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

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PRELIMINARY AND INCOMPLETE

Abstract

Schuh (2018) demonstrates that the 2012 (first) U.S. Diary of Consumer Payment Choice (DCPC) yielded the unintended benefit of providing superior daily data on individual- and transaction-level consumption that tracks aggregate U.S. data very well. This paper extends the analysis through 2020, demonstrating how innovations in the survey instrument improved the precision of consumption and added collection of income that tracks aggregate U.S. income surprisingly well too. Daily DCPC consumption and income are comparable to data from proprietary financial transactions data but publicly available and often more representative, thus reflecting real-time economic developments with potentially valuable informative precision. Key results in the literature on high-frequency consumption and income dynamics are replicated in the DCPC data, and extended to new perspectives such as hard-to-measure payments like credit cards. Evidence on potential selection effects in micro data samples is quantified for consumers who opt to use personal financial management (PFM) methods.

JEL Codes: E21, D12, D14

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1 Introduction

Recent work in consumer payments demonstrates a potential value of tracking individual consumer payments for measuring and understanding consumption behavior by separating consumer expenditures from non-consumption expenditures. Bagnall *et al* (2016) reported that aggregate payments from consumer diaries in advanced economies were on the order of magnitude of national consumption. Schuh (2018) extended this unintended potential side benefit by studying the 2012 (first) U.S. Diary of Consumer Payment Choice (DCPC) in more detail and reported two surprising results. First, aggregate payments in the DCPC identified as consumption are remarkably close to aggregate personal consumption expenditures (PCE) in the national income accounts, notably closer than estimates from the Consumer Expenditure Survey. Second, aggregate total payments in the DCPC are remarkably close to aggregate disposable personal income (DPI) in the national income accounts.

Although intriguing and potentially encouraging, the 2012 DCPC results begged several questions. Were the 2012 results a fluke or would they hold up with additional years of DCPC data? Was the limited information used to identify consumption expenditures separately from non-consumption expenditures accurate, or would better identification in subsequent diaries alter significantly the correspondence of DCPC consumer expenditures to PCE? Would the correspondence of total payments to aggregate DPI be confirmed by direct collection of consumer income data or not? And, perhaps most importantly, are the DCPC individual-level data 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 since 2012, for two validation exercises: 1) assess how better identification of consumption expenditures affected the relationship of DCPC to PCE and CE; and 2) examine whether direct measurement of daily income receipts matches aggregate DPI data. Validated 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. Encouraging validation and prediction results

motivate estimation of basic consumption models and comparison with the literature. Finally, because the DCPC is perhaps the most nationally representative transactions data set (see Baker and Kueng (2022)), we use adoption of personal financial management methods by some consumers to test for sample selection effects.

After 2012, DCPC aggregate consumption data continue to match PCE data better than CE data and aggregate income received data match the bulk of DPI data even more closely. Improvements in DCPC transaction classification has increased accuracy in consumption identification, resulting in more payments excluded from consumption since 2012. However, the DCPC still matches 81% of PCE comparable consumption categories, and is 28% higher than CE between 2016-2020 on average. The results are relatively smaller than found in the 2012 DCPC as a result of increased identification of expenditure types in these later diaries. Additionally, this study presents the new finding that the DCPC matches 98% of DPI and is 15% higher than IRS aggregate income estimates on average over the five years respectively when adjusted for differences between income measurements. These results provide evidence that the payment diaries continue to supply excellent and accurate consumption and income estimates, representative of U.S. statistics.

We find additional evidence that the diary diaries have predictive power for government monthly data that could provide public value to the private sector. The real-time data analysis shows that the daily DCPC estimates and forecasts of PCE are both precise and realized early within the month. We find that daily estimates of representative monthly consumption expenditures reach their average remarkably quickly within the diaries, with estimates converging in the beginning to middle of the month. Using daily estimates of monthly DCPC growth rates, forecasting results imply that within the month, roughly 10 days of data are needed to predict October PCE for most years. This analysis exemplifies the real-time data potential of the payment diaries in identifying representative consumption behavior at the daily frequency.

Furthermore, the analysis indicates that the DCPC exhibits common consumption behavior found within the literature when estimating basic consumption models. Implementing a synthetic panel structure, the results imply that monthly-aggregated marginal propensity to consume (MPC) estimates are between .15 - .21, which is similar but on the lower end of results found by the literature. Notably, when measuring daily consumption responses to income for the panel, daily MPC esti-

mates are between .07 -.09, indicating that MPC decreases at higher frequencies. This finding is also true when looking at total daily consumption and income without the synthetic panel, finding a daily MPC of approximately .05 - .09. 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 relative to the income payment. These analyses show that the payment diaries capture similar consumer behavior found within the broader consumption literature, demonstrating the value of the DCPC as a means to study consumption and income dynamics.

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. Initial results of convenience samples find that personal financial management (PFM) users show significant differences in demographic characteristics, and larger MPCs than those who do not use PFM software. PFM users tend to be younger, yet have much higher levels of education and income levels than their counterparts. While the higher MPC may be due to demographic differences, further research in models of PFM adoption are necessary to help understand the causal relationship between PFM use and consumer behavior. Additionally, we find that while credit card adopters tend to exhibit lower MPCs, credit card users which revolve their debt month-to-month exhibit higher MPCs than those that do not.

Although payment diaries like the DCPC were not intended and designed to be a rich source of micro transactions-level individual data for analysis of consumption and income dynamics, this paper provides additional evidence of their value for such endeavors. Relative to other transactions data, the DCPC offers two main advantages: representativeness and public access. However, the DCPC and other payment diaries have relative tiny, infrequent samples compared to other large transactions data sets. 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 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.

2.2 The Trade-offs of Transaction Data

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 dataset. 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.

While these data sets offer ample opportunity for studying consumption flows, they are also prone to limitations. First, individuals are usually identified by the account and not necessarily the exact

individual. This can lead to measurement issues in regards to who is conducting the transaction within the household. Second, due to the nature of the data source, transaction data may exhibit sample selection effects. For example, data from personal financial management software is not necessarily representative by nature as those who sign up for the service may exhibit sample selection effects. Third, transactions involving cash cannot be observed directly, and check payments can be difficult to categorize. Fourth, as many of these data are proprietary, the results cannot be directly replicated by researchers.

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 income receipts relative to BEA Personal Income and IRS aggregate income estimates.

2.4 The Trade-offs of Payment Diaries

Due to the structure of payment diaries, the DCPC are not constrained by many of the limitations found from other transaction data sets. 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, and is less subject to

selection effects found in other transaction data sources. Further, because the diary is sponsored by the Fed, data sets are publicly available to researchers. This 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[1], 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. However, because of the benefits discussed, the DCPC can be used jointly with other data to understand nationally representative consumer behavior.

2.5 Research with Transaction 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 information on payments, and detailed heterogeneity of agents. Much of the literature has used these advantages to study possible explanations for deviations in standard life-cycle models[2]. The benchmark model predicts that consumption responses to income shocks should be low, however the empirical literature finds estimates of MPCs between 0.2 - 0.6 as discussed by Carroll et al. (2017). Transaction data is often used to understand these findings. This includes studying how consumption changes to anticipated or unanticipated income (Baker (2018), Kueng (2018), Baugh et al. (2021)) 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 even if the income payment is anticipated. Papers with credit card or other forms of consumer debt also examine how consumers pay back their debt or consume relative to consumer debt (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

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

[2] See Jappelli and Pistaferri (2010) for a review of the MPC literature and their methods.

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 unobservable characteristics of consumers. Kuchler and Pagel (2021) find that financial sophistication and impatience are associated with consumers committing to paying debts. Finally, 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 the payment diaries, we replicate the studies which the data is best capable of reproducing to examine if the DCPC finds similar results found in the literature.

3 The DCPC

3.1 Brief Overview

This section offers a brief overview of the DCPC. See Schuh (2018) for a comprehensive analysis of the payment diaries. The DCPC was first implemented in 2012 by the Federal Reserve Bank of Boston to compliment the Survey of Consumer Payment Choice (SCPC), an annual survey which tracks payment behavior of consumers[3]. The purpose of the DCPC is to measure daily payment behavior and consumer spending with detailed recorded transaction information through diaries (Greene and Stavins (2021)). The DCPC questionnaire records seven essential variables relating to transactions: time and date of the payment, dollar amount, payment instrument, payment location, merchant type and merchant name. Respondents use numerous memory aids through their diary days to track their payments and cash management. Each diary day, the respondent fills out the online questionnaire which records the transaction information filled out in the memory aid. Respondents participate for three consecutive days during one of 31 waves, which they were randomly assigned through October. Waves begin during September 29th and end November 2nd in order for each wave to complete three diary days. This process of randomly assigning diarists for three days over the month of October ensures that there are representative transactions being recorded each day during over the month. While respondents begin keeping track of transaction on

[3] The SCPC is an annual survey which studies payment information, such as payment instrument adoption and frequency throughout the year, while the DCPC records payment details of daily specific transaction values.

the first diary day, there is an initial diary day (diary day 0) in which individuals are asked account and other demographic information.

While the primary purpose of the DCPC is to measure payment behavior of respondents, the diaries are able to successfully track consumption expenditures due to the detailed nature of the diary format. For each transaction, respondents record the merchant and purpose of the payment. This allows researchers to identify transfer payments as well as categorize consumption by merchant and purpose category. Respondents also record the amount of the transaction as well as the payment instrument used for the payment. Respondents for the DCPC are taken from the Understanding America Study (UAS) panel, in which respondents are representative of the U.S. population. The Fed also provides day-of-the-week, daily, and individual poststratification weights to match any discrepancies arising from the variation of annual recruitment differences[4]. Because of the representative sample and weights, Schuh (2018) shows that the 2012 DCPC is capable of measuring U.S. consumption, even though it is not the diary's primary purpose.

3.2 Additions to the DCPC 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. A notable change occurred in the survey vendors. In 2015, the survey vendor changed from the RAND Corporation's American Life Panel to the University of Southern California's UAS panel. Due to a smaller size of the UAS panel, in 2015 additional third-party vendors were used. Respondents came from UAS, Growth from Knowledge (GFK), and Qualtrics[5]. Because of these limitations, it was not possible to implement the DCPC in only the month of October, and thus the diary dates were changed. Instead, the diary ranged from October 13 through December 17th. However, from 2016 forward the diary contains data on the entire month of October while the 2015 diary does not. Because of this discrepancy, this paper excludes the 2015 data from its analysis. For further details on the 2015 diary, see Angrisani et al.

[4] 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

[5] Because the response rate for the Qualtrics subsample was low and issues with the quality of the data, these observations are excluded from the public dataset.

(2018).

Additional changes include redefining merchant categories, and further identifying loan repayments. 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 0, respondents are asked if they receive any of the income types from Table A1 found in Appendix A. Throughout the three diary days, respondents record if they received income on the diary days, the income type, and how it was deposited[6]. Additionally, the diarists are asked their the date of their last income payment on diary day 0 and date of their next income payment on the third diary day. 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 (for example, money from a family member). 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.

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

3.3 Data Construction

In order to calculate aggregate consumption from the DCPC, transactions are first identified as expenditures or transfer payments. Expenditures are further categorized by consumption and non-consumption expenditures. Specifically, the analysis includes only consumption expenditures C from all possible transactions T such that $C \subset T$. To compare the results with PCE and CE estimates, consumption is further classified into consumption categories which match those from PCE and CE consumption[7]. The total daily consumption expenditures for individual i in consumption category j on day d is found by taking the sum of all consumption transactions k:

$$C_{idjy} = \sum_{k=1}^{K} C_{kidjy} \tag{1}$$

Where K are the total amount of consumption transactions for an individual on day d, and y is the year of the diary. The sum of each consumption category identifies the total amount of consumption for individual i on day d:

$$C_{idy} = \sum_{j=1}^{J} C_{idjy} \tag{2}$$

Where J are the total amount of consumption categories. Next, we find the average daily consumption ($\hat{C}_y^{daily}$) for all consumers using day-of-the-week weights (w_{idy}) to account for demographic differences in respondents as well as day-of-the-week fluctuations:

$$\hat{C}_y^{daily} = \sum_{i}^{I} \sum_{d=1}^{D=31} C_{idy} \cdot w_{idy} \tag{3}$$

Finally, to find the annual estimates of aggregate consumption, daily consumption is multiplied by the DCPC targeted population (U.S. non-institutional population ages 18 and over) as well as the average number of days in a given month (30) and the number of months in a year (12):

$$C_y^{Annual} = \hat{C}_{daily} \cdot N_y \cdot 30 \cdot 12 \tag{4}$$

[7] See Appendix A, Tables A2-A8 for how income and consumption were categorized for each of the datasets.

Where N_y is the population in year y. When examining consumption categories j, equation 2 is skipped. It follows that the sum of all annual aggregate consumption categories equal total annual aggregate consumption, C_y^{Annual}.

A similar process is conducted to find annual aggregate income estimates, in which we find average daily income receipts in each category and aggregate the results annually[8]. In the process of aggregating consumption and income, the raw observations from the DCPC public data are used. However, the Fed cleans the observations when calculating DCPC reports published on their website. The consumption and income results in the main body of the paper 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 by the Fed. A comparison of the results without Fed cleaning (WOFC) and with Fed cleaning (WFC) can be found in Appendix D. When calculating forecasts and running regressions, observations are cleaned using the Fed cleaning scripts.

4 Aggregate Consumption and Income Statistics

To assess if the DCPC continues to capture household spending since 2012, this section compares the DCPC estimates of aggregate consumption with PCE and CE consumption similar to Schuh (2018). Furthermore, to asses if the DCPC captures representative income payments, this section compares the DCPC estimates of aggregate income to BEA Personal Income and IRS aggregate income. For information on how consumption and income were categorized, please refer to Appendix A. The results reported in sections 4.1 and 4.2 are with the publicly-available raw data. To test the sensitivity of these results to outlier, Appendix D reports the results using the cleaning methods used by the Fed[9]. 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.

[8] Income categories correspond to Table A1, as well as unidentifiable income discussed in section 3.2. Day-of-the-week weights are used to find annual aggregate income results.

[9] The cleaning scripts are not publicly available on the DCPC website at the time of this paper. Cleaning scripts were obtained from the Fed.

4.1 Consumption Expenditures

The consumption estimates calculated from equation 4 are compared to PCE and CE consumption to measure how well DCPC results compare to aggregate statistics. The PCE is a comprehensive estimate of consumption expenditures within the U.S. that pulls from many data sources. Both the CE and DCPC are not able to replicate the PCE completely given the differences in methodology of survey and diary data. Due to these discrepancies between datasets, consumption is organized into comparable categories which allows for an accurate comparison between datasets. The BLS publishes comparable categories between the PCE and CE, which are utilized in this paper for measuring comparable categories[10]. The DCPC estimates within these categories are matched to the PCE and CE categories through the merchant categories, defined in Tables A7 and A8.

Table B1 reports the five year averages from 2016-2020 of the CE, PCE, and DCPC consumption estimates. For CE and DCPC estimates, the ratio of the estimates relative to PCE are included in columns (4) and (5). The DCPC matched 97% of PCE expenditures from 2016-2020 before any adjustments, while the CE matched approximately 58% of PCE consumption. However, because the approaches of the datasets all differ in their measurement, there exists unique categories within the data. These unique categories are removed to create a more accurate comparison between datasets. Imputed rent and non-profit goods and services are not found in the DCPC and are thus removed. However, mortgage payments and expenses for owned dwellings are conceptually related and are removed. The additional unique categories removed from the DCPC include taxes, payments to person, non-classifiable payments, and loan repayments.

Adjusted consumption reports the consumption expenditures across all three categories which are more closely related. The DCPC contains approximately 73% of PCE adjusted consumption over the five years. However, recall that adjusted consumption contains categories which are similar, yet have important discrepancies which make some categories as as comparable as defined by the BLS. Thus, adjusted consumption is categorized into mostly comparable and mostly noncomparable categories. Comparable categories are those between all three datasets in which the DCPC matches the closest, while noncomparable contains consumption categories which have similar definitions

[10] For more information regarding the adjustment of CE and PCE categories by the BLS, see the BLS.

but include important discrepancies in definitions and measurability[11]. Therefore, the mostly comparable category is the most accurate comparison within the datasets. A more detailed comparison of consumption categories within mostly comparable can be found in Table B1.

Figure 1: Annual Comparable Expenditures

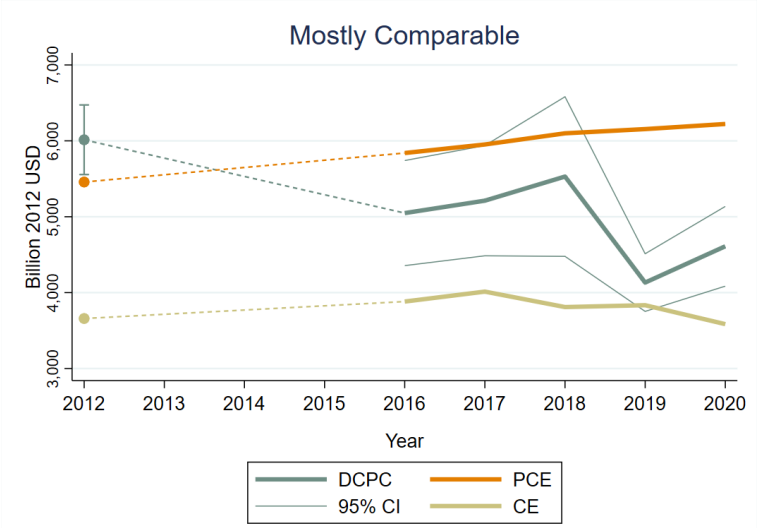


Figure 1 shows the annual estimates of comparable consumption across DCPC, PCE, and CE. 2012 estimates are reported by circles for comparison, with bars indicating confidence intervals in 2012. Dashed lines are to indicate missing values from 2013-2015. Thick solid lines are point estimates, while thin lines are the 95% confidence intervals for DCPC estimates. All estimates are reported in billions 2012 USD.

Annual estimates of comparable consumption for all three datasets are found in Figure 1. As shown by the figure, the DCPC estimate of comparable consumption fall between CE and PCE consumption through 2016-2020. Between 2016-2018, PCE consumption is within the DCPC 95% confidence intervals, while in 2019 to 2020 DCPC is closer to CE estimates. Table B1 shows the DCPC matches 81% of PCE estimates on average over the five years, while the CE covers approximately 63%. Over the five years, the DCPC is approximately 28% higher than CE consumption results on average for comparable consumption.

[11] For example, while the DCPC allows for a payment category in tuition payments, the DCPC us unlikely to capture representative tuition payments during the month of October, and is thus included in mostly noncomparable consumption. Broadly, mostly noncomparable contains consumption 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.

4.2 Income Receipts

The income estimates calculated from section 3.3 are compared to BEA and IRS income to measure how well DCPC results compare to aggregate statistics. Out of the three datasets, 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[12]. 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 income separately in order to make the most accurate comparison.

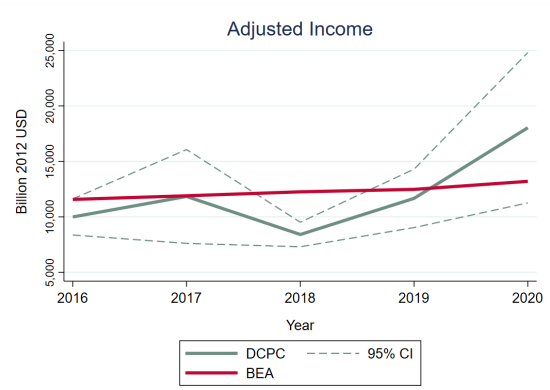
Table B2 reports the 5 year average income estimates of the BEA and DCPC from 2016-2020, while Table B3 reports the 4 year average income estimates of IRS and DCPC from 2016- 2019[13]. Column (3) in both tables report the ratio of DCPC estimates to the corresponding dataset. The first row of the tables reports total income with no adjustments. Because there exists differences between DCPC income and the other data, total income is categorized by comparable and noncomparable income. Comparable income categories in the DCPC are those that can be identified directly from the DCPC, while noncomparable categories are income receipts that cannot be categorized as discussed in section 3.2. 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. Income is adjusted to remove taxes and other income categories unique to each dataset, which is reported by adjusted income. Because income reported in the BEA is pre-tax income, unique categories from each dataset are removed after the comparison of comparable categories. 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.

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

[13] 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.

Figure 2: Annual Adjusted Income

(a) DCPC and BEA Income



(b) DCPC and IRS Income

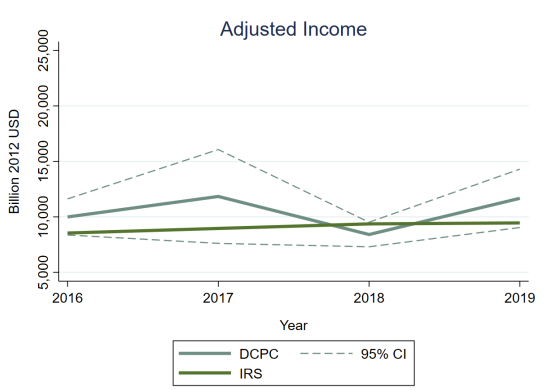


Figure 2 shows the annual estimates of adjusted income across DCPC, BEA, and IRS. Figure 2a compares DCPC and BEA adjusted income, while figure 2b compares DCPC and IRS income. 95% confidence intervals are reported for DCPC by dashed lines. All estimates are reported in billions 2012 USD.

Annual estimates of adjusted income between the DCPC/BEA and DCPC/IRs are found in Figure 2. Even before any adjustments for comparability, it can be seen from Tables A2 and A3 that DCPC income matches a significant portion of both BEA and IRS income. For the comparable income categories, the DCPC tends to match 54% and 74% of BEA and IRS results comparably. A significant portion of DCPC income comes from uninidentiable income types. As discussed in section 3.2, this may be other forms of income or an income type that was not reported by the respondent. After removing taxes and other unique categories in each dataset, adjusted income offers the closest comparison between the DCPC/BEa and DCPC/IRS. As shown in Figure 2, BEA adjusted income falls within the 95% confidence interval of the DCPC except for 2018. IRS income falls within the confidence interval for DCPC for all years. 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.

4.3 Discussion of Results

The results of sections 4.1 and 4.2 suggest that the DCPC captures a significant portion of U.S. consumer spending and income payments. As shown in Table B1, the DCPC estimates of comparable consumption matches 81% of PCE consumption and is 28% higher than comparable CE consumption from 2016 - 2020. Figure 1 shows that DCPC consumption tends to lie in between PCE and

CE consumption throughout the time frame, approaching CE consumption towards the end of the sample period. The discrepancy between PCE and DCPC consumption is due to the fact that the DCPC does not obtain all of the data and resources PCE consumption contains. Importantly, the DCPC is not implemented to measure U.S. consumption, but it is meant to measure representative U.S. payment choice decisions such as payment instrument choice. Additionally, Table B1 shows that the 5 year average is lower than the 2012 annual estimate from Schuh (2018). This is mainly due to the inclusion of being able to identify loan repayments at a higher accuracy than in 2012. However, the DCPC is still able to remarkably capture a nontrivial portion of U.S. consumption. Therefore, even though the DCPC is not intended to measure DCPC consumption, it continues to be able to do so successfully.

A similar story holds for DCPC income estimates: though the DCPC is not implemented to capture U.S. income payments, the diaries encapsulate a considerable amount of U.S. income payments as shown by Tables B2 and B3. Specifically, the DCPC accounts for 98% of BEA adjusted income and is 15% higher than IRS adjusted income. As shown by Figure 2, the DCPC income estimates falls slightly below BEA adjusted income from 2016-2019, while being slightly above in 2020. Similarly, DCPC income tracks IRS income closely throughout the entire sampel period. These new results show that the DCPC is able to represent a significant portion of U.S. income, even though its not the DCPC's intended purpose.

Given these results, this study concludes that the DCPC captures a significant portion of representative U.S. consumption and income behavior. There, the DCPC shows potential promise as an alternative data source to study the nature of consumption and income within the US. The daily frequency of the the DCPC data offers opportunities to study consumption decisions jointly with income receipts of individuals at a high-frequency, representative of U.S. consumption and income. Due to the success of the DCPC, Section 5 briefly investigates the real-time data capabilities of the DCPC.

5 Real-Time Data Analysis and Forecasting

5.1 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):

$$\bar{X}_{y,t,d} = \sum_{s=1}^{d} (\frac{31}{d}) \bar{X}_{st,y} \tag{5}$$

Where $\bar{X}$ is the monthly consumption per consumer during October ($t = 10$) on day of the month d in year y. Therefore, the equation estimates the 31-day projection of average daily payments derived 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[14]. 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 3.2. 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.

[14] Using the raw observations for analyzing the daily estimates of monthly consumption per consumer results in deviations from the final mean, which persist throughout October given the cumulative component of equation 5. Since the aggregate income and consumption statistics both capture a significant portion of representative US consumption and income as shown in section 4, WFC observations are used for a cleaner interpretation.

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

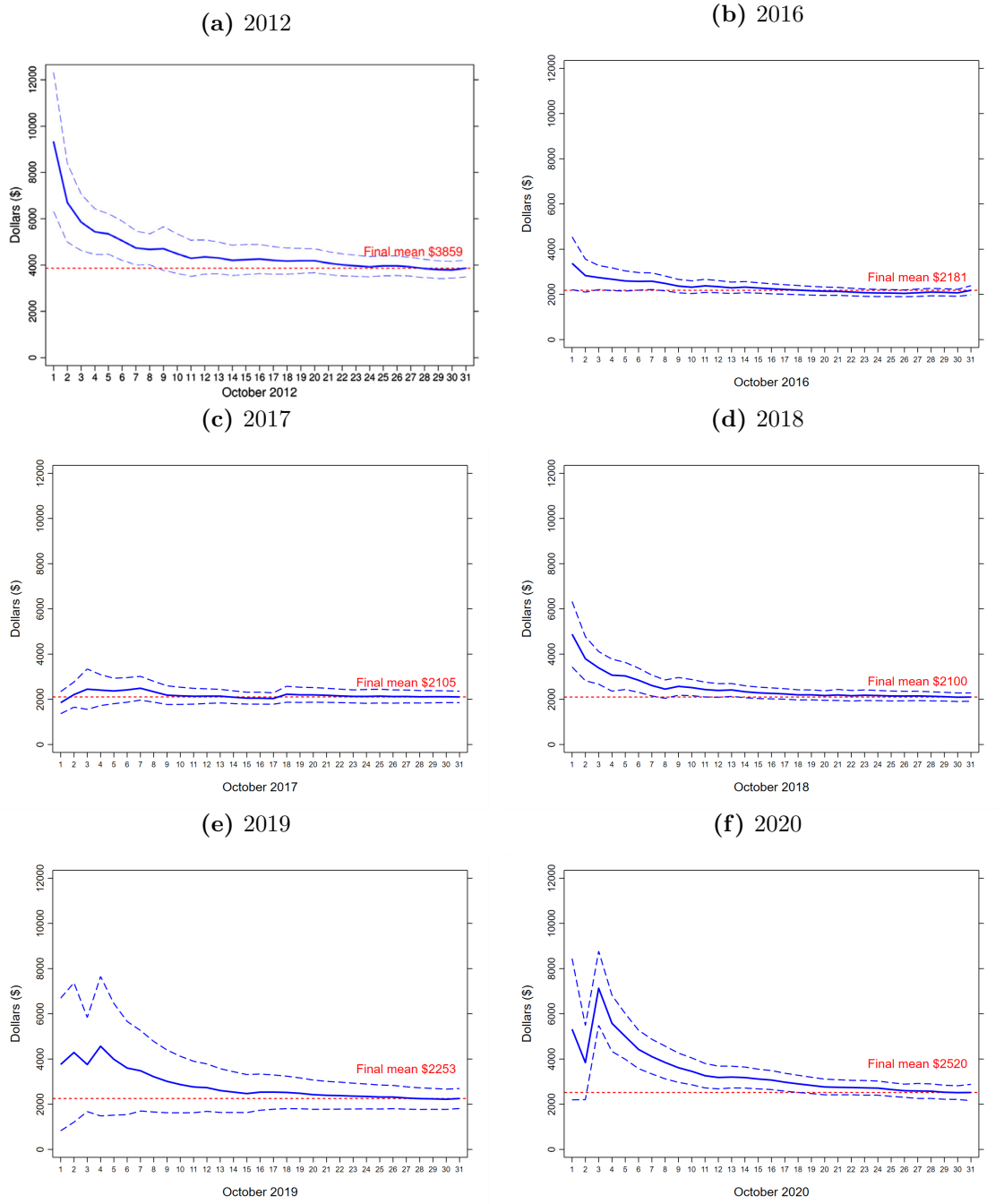


Figure 3 reports the results of the daily estimates of monthly payments per consumer, as discussed in section 5.1. Dashed lines indicate 95% confidence intervals, and dotted red lines are the final mean. Subfigure 3a is taken directly from Schuh (2018), while subfigures 3b - 3f are calculated from the 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 5). The estimation procedure from Schuh (2018) is used for calculating standard errors.

5.2 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:

$$\hat{X}^*_{d,t,y} = X^*_{t-1,y} \cdot G_{d,t,y} \tag{6}$$

$$G_{d,t,y} = \left[\frac{\sum_{s=d-2}^{d} X_{st,y}}{\sum_{k=D_{t-1,y}-2}^{D_{t-1,y}} X_{kt-1,y}} \right]^{\frac{D_t}{d}} \quad if\ d \geq 3 \tag{7}$$

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 y is the year ($y \in \{2016, 2017, ..., 2020\}$). X^* is PCE consumption, while X is DCPC consumption. $G_{d,t,y}$ 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[15]. This ratio is then raised to the power of $\frac{D_t}{d}$ to project the monthly growth rate of September to October DCPC. Therefore, $G_{d,t,y}$ is a daily estimate of the monthly DCPC growth rate in a given year y. Multiplying $G_{d,t,y}$ by September PCE ($X^*_{t-1,y}$) 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.

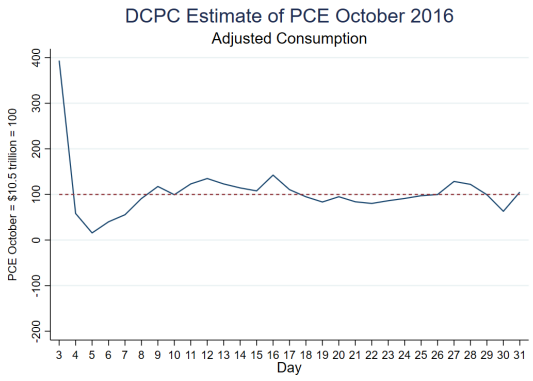
The daily forecast estimation of October PCE using the diaries[16] can be found in Figure 4. The blue line shows the daily DCPC forecast of October PCE estimates, which have been indexed to the PCE estimate of that year. As of this draft, confidence intervals for the diary forecasts have yet to be calculated. 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

[15] 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.

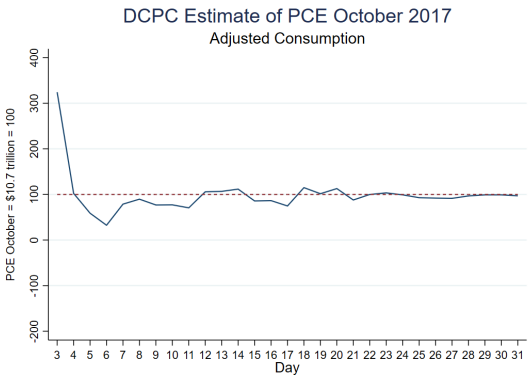
[16] Results were seasonally adjusted by regressing daily DCPC aggregate consumption on day-of-week and week-of-month indicator variables. Observations were cleaned using Fed scripts.

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

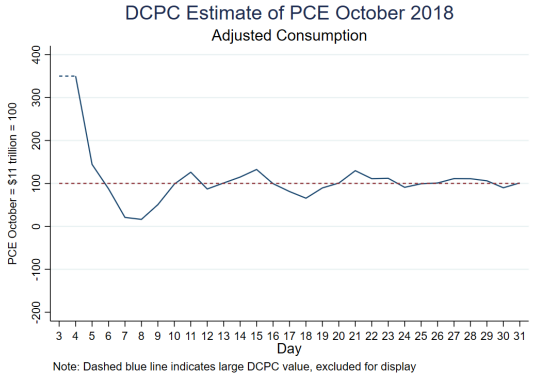
(a) 2016



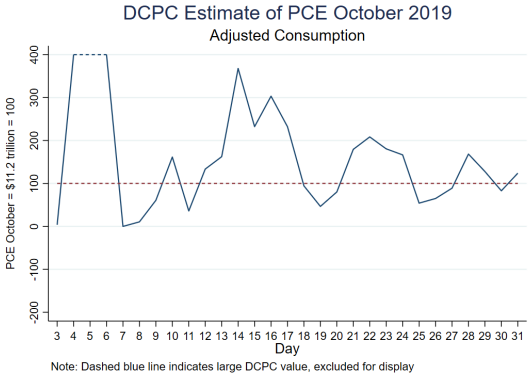
(b) 2017



(c) 2018



(d) 2019



(e) 2020

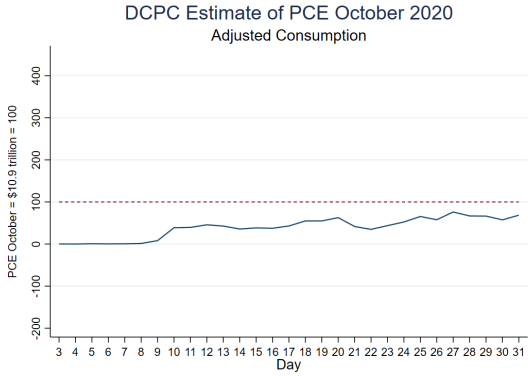


Figure 4 reports the results of the daily estimates of PCE October, as discussed in subsection 5.2. Estimates are indexed to PCE October of each year, where DCPC estimates are denoted by the blue line and the October PCE value is denoted by the red dashed line. Index values are reported on the y-axis 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.

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.

6 Consumption and Income Dynamics

Thus far, the DCPC has shown success in both measuring representative consumption and income data as well as its real-time data capabilities. We therefore turn to analyzing the relationship between consumption and income at daily and monthly frequencies by replicating results found within the consumption literature which use similar forms of transaction data. Though there is a large magnitude of studies within this literature, the topics replicated are those that measure the fundamental relationship between consumption and income in which the DCPC is best capable of replicating.

To begin, section 6.1 examines the changes in respondent consumption at the monthly and daily frequency utilizing income payments, which is discussed relative to the overall MPC literature. Then, section 6.2 studies high-frequency consumption patterns on and surrounding the consumers' paydays. Section 6.3 offers a conclusion on the performance of the DCPC in measuring consumption and income dynamics. In all sections, observations are cleaned using Fed scripts.

6.1 Marginal Propensity to Consume

There exists a large body of literature which examines the marginal propensity to consume from changes in income. According to the benchmark Life-cycle Hypothesis, consumption spending should not change significantly from a temporary income shock. However, it is a well known empirical finding that consumption responses tends to deviate from the benchmark economic theory, as reviewed by Jappelli and Pistaferri (2010). These deviation may be explained by liquidity constraints (Zeldes (1989)) and buffer-stock behavior (Carroll (1997)), though excess responses to income are still often found when accounting for these factors. As discussed in Carroll et al. (2017), transaction data which measures MPC tends to find estimates between 0.2 - 0.6 from shocks to transitory income.

Most studies which measure MPC do so at the annual or quarterly level, depending on the data being used. Because the DCPC is measured over three consecutive days of October for each respondent, the diaries capture a snapshot of representative consumption over three days. Aggregating consumption and income over annual or quarterly horizons becomes challenging using diaries due to two primary reasons. First, three days of consumption for any given individual may not reflect all payments within a quarter or year. Second, not all respondents receive income payments over the diary. This second constraint is particularly limiting at the daily level, as it limits the number of observations available. Most respondents who are observed receiving only one income payment during the their three diary days, and many of these respondents do not receive income during the next diary year. This limits the analysis when examining MPC for individuals, both within and across diary years.

While the measurement of each respondent's consumption is limited to three days, many demographic characteristics are represented throughout each day of the diary. This is due to the diary days of respondents being assigned randomly, and results in the average composition of respondents for each day being the same[17]. Therefore, by utilizing specific demographic characteristics which repeat throughout the diary days, it is possible to group consumption by respondent demographics and still maintain the representative nature of the data. This allows for creation of a daily panel of consumption and income by consumer demographics throughout the month of October in each

[17] As discussed in Angrisani et al. (2018).

diary year. With this in mind, we construct a synthetic panel in which we aggregate consumption and income receipt by consumer demographics in the panel. Let C_{ikdy} be consumption for respondent i within demographic cohort k on calendar day d in year y. We collapse the data into the following cohorts:

$$C_{kdy} = \sum_{i}^{I_k} C_{ikdy} \cdot w_{idy} \tag{8}$$

Where k is the cohort of chosen demographic variables, and w is the day-of-week weights for each respondent. Therefore, we find the summation of all respondent within each cohort for each day in October through 2016-2020. An analogous procedure is used for income receipts. By construction, each cohort will have a longer time dimension that any individual respondent, while the number of cohorts will be less than the number of respondents. In this way, there is a trade-off between the number of cohorts chosen and the amount of days observed. We then examine total consumption and income aggregated to the monthly level by taking the sum of each cohort's daily consumption. Cohorts are chosen to include important demographic information that will be important for consumption characteristics, while also allowing for consumption and income estimates during most days. We allow cohorts to vary by sex, race, education, and age for a total of 24 possible cohorts[18]. To examine each cohort's MPC, we use the following regression:

$$\Delta ln(C_{kty}) = \beta_0 + \beta_1 \Delta ln(Income_{kty}) + \varepsilon_{kty} \tag{9}$$

Where $Income$ is total income payments for cohort k at time t in year y. Time t can be either the daily or monthly analysis. We therefore are measuring the change in the natural log of consumption with the change in the natural log of income, which is an estimation of the elasticity of consumption with respect to income. Because the diaries are conducted in October, results are differenced at the annual level while aggregated to the monthly frequency. This simple specification allows for

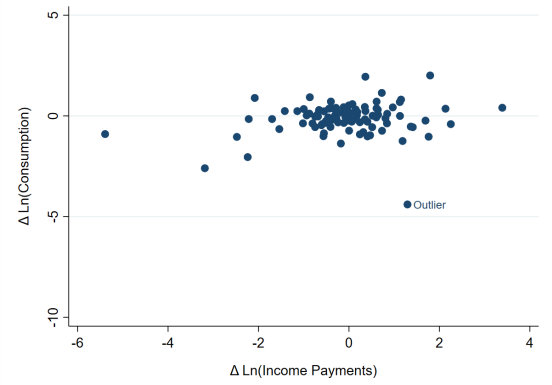
[18] Sex is categorized by male and female. Race: white and non-white. Education: no college or any amount of college. Age: <35, 35-55, >55.

the analysis of payment diaries capturing the fundamental relationship between consumption and income. It is important to note that the income payments used for this regression are all forms of income payments. While many forms of income are most likely expected by the respondents (such as regular wages), it is also possible that income includes unexpected income, whether from employment or elsewhere. Therefore, the results cannot distinguish between anticipated and unanticipated income payments. While we cannot distinguish between these two types of income, as a robustness check we limit our selection of income payments to only identified income (as discussed in section 3.2) to see if unidentified income payments are driving the results. These estimates are reported in Appendix C.

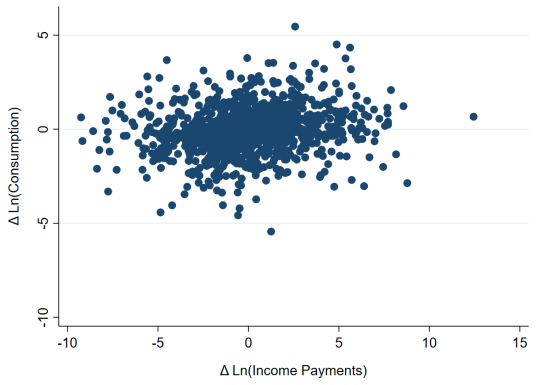
Figure 5 plots Δ ln(C) and Δ ln(Income) by cohorts over all years, at both the monthly level (Figure 5a) and the daily level (Figure 5b). At both frequencies, it is apparent that there is a positive relation between both variables. At the monthly frequency, there is a potential outlier (marked in the graph) which seems to deviate from the overall trend. When running the regression from equation 9, the results are reported with and without this outlier.

Figure 5: Synthetic Panel: Δ Ln(C) and Δ Ln(Income)

(a) Monthly



(b) Daily



The β_1 coefficients from equation 9 are presented in Table 1. Columns (1) - (4) report the results when examining monthly consumption and income by cohort, while (5) - (6) examine daily consumption and income by cohort. Each regression includes year fixed effects, and columns (3) and (6) report the results with cohort fixed effects. When examining monthly MPC, the results are statistically insignificant when the outlier identified in the previous figure is included in the

regression. However, when the outlier is excluded, the results are statistically significant and show an elasticity ranging from approximately .15 - .17. When examining the daily MPC, it can be seen that the point estimates are lower with an elasticity at .08. Notably, the results imply that at MPC declines at higher frequencies. Gelman et al. (2014) notes a similar finding in that MPC tends to increase at longer horizons when comparing their results to other studies. To further examine this frequency effect, we take the total amount of consumption and income payments of all respondents over each day of the diary days, weighted by day-of-week weights[19] and run the following regression at the daily frequency: $\Delta ln(C_{dy}) = \beta_0 + \beta_1 \Delta ln(Income_{dy}) + \varepsilon_{dy}$. The results can be found in Appendix C, Figure C1 and Table C1. The results from total daily consumption are similar to the daily cohort results in Table 1, implying further that at higher frequencies, MPC estimates decrease.

Table 1: Synthetic Cohorts: Monthly and Daily Δ Ln(C) and Δ Ln(Income)

	Monthly				Daily	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Ln(Income Payments)	0.099	0.150***	0.107	0.168**	0.079***	0.079***
	(0.069)	(0.054)	(0.081)	(0.065)	(0.012)	(0.012)
Observations	95	94	95	94	1131	1131
Year Fixed Effects	X	X	X	X	X	X
Cohort Fixed Effects			X	X		X
Without Outlier		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). All columns include year fixed effects. Cohort fixed effects included when noted. Outlier corresponds to Figure 5a. Utilizes total consumption and income monthly (columns 1-4) and daily (5-6) by cohort. The dependent variable in each regression is the change in the natural log of consumption.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of this section have shown that the DCPC exhibits a similar relation between consumption and income found within the overall literature. At at a monthly frequency, the estimated MPC is approximately between .15 - .17 which is slightly below the lower end of the MPC literature. This may be due to the fact that most studies use quarterly to annual data, or the income in the DCPC cannot be identified into anticipated and unanticipated income. The results also imply that at higher frequencies, the response of consumption to income tends to increase. Specifically,

[19] Specifically, we collapse the data using the following method: $C_{dy} = \sum_i^I C_{idy} \cdot w_{idy}$. For income: $Income_{dy} = \sum_i^I Income_{idy} \cdot w_{idy}$.

when measuring daily cohort consumption and total overall daily consumption, MPC estimates are between .08 - .09. In Appendix C where only identified results are used, the results are similar to those found above. The monthly cohort MPCs from identified income are estimated to be between .19 - .21 when excluding outliers, while the daily cohort MPCs are closer to .06. Additionally, the daily MPCs across all respondents are closer to .5. These results further support that the DCPC captures representative MPC patterns, and MPC decreases with frequency.

6.2 Daily Consumption Response to Income

Section 6.1 utilized a synthetic panel based on respondent demographics in order to measure MPC results comparable to studies which measure aggregate MPC. Given the high-frequency nature of the DCPC, it is also 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. Indeed, other studies which utilize transaction data have researched this payday effect on consumption at the daily level. Using transaction data, Gelman et al. (2014) and Olafsson and Pagel (2018) examine how consumption changes to the arrival of regular income payments. According to the standard life-cycle hypothesis, consumer spending should not respond to the anticipated arrival of income payments. The authors measure the consumption response to income using the following equation:

$$x_{it} = \sum_{k=-7}^{7} \beta_k I_i(Paid_{t+k}) + \eta_i + Z_t + \varepsilon_{it} \tag{10}$$

Where x is the ratio of consumption spending by consumer i on day 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 $t+k$, η_i are consumer fixed effects, and Z_t is a vector of time fixed effects[20]. 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_k measures the fraction by which individual consumption deviates from average daily spending in the days surrounding

[20] Gelman et al. (2014) examines consumption seven days before income payments until 6 days after: $\sum_{k=-7}^{6} \beta_k I_i(Paid_{t-k})$

income payments. Both papers examine multiple categories for x. Gelman et al. (2014) examine total spending, nonrecurring spending, and fast food and coffee shop spending. Olafsson and Pagel (2018) examine total spending, groceries, fuel, ready-made food (such as restaurants) and alcohol spending. While both authors find a payday response to income for total spending, 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 shop spending 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.

The DCPC asks respondents the date of their next and last income date. Using these variables along with identifying when respondents are paid in the diary, it is possible to identify consumer spending relative to each respondent's income days. 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 MPC analysis of Section 6.1. Following the authors discussed above, this study follows equation 10 where the dependent variables analyzed are total consumption, nonrecurring spending, and restaurants and fast food spending. Fast food and restaurant spending is chosen to measure discretionary, nondurable consumption. Nonrecurring spending is identified as consumption excluding billed spending. Day of week and week of month time fixed effects are included in the specification under Z_t. For this analysis, only identifiable income types are used.

Table 2: 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	30182	21136	29191	26855

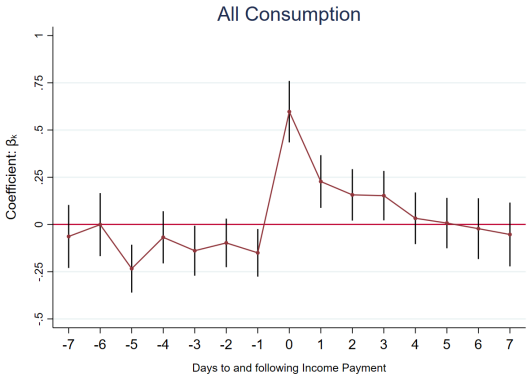
Table 2 reports the regression results from equation 10. Dependent variable denoted by columns. The dependent variable is the ratio of spending within the consumption category to the average daily spending on the payday. Includes dummy variables for date of income payments, and days for leading to and following income days. Controls for day of week effects and week of month effects. Errors are clustered by respondent. * p<0.1, ** p<0.05, and *** p<0.01.

Table 2 reports the spending response of consumption in each category for each category type (β_0 from equation 10). Only the payday effect is included in the table, while a graph of all values of β_k are shown in Figure 6 for all consumption, non-bill consumption, and food consumption. As shown by the table, there exists a statistically positive payday effect for total consumption,

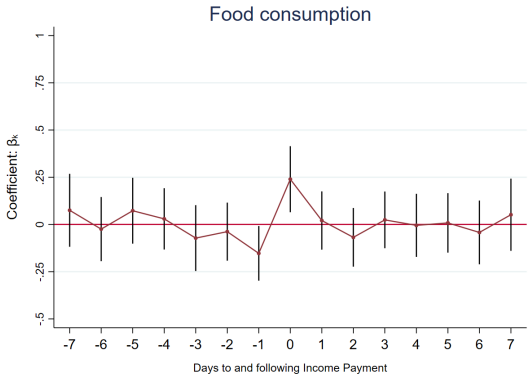
indicating that a respondent's consumption increases by approximately 60% on paydays. This is similar to Gelman et al. (2014) who finds a payday effect of about 70%. As shown by Subfigure 6a, consumption stays at or below average on the days leading up to the payday, and increases significantly on the 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.

Figure 6: Consumption Response to Income Payments

(a) All Consumption



(b) Food Expenditures



(c) Non-bill Consumption

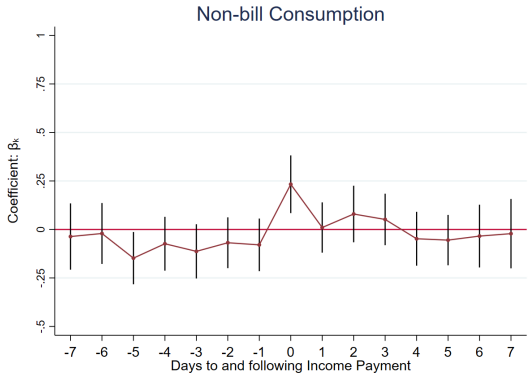


Figure 6 reports the β_k coefficients from equation 10 over the four consumption categories. Negative days denote days before income payment (-7 through -1), while positive days denote days after income payment (1 through 7). Day 0 corresponds to estimates reported in Table 2. Black lines denote 95% confidence intervals.

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

6.3 Discussion of Results

The analysis in Section 6 showed the capability of the DCPC in analyzing consumption and income dynamics by replicating multiple results in the literature. In Section 6.1, MPC results were found that are similar to the overall MPC literature. Utilizing a synthetic panel of consumer demographics, the monthly MPC results range from .15 - .21, while daily estimates are between .07 - .08. When examining the total consumption and income of all consumers per day, MPC estimates are within .05-.09. These results suggest that MPC estimates decrease when measured at higher frequencies. However, more exploration is needed to understand why this may be. In Section 6.2, the results indicated that the DCPC captures a consumption response to income, as has been found in other studies. While the DCPC finds similar results to Gelman et al. (2014) and Olafsson and Pagel (2018) in that regular consumption payments coincide with income payment days, the results differ from these authors by finding a higher food spending response than Gelman et al. (2014), and lower magnitudes than Olafsson and Pagel (2018). While this may be due to differences in the demographics of consumers within each dataset, this discrepancy requires more exploration for a definitive answer. Yet it is still apparent that the DCPC captures a payday effect found within the literature when examining consumption and income at high frequencies.

The results from both analyses indicate that the DCPC can be used to study consumption and income dynamics, as the diaries successfully capture consumption and income patterns found within

the literature. While there are differences in some estimates, the DCPC tends to pick up on the core trends found within the selected literature. Given the public availability of the payment diaries, its representative sample, and the additional payment behavior variables not found in many other transaction data sets, the DCPC offers a valuable opportunity to study consumption as an alternative to other proprietary data sources.

7 Consumption and Income Dynamics by Convenience Samples

The previous sections have demonstrated that the DCPC is able to capture representative aggregate consumption and income, as well as finding similar patterns of consumption and income dynamics from the literature. It is important to highlight that the primary purpose of the DCPC is to track U.S payment behavior, but is capable of analyzing consumption and income due to the successful implementation and structure of the diaries. Given the DCPC is first and foremost a payments dataset, the diaries contain additional payments information that is often not found in other transaction datasources. In this section, we utilize a number of these unique variables to see how consumption and income varies along payment instrument choice and personal financial management. In doing so, we document patterns which have not been explored in the previous literature.

7.1 MPC by Personal Financial Management

Transaction data offers a vital resource in examining consumption behavior relative to income due to the rich amount of high-frequency expenditures and demographics, which often cannot be obtained through aggregate datasources. As discussed in Section 2, a common source of transaction data comes from personal financial management software. Users of these softwares keep detailed records of their spending and budgeting behavior, which allows researchers to obtain long panel data for studying consumption and income dynamics. However, a potential concern using personal financial management data is sample selection effects. The effect may arise in that the users are participating in detailed financial management by using the software, and therefore their consumption decisions may not reflect aggregate consumption.

During the 2015 and 2016 surveys, the SCPC asked respondents if they use personal financial

management services or applications in budgeting and monitoring account balances[21]. In the 2016 Survey, approximately 6.4% of respondents had adopted a personal financial management software. Because the respondents of the SCPC are asked to be a part of the DCPC, it is possible to identify within the diaries which respondents used personal financial management services. Of the 2,848 respondents in the 2016 diary, 6.4% are identified as using personal financial management software[22]. Because the DCPC has been shown to be representative of U.S consumption and income behavior, it is possible to compare personal financial management (PFM) users consumption patterns relative to the representative population. Since we do not use 2015 in our analysis, and 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. 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.

Table 3 reports the demographics of the 2016 DCPC. The first column is the demographics for the full sample, while the second and third columns report the demographics of only the PFM subsample and respondents who didn't use PFM services, respectively. The last column reports the percentage point differences between PFM and Non-PFM respondents. As seen from the table, there are significant differences between respondents who do and don't use PFM services. There tends to be a higher concentration of PFM users between the ages of 25 - 44, as well as a lower concentration of white respondents. Additionally, PFM users see a much higher percentage of respondents with college attainment than Non-PFM respondents. While there were no PFM users with above $500,000 in household income, the respondents which use PFM services also have a significantly greater composition of income levels above $100,000. In summary, PFM users are composed of individuals with higher education and income levels than those who do not use PFM software. These demographic comparisons immediately suggest that there important demographic differences in PFM users from the rest of the population.

[21] In the 2016 survey, the options available for respondents to choose from were the following: Mint.com, You Need a Budget, Moneystream.com, moneyStrands, BudgetSimple, MoneyWiz, GoodBudget, or Other. Respondents could record the service used if they chose Other.

[22] The weighted average is 6.1%.

Table 3: 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
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 - $499,999	3.5%	6.4%	3.3%	3.1
$500,000 +	0.2%	-	0.2%	-

Table 3 presents selected demographics comparisons of the DCPC. 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.

Table 3 has shown that PFM users seem to not be a representative sample, implying the possibility of 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 a number of the analyses from Section 6. To begin, we first conduct the MPC analysis using the methods from Section 6.1 to examine differences in MPC between PFM and non-PFM users. A synthetic panel is created using the same cohorts previously, with an additional cohort for respondents using a PFM. We examine the MPCs at the monthly frequency to increase the amount of observations possible

for PFM users, using all forms of income payments. It is important to note that all respondents in 2017-2020 who did not participate in the 2016 diary are treated as not using PFM services. While there are likely respondents who did have use PFM services, we are not able to identify these users.

Figure 7: Synthetic Panel for PFM Users: Δ Ln(C) and Δ Ln(Income)

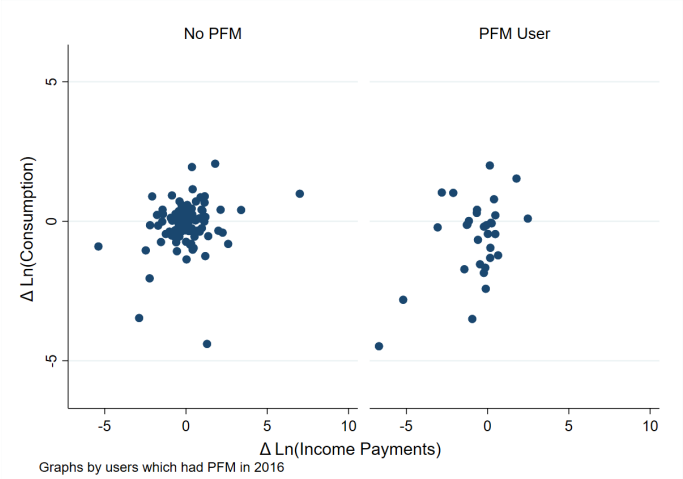


Figure 7 shows Δ Ln(C) vs. Δ Ln(Income) for respondents who did and did not use PFM services. While there are fewer observations for PFM users, there seems to be a slightly stronger relationship in MPC for PFM users. Exploring this difference further, Table 4 uses equation 9 to measure the MPC for all cohorts, and along those who did and did not adopt a PFM service. When examining all cohorts, the elasticity of consumption is approximately .24, which is similar but slightly higher than the results found in Table 1.

Table 4: Synthetic Cohorts with PFM: Δ Ln(C) and Δ Ln(Income)

	(1) All	(2) Non-PFM	(3) PFM
Δ Ln(Income Payments)	0.236***	0.119*	0.390***
	(0.055)	(0.061)	(0.117)
Observations	126	95	31
Adjusted R^2	0.194	0.099	0.386
Year 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 (PFM Users, Non-PFM Users). All columns include year fixed effects. Utilizes total monthly consumption by cohort. The dependent variable in each regression is the change in the natural log of consumption.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns (2) and (3) present the MPC estimates for Non-PFM and PFM respondents respectively. There is a clear difference in MPCs: Non-PFM respondents estimates are .12, while PFM users' average MPC is approximately .39 and highly significant. This implies that agents which have PFM software increase their consumption significantly more than those without, and are higher than the representative population. However, it is important to note that the number of observations is significantly smaller compared to Non-PFM users.

These results suggest that there is a difference in 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 when they receive income at the daily frequency. Replicating the analysis from Section 6.2, we run equation 10 by all respondents, and those who adopted PFM in 2016 and those that did not. Table 5 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. The dependent variable in the table uses all consumption types, and all controls from equation 10 are included. Column (1) reports the payday effect for all respondents, which corresponds directly to column (1) of Table 2. 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 $p<0.1$. The number of observations for PFM users is much smaller compared to the rest of the sample, given the little amount of PFM users within the data. These results suggest there is some slight evidence that PFM users increase their relative consumption on paydays more than the rest of the population. However, a payday effect is still evident for respondents without PFM, and the difference in coefficients between each is not large.

Table 5: 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	30182	1532	28650

Table 5 reports the regression results from equation 10 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. When examining monthly consumption elasticity with respect to income, the MPC of PFM users are significantly higher than those who do not use PFM software. When looking at how each individual's consumption responds on paydays relative to non-paydays, the change in consumption appears to be higher for PFM users, though the difference is not large and the significance is weak. Because of the smaller sample size of the DCPC, as well as the even smaller sample of PFM users, these results should be interpreted as suggestive and not definitive. Specifically, they suggest there is cause for concern of sample selection effects when using PFM samples to infer consumption and income patterns for the aggregate population. A more detailed exploration is needed to understand why these differences may exist, specifically with the higher MPC of PFM implied through these results.

7.2 MPC by Payment Choice

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 MPC 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 6.1, we first measure the MPCs 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 6: MPC by Credit Card Characteristics: Synthetic Panel, Monthly Frequency

	All	Adoption		Revolving	
	(1) Base	(2) Non C.C Adopters	(3) C.C Adopters	(4) Revolvers	(5) Non Revolvers
Δ Ln(Income)	0.140^{***}	0.186^{***}	0.120^{***}	0.137^{***}	0.101^{**}
	(0.028)	(0.063)	(0.029)	(0.037)	(0.046)
Observations	239	81	158	82	76
Year Fixed Effects	X	X	X	X	X

Table 6 reports the MPC results by credit card adoption and those who revolve credit card debt. Dependent variable in all columns is Δ Ln(C). Utilizes a synthetic panel, where the cohorts are as follows: Age ($<$ 35, 35-55, 55 $>$), Edu (No College, Any College), Race (White, Non-White), Gender (Male, Female), Credit Card Adoption (Adopters, Non Adopters), and Credit Card Debt Revolvers (Revolvers, Non Revolvers). Column (1) is the entire sample with all cohorts. Column (2) present the results with those who do not have a credit card, and column (3) are those who do. For those who do have credit cards, column (4) reports MPC for those who roll over credit card debt, while column (5) reports MPC for those who pay their credit cards off in full each month. For all results, one outlier was excluded which differed substantially from other observations. Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimated MPC for these subsamples can be found in Table 6. Results presented in the table utilize equation 9 with the synthetic panel structure, aggregated to monthly consumption and income[23].

[23] Cohorts included are credit card adoption, credit users who are revolvers or convenience users, as well as the demographic cohorts discussed in 6.1. The results including fixed effects and a daily analysis can be found in Appendix C.3.

When looking at the entire synthetic panel, MPC is .14 as shown in column (1). When examining the credit card adoption sample, those who do not use credit card show a greater MPC than users which do use credit cards as found in columns (2) and (3) respectively. This implies that credit cards are being used to smooth consumption by respondents, however excessive responses to consumption still exist. Next, the MPC is analyze for the credit card adopter in column (3) by those who revolve their debt and those who don't. Column (4) indicates that revolvers show a higher MPC than the average credit card adopter and the convenience users in column (5). While only significant at $p<0.5$, even convenience users show an MPC higher than predicted by the benchmark Life-cycle hypothesis model. This is a similar finding when including cohort fixed effects found in Table C4 of the Appendix, except convenience users show no significant change in consumption to income payments. We additionally examine these results when aggregated and differenced at the daily level, for all cohorts (Tables C5 and C6) and only the credit cohorts (Table C7). At the daily aggregation, MPCs are lower which is consistent with Section 6.1, and the same patterns hold from Table 6: Credit card adopters have lower MPCs, and of those users revolvers have higher MPCs than convenience users[24].

From these findings, there is suggestive evidence which indicates credit card users exhibit MPC heterogeneity. Specifically, the results suggest that credit card adopters have lower MPCs than non-adopters. The analysis implies that not all credit card users show the same consumption pattern relative to income: those who carry credit card month to month have higher MPCs than individuals who pay back their debt in full every month. This finding indicates that convenience users utilize short-term credit to smooth their consumption, while revolvers may face liquidity constraints causing their MPC to be higher. However, a further exploration is needed to definitively explain the nature of these results.

8 Conclusion

This study has demonstrated the capability of the DCPC in measuring accurate consumption and income behavior as a high-frequency dataset. The proficiency of the payment diaries as a

[24] An exception to this pattern is found in Table C6, where all cohorts are included with cohort fixed effects at the daily level. This regression finds an insignificant coefficient for respondents which do not use a credit card.

transaction datasource 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 and BEA Personal Income. 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 is qualified to estimate consumption and income behavior by replicating common results found within the consumption literature. Together, these findings highlight the exceptional capacity of the DCPC as a high-frequency datasource in measuring daily consumption behavior.

From these findings, this study advocates the DCPC as a promising alternative to proprietary transaction datasets. 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 conducted a preliminary analysis in quantifying the selection effects that may arise when examining consumption behavior from convenience samples. The results suggest there are key characteristic differences in personal financial management users, who seem to have greater consumption responses to income payments. Additionally, credit card adopters have lower MPC estimates that non-adopters, while individuals which revolve credit debt have higher MPC estimates. Although these findings need to be explored further for a definitive inference, the evidence shows both the need of representative data as a comparison with convenience samples as well as the novel insights the DCPC is able to provide.

While the DCPC offers a viable alternative to other transaction datasets, 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

Table A1: DCPC Income 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: Evolution of Payment Categories in the DCPC

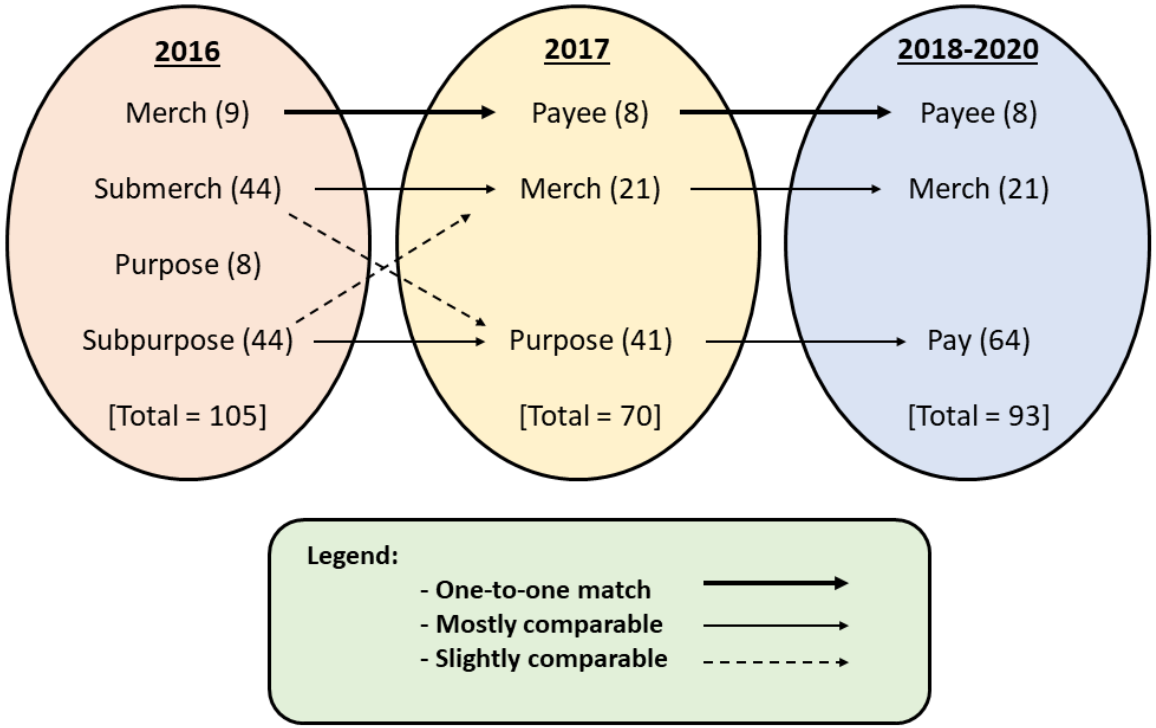


Figure A1 offers a simple overview of changes to DCPC payment categories over the years. In 2012, there were 45 possible merchant categories in which expenditures could be categorized. In 2015, merchant was simplified into 9 categories, and submerch categories were added to add more details to the merchant 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

Table B1: 5 Year Averages of Consumption

5 Year Averages (2012 Billions USD)	CE (1)	PCE (2)		DCPC (3)	CE/PCE (4)	DCPC/PCE (5)
Total Expenditures	**7,360**	**12,749**		**12,356**	**.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.

Appendix C MPC Details

The MPC results presented in the main paper use all income payments received by respondents throughout all years of the DCPC. As a robustness check, we also analyze the MPC results when only using identified income reported by the DCPC. Ideally, income should be categorized into unanticipated income in order to create a closer comparison to the literature. However, since this not available, we attempt to create a more uniform use of income by using only identified income. The results are similar to those found in the primary paper, finding higher MPCs at lower frequencies. Figure C1 and Table C1 report the MPC results at the daily frequency for all consumers as referenced in the primary paper, while the remaining tables and figures utilize only identified income types.

C.1 MPC: Daily Aggregation

Figure C1: Aggregate Daily Δ Ln(C) and Δ Ln(Income)

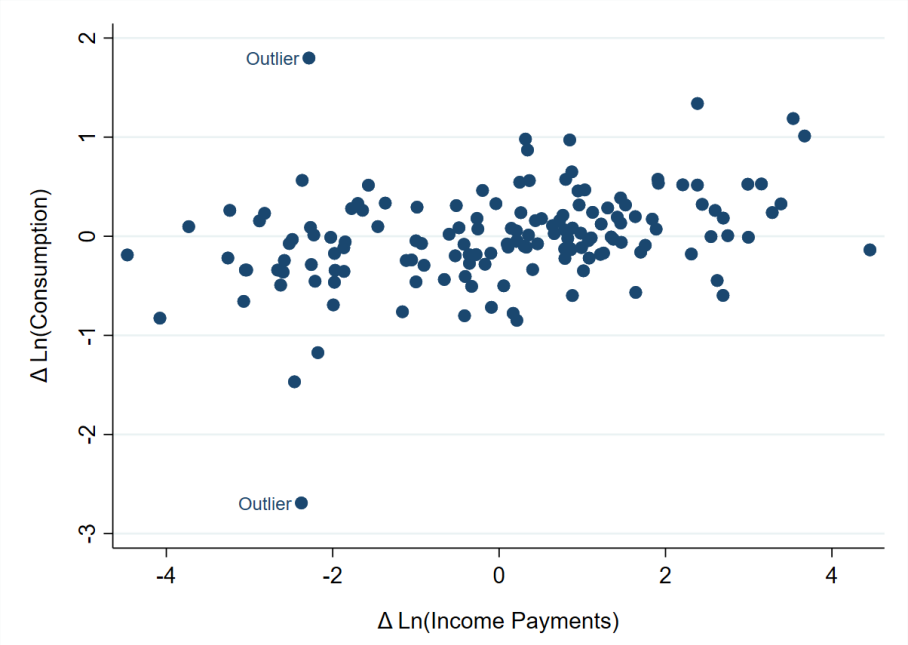


Table C1: Δ LN(C) and Δ LN(Income): Aggregate Daily MPC

	(1)	(2)
Δ Ln(Income Payments)	0.093***	0.091***
	(0.021)	(0.018)
Observations	150	148
Year FE	X	X
Ex. Outliers		X

[1] Standard errors in parentheses

[2] Table C1 reports the daily total consumption and income results for all years. Year fixed effects included in both columns. The outliers excluded correspond to Figure C1.

[3] Consumption is aggregated by using the following equation: $C_{dy} = \sum_i^I C_{idy} \cdot w_{idy}$. Consumption for all respondents are summed and weighted by day-of-week weights. An analgous calculation is used for daily income payments.

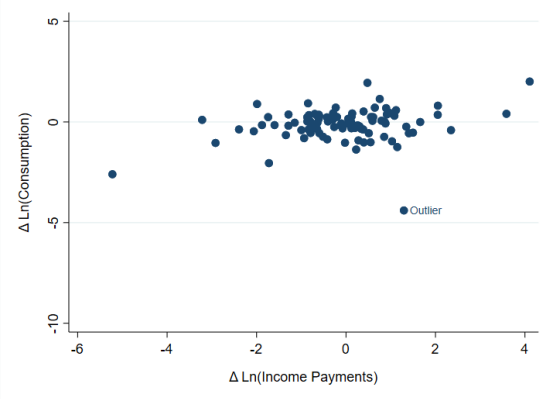
[4] The following regression is used: $\Delta ln(C_{dy}) = \beta_0 + \beta_1 \Delta ln(Income_{dy}) + \varepsilon_{dy}$

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

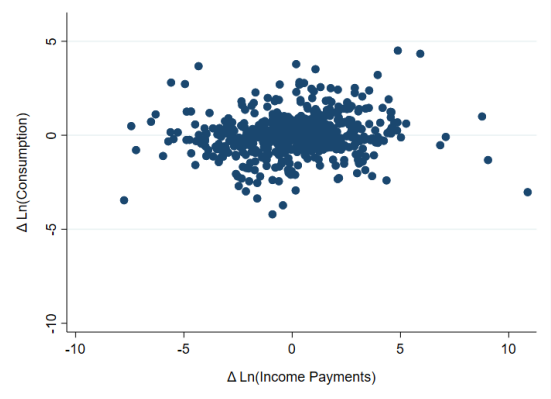
C.2 MPC: Identified Income

Figure C2: Synthetic Panel: Δ Ln(C) and Δ Ln(Income) with Identified Income

(a) Cohorts: Monthly



(b) Cohorts: Daily



(c) Aggregate Daily

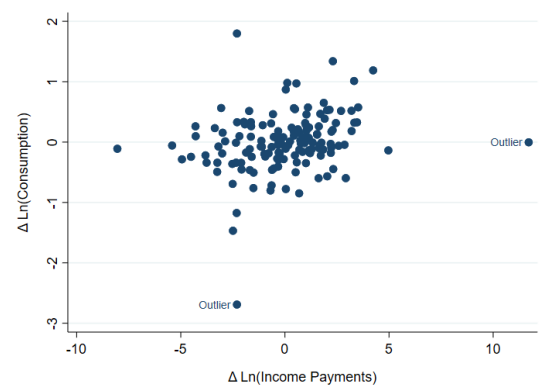


Figure C2 repeats the analysis from 6.1 but with only identified income payments. Figures C2a and C2b utilize monthly and daily frequencies across cohorts, while Figure C2c looks at total consumption and incomes of all respondents per day.

Table C2: Synthetic Cohorts: Monthly and Daily Frequencies with Identified Income

	Monthly				Daily	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Ln(Income Payments)	0.145**	0.193***	0.163**	0.211***	0.066***	0.063***
	(0.061)	(0.047)	(0.069)	(0.053)	(0.019)	(0.020)
Observations	94	93	94	93	576	576
Year Fixed Effects	X	X	X	X	X	X
Cohort Fixed Effects			X	X		X
Without Outlier		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). All columns include year fixed effects. Cohort fixed effects included when noted. Outlier corresponds to Figure C2a. Utilizes total consumption and income monthly (columns 1-4) and daily (5-6) by cohort. The dependent variable in each regression is the change in the natural log of consumption. Uses only income payments which can be identified.
[3] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Identified Income: Aggregate Daily MPC

	(1)	(2)
Δ Ln(Income Payments)	0.052***	0.054***
	(0.018)	(0.017)
Observations	144	142
Year FE	X	X
Ex. Outliers		X

[1] Standard errors in parentheses
[2] Table C3 reports the daily total consumption and income results for all years. Year fixed effects included in both columns. The outliers excluded correspond to Figure C2c.
[3] Consumption is aggregated by using the following equation: $C_{dy} = \sum_i^I C_{idy} \cdot w_{idy}$. Consumption for all respondents are summed and weighted by day-of-week weights. An analgous calculation is used for daily income payments.
[4] The following regression is used: $\Delta ln(C_{dy}) = \beta_0 + \beta_1 \Delta ln(Income_{dy}) + \varepsilon_{dy}$
[5] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
[6] Only identified income is used in this table.

C.3 MPC: Credit Card Convenience Subsamples

Table C4: MPC by Credit Card Characteristics: Synthetic Panel with Fixed Effects

	All	Adoption		Revolving	
	(1) Base	(2) Non C.C Adopters	(3) C.C Adopters	(4) Revolvers	(5) Non Revolvers
Δ Ln(Income)	0.135***	0.205***	0.105***	0.137***	0.070
	(0.032)	(0.070)	(0.035)	(0.045)	(0.056)
Observations	239	81	158	82	76
Year Fixed Effects	X	X	X	X	X
Cohort Fixed Effects	X	X	X	X	X

Table C4 reports the MPC results by credit card adoption and those who revolve credit card debt. This table is analogous to Table 6, but includes cohort fixed effects. Dependent variable in all columns is Δ Ln(C). Utilizes a synthetic panel, where the cohorts are as follows: Age (< 35, 35-55, 55 >), Edu (No College, Any College), Race (White, Non-White), Gender (Male, Female), Credit Card Adoption (Adopters, Non Adopters), and Credit Card Debt Revolvers (Revolvers, Non Revolvers). Column (1) is the entire sample with all cohorts. Column (2) present the results with those who do not have a credit card, and column (3) are those who do. For those who do have credit cards, column (4) reports MPC for those who roll over credit card debt, while column (5) reports MPC for those who pay their credit cards off in full each month. For all results, one outlier was excluded which differed substantially from other observations. Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C5: MPC by Credit Card Characteristics: Daily Frequency

	All	Adoption		Revolving	
	(1) Base	(2) Non C.C Adopters	(3) C.C Adopters	(4) Revolvers	(5) Non Revolvers
Δ Ln(Income)	0.090***	0.103**	0.088***	0.108***	0.070***
	(0.013)	(0.048)	(0.013)	(0.018)	(0.019)
Observations	1201	191	1009	584	424
Year Fixed Effects	X	X	X	X	X

C5 reports the MPC results by credit card adoption and those who revolve credit card debt at the daily frequency. Utilizes a synthetic panel, where the cohorts are as follows: Age (<35,35-55,55>), Edu (No College, Anny College), Race (White, Non-White), Gender (Male, Female), Credit Card Adoption (Adopters, Non Adopters) and Credit card Debt Revolvers (Revolvers, Non Revolvers). Column (1) is the entire sample with all cohorts. Column (2) present the results with those who do not have a credit card, and column (3) are those who do. For those who do have credit cards, column (4) reports MPC for those who roll over credit card debt, while column (5) reports MPC for those who pay their credit cards off in full each month.

Table C6: MPC by Credit Card Characteristics: Daily Frequency with Fixed Effects

	All	Adoption		Revolving	
	(1) Base	(2) Non C.C Adopters	(3) C.C Adopters	(4) Revolvers	(5) Non Revolvers
Δ Ln(Income)	0.083***	0.068	0.086***	0.107***	0.062***
	(0.013)	(0.050)	(0.013)	(0.019)	(0.019)
Observations	1201	191	1009	584	424
Year Fixed Effects	X	X	X	X	X
Cohort Fixed Effects	X	X	X	X	X

C6 reports the MPC results by credit card adoption and those who revolve credit card debt at the daily frequency. Utilizes a synthetic panel, where the cohorts are as follows: Age (<35,35-55,55>), Edu (No College, Anny College), Race (White, Non-White), Gender (Male, Female), Credit Card Adoption (Adopters, Non Adopters) and Credit card Debt Revolvers (Revolvers, Non Revolvers). Column (1) is the entire sample with all cohorts. Column (2) present the results with those who do not have a credit card, and column (3) are those who do. For those who do have credit cards, column (4) reports MPC for those who roll over credit card debt, while column (5) reports MPC for those who pay their credit cards off in full each month.

Table C7: MPC by Credit Card Characteristics: Daily Frequency with Only Credit Card Cohorts

	All	Adoption		Revolving	
	(1) Base	(2) Non C.C Adopters	(3) C.C Adopters	(4) Revolvers	(5) Non Revolvers
Δ Ln(Income)	0.064***	0.081**	0.056***	0.063***	0.056**
	(0.015)	(0.035)	(0.015)	(0.021)	(0.022)
Observations	436	140	295	148	144
Year Fixed Effects	X	X	X	X	X

C7 reports the MPC results by credit card adoption and those who revolve credit card debt at the daily frequency. Utilizes a synthetic panel, where the cohorts are as follows: Credit Card Adoption (Adopters, Non Adopters) and Credit card Debt Revolvers (Revolvers, Non Revolvers). Column (1) is the entire sample with all cohorts. Column (2) present the results with those who do not have a credit card, and column (3) are those who do. For those who do have credit cards, column (4) reports MPC for those who roll over credit card debt, while column (5) reports MPC for those who pay their credit cards off in full each month.

Appendix D Cleaning Consumption and Income Comparison

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

Column (1) reports the consumption and income estimates without Fed cleaning (WOFC). Column (2) reports these same estimates using the cleaned Fed estimates (WFC). Column (3) reports the ratio of WOFC to WFC. As shown in column (3), the WOFC estimates are 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 D1 show that while the WFC effects the point estimates, the core results do not change in that the DCPC still matches a significant amount of aggregate comparable consumption and aggregate income.

Table D1: With Fed Cleaning Comparison

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