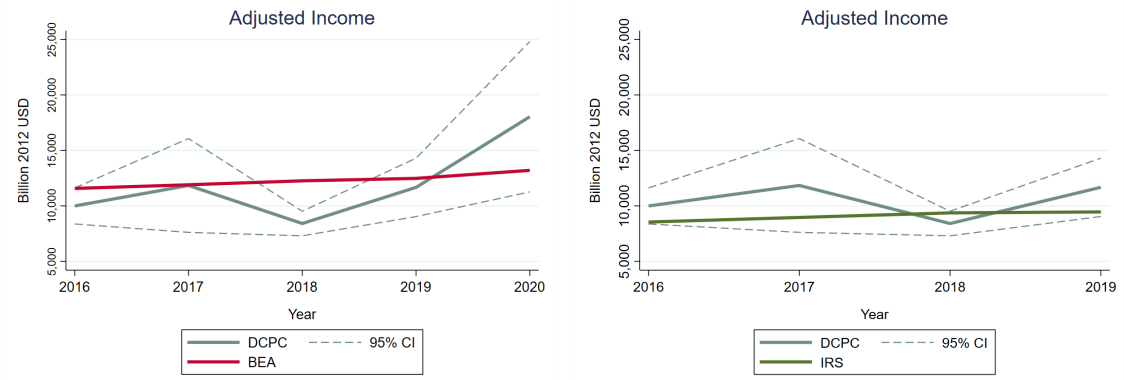
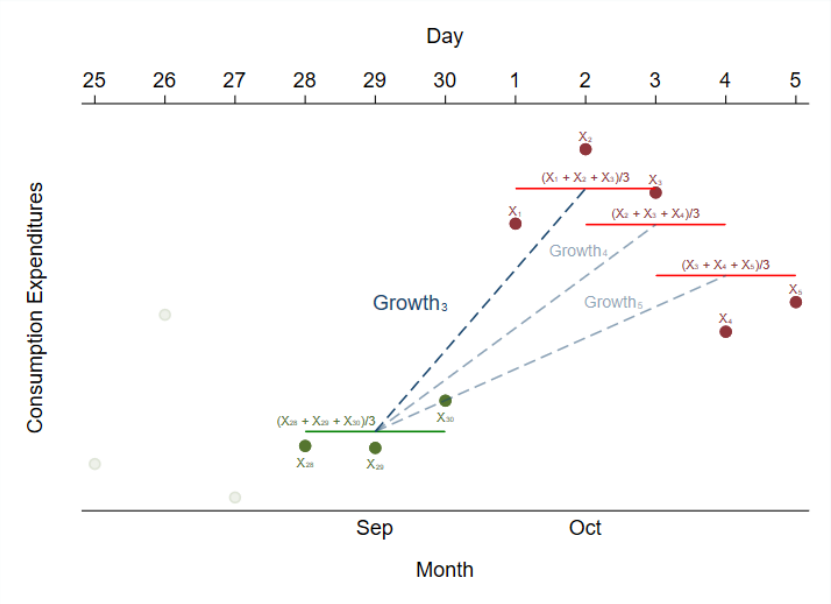


Figure B2 shows the annual estimates of adjusted income across DCPC, BEA, and IRS. Figure B2a compares DCPC and BEA adjusted income, while figure B2b compares DCPC and IRS income. 95% confidence intervals are reported for DCPC by dashed lines. All estimates are reported in billions 2012 USD.

Figure B3: Forecasting Visualization

(a) Daily Growth Estimation



(b) Monthly Projection

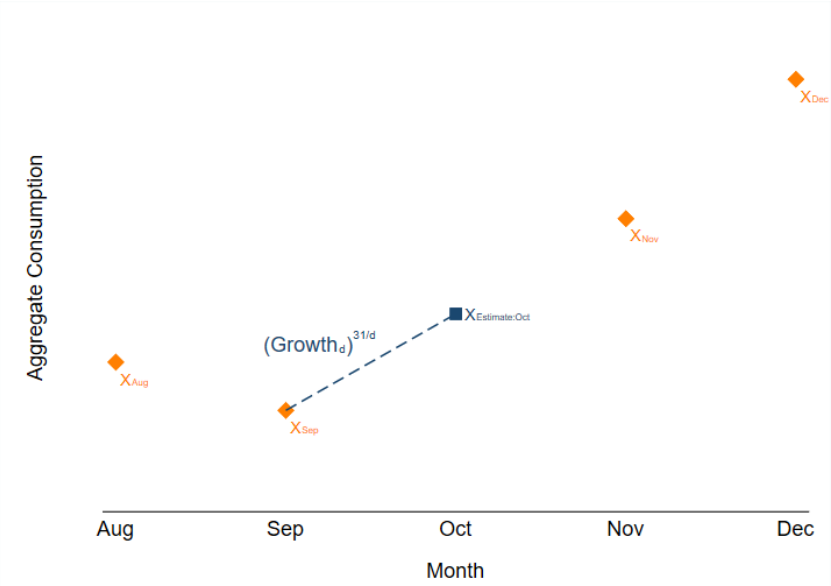


Figure B3 provides a graphical description of the forecasting method used in section 6.2. Subfigure B3a shows the average consumption expenditures recorded for the end of September and throughout October in the DCPC. To measure growth, the three-day average of consumption calculated for September, and with a rolling window through October (depicted by horizontal lines). Growth from September to October is calculated by taking the ratio of each October three-day average to September three-day average. While only 5 days of October are shown in the figure, we calculate this for each day in October. Using these growth rates, we project growth to the end of the month and the use PCE September estimate to forecast October PCE as shown in Subfigure B3b. Therefore, this allows for a daily forecast of PCE consumption as depicted in Figure 4.

Appendix C Cleaning Consumption and Income Comparison

The results presented in the main paper use the original expenditure and income amounts available in the public datasets. However, the Boston Fed also publishes research reports annually for the DCPC which summarizes key facts regarding consumer payment choices. In this report, the Boston Fed also cleans the data with respect to large outliers in payment amounts. To examine the robustness of the results relative to outliers influencing the estimates, this section presents estimates of the high level consumption/income categories from the consumption and income tables of the primary paper using the cleaning methods by the Federal Reserve. These estimates are reported in Table C1. Cleaning scripts were obtained from the Boston Federal Reserve. The cleaning method used involves replacing outliers given a threshold determined by a beta distribution. However, in 2020 this method was not used and instead individual observations were removed. One of the observations removed was a car purchase. Because car purchases are included in PCE and CE consumption, this observation was kept for the cleaning results.

Column (1) reports the consumption and income estimates without Fed cleaning (WOFC). Column (2) reports these same estimates using the cleaned Fed estimates (WFC). Column (3) reports the ratio of WOFC to WFC. As shown in column (3), the WOFC estimates are 15% higher for total expenditures and 20% higher for adjusted consumption. When examining income, WOFC estimates are 5% higher for both total and adjusted income. Columns (4) and (5) report the cleaned estimates of the DCPC as a ratio of the PCE estimates for consumption and the BEA estimates for income. The DCPC matches 76% of comparable consumption categories and 93% for adjusted income. WFC comparisons to IRS income is excluded from the table due to space, however WFC adjusted income estimates are 7% higher than adjusted IRS income. The results of Table C1 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 C1: With Fed Cleaning Comparison

With Fed Cleaning (WFC) and Without Fed Cleaning (WOFC) Comparisons					
(A) 5 Year Consumption Averages	(1) WOFC	(2) WFC	(3) WOFC/WFC	(4) WOFC/PCE	(5) WFC/PCE
Total Expenditures	12,356	10,734	1.15	.97	.84
Adjusted Consumption	7,774	6,441	1.21	.72	.59
Mostly Comparable	4,907	4,582	1.07	.81	.76
Mostly Noncomparable	2,867	1,859	1.54	.6	.39
(B) 5 Year Income Averages	WOFC	WFC	WOFC/WFC	WOFC/BEA	WFC/BEA
Total Income	12,208	11,577	1.05	.74	.71
Comparable Income	7,573	6,979	1.09	.52	.48
Noncomparable Income	4,635	4,598	1.01	2.4	2.38
Adjusted Income	11,991	11,392	1.05	.98	.93

Table C1 reports the consumption and income estimates without fed cleaning (WOFC) which is used in the paper, and with fed cleaning (WFC). Panel A reports the consumption results, while panel B reports the income results. Panel B reports BEA comparable income, while IRS is excluded for space. Column (1) reports the consumption and income results found in the paper, while column (2) reports the same results using the cleaned data. Column (3) reports the ratio of column (1) to column (2). Column (4) reports the ratio of WOFC estimates to PCE in panel A and BEA in panel B, while column (5) reports the ratio of WFC estimates to PCE and BEA income. Dollar values are in 2012 USD billions.