

The 2011 and 2012 Surveys of Consumer Payment Choice: Technical Appendix

Marco Angrisani, Kevin Foster, and Marcin Hitczenko

Abstract:

This document serves as the technical appendix to the 2011 and 2012 Survey of Consumer Payment Choice. The Survey of Consumer Payment Choice (SCPC) is an annual study designed primarily to collect data on attitudes to and use of various payment instruments by consumers over the age of 18 in the United States. The main report, which introduces the survey and discusses the principal economic results, can be found at <http://www.bostonfed.org/economic/cprc/SCPC>. In this data report, we detail the technical aspects of the survey design, implementation, and analysis.

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Marco Angrisani is an associate economist at the University of Southern California Dornsife Center for Economic and Social Research. Kevin Foster is a survey methodologist and Marcin Hitczenko is a statistician; both are members of the Consumer Payments Research Center in the research department of the Federal Reserve Bank of Boston. Their e-mail addresses are marco.angrisani@usc.edu, kevin.foster@bos.frb.org, and marcin.hitczenko@bos.frb.org, respectively. This paper, which may be revised, is available on the web site of the Federal Reserve Bank of Boston at <http://www.bostonfed.org/economic/wp/index.htm>.

The views expressed in this paper are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Boston or the Federal Reserve System.

The Survey of Consumer Payment Choice is a product of the Consumer Payments Research Center (CPRC) in the research department at the Federal Reserve Bank of Boston. Staff at the USC Dornsife Center for Economic and Social Research (CESR) and the RAND Corporation also contributed to the production of the survey.

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1 Introduction

The Survey of Consumer Payment Choice has been conducted annually since 2008 through a partnership between the Consumer Payment Research Center (CPRC) at the Federal Reserve Bank of Boston and the RAND Corporation (from 2013 the partnership includes the Dornsife Center for Social and Economic Research at the University of Southern California). Each year, this partnership involves the careful planning and execution of a series of steps ranging from gathering the data to analyzing the survey data. This begins with data collection, namely the design of a questionnaire, the selection of the sample, and the administration of the questionnaire. Once the data are collected, a coherent methodology for analysis must be adopted. In the case of the SCPC, this involves calculating post-stratification weights, devising a strategy to clean the data, and developing a model that allows for population-based inference. In this appendix, we provide details concerning each of these steps.

The organization of this work is designed to follow the natural, chronological progression of considerations involved in conducting and analyzing a survey. After establishing the context and goals of the survey in Section 2, we highlight changes in the survey from the 2010 version to the 2011 and 2012 versions. Section 3 discusses the design of the questionnaire, focusing on changes from previous years' versions. In Section 4 we begin by detailing the selection and composition of the survey sample and present statistics related to survey response and completion. Section 5 delineates the generation and properties of the sample weights developed to make inferences about the entire population of U.S. consumers. Section 6 discusses our general philosophy toward data preprocessing of categorical and quantitative variables and provides details of two new data-editing procedures. In Section 7, we give details about the assumed mathematical models used to determine the population estimates and their standard errors. Section 8 builds on these results by conducting a variety of hypothesis tests. The hypothesis tests are mostly applied to the SCPC data concerning the number of payments, by instrument and transaction type. Finally, Section 9 describes work being done by the CPRC and RAND to improve the survey and its analysis.

2 Survey Objective, Goals, and Approach

In this section we describe the SCPC survey program's overall objectives, goals, and approach, and explain the choices made in selecting the observation unit and the interview mode of the SCPC. In both cases, the choice was made to use best survey practices, within the constraints of the SCPC budget.

2.1 Survey Objective and Goals

As noted in Foster, Schuh, and Zhang (2012), the main objective of the SCPC program is to measure U.S. consumer payment behavior. The main goals of the program are to provide a consumer-level longitudinal dataset to support research on consumer payments and to provide aggregate data on trends in U.S. consumer payments.

2.2 Unit of Observation

The SCPC uses the individual consumer as both the sampling unit and the observation unit. This choice stands in contrast to those of the Survey of Consumer Finances, which is organized by primary economic units in the household, and the Consumer Expenditure Survey, which uses the household as the sampling unit and observation unit. The reason the SCPC uses the individual consumer is that asking one consumer to estimate the payment behavior and cash behavior of all members of the household would be too burdensome. Each respondent is asked to recall only his or her own payments, not those of other members of his or her household. In addition, asking one individual about all household members would increase the cost of the incentive payments the survey pays out. SCPC incentives are based on the average length of time it takes respondents to complete the survey. Instead of interviewing one consumer about his or her self plus several household members, we can interview several different consumers and potentially increase the number of demographic groups included in the sample.

We believe that the respondent will be able to accurately report his or her own payment behavior, but might not be able to accurately estimate the payment behavior of other household members. This is especially true for two major sections of the survey. In the *Cash Use* section, we ask consumers to report where they get cash, how much cash they get, and how often they get it. In addition, we ask the consumers to report the amount of cash on their person—in other words, the amount of cash currently in their pocket, wallet, or purse. Cash differs from other payment instruments in that there is no concept of “joint” ownership of cash. Each member of a household has his or her own cash, even if it all comes from the same bank account. Therefore, it is most appropriate to ask the individual consumer about his or her own cash behavior and not about the cash habits of other household members.

The second area of the survey that benefits from using the respondent as the observation unit is the *Payment Use* section, where we ask the respondent to estimate the number of payments he or she makes in a typical period (week, month, or year) (Angrisani, Kapteyn,

and Schuh 2013; Hitczenko 2013b). Only the respondent can accurately estimate the number of payments he or she makes in a typical time period. It would be impossible for the average consumer to know the complete payment behavior of all members of the household. We believe this gives us more accurate measurements of the number of nonbill payments made by consumers. In addition, we ask respondents to tell us their level of responsibility for several household tasks, such as shopping or paying bills. This allows us to compare the number of payments reported by the respondent with those reported by others with similar levels of responsibility.

However, we believe that interviewing the consumer as the unit of observation may lead to some double counting in the bills section of *Payment Use*, because bills are often a household expense, rather than a personal one. To accurately measure bills, it might be better to ask about the entire household's bill payment behavior. Currently, the SCPC asks respondents to estimate only the number of bills that they physically pay themselves, either by mail, by phone, online, or in person. Ongoing research will allow us to determine better ways to ask about household bills.

2.3 Interview Mode

The SCPC is a computer-assisted web interview (CAWI). This mode of interview fits best with our sampling frame, which is the internet-based American Life Panel (ALP), jointly run by RAND and the Center for Social and Economic Research at USC.¹ To minimize undercoverage, all ALP members are given internet access upon recruitment into the panel. The survey instrument is the MMIC survey system, developed by the RAND Corporation.²

The CAWI mode is beneficial to the SCPC because of the length of the survey. The median length in minutes for each year of the survey is around 30 minutes. Using a CAWI allows the respondent to log off and come back to the survey later if interrupted. In addition, it is cheaper than using face-to-face interviews or telephone because there are no interviewers who need to be paid. Finally, respondents may be more willing to answer some sensitive questions, like the amount of cash stored in their home, if the survey is conducted via the web (De Leeuw 2005).

¹More information about the ALP can be found at <https://mmicdata.rand.org/alp/>.

²MMIC stands for Multimode Interviewing Capability. More information on MMIC is available at <https://mmicdata.rand.org/mmic/index.php>.

2.4 Public Use Datasets

The 2011 and 2012 SCPC data can be downloaded from the Boston Fed’s SCPC website.³ The data are available in Stata, SAS, and CSV formats. Before starting any analysis, it is highly recommended that the data user read the companion document, “SCPC Data User’s Guide” (Foster 2014), which is available at the same website. In addition, it is useful to read the warning against using consumer-level estimates to aggregate up to U.S. total population estimates, in Section 7.2.1 of this paper.

Users who are interested in downloading the original, raw datasets can obtain these from the RAND Corporation’s website. The Boston Fed SCPC website contains a link to the RAND data download site. Interested users must create a username and password to download data from the RAND website. These data contain only the survey variables. These data have not been cleaned for outliers and there are no created variables in the dataset. Additionally, survey items that allow the respondent to choose a frequency have not been converted to a common frequency, and randomized variables have not been unrandomized. The variable `prim_key` is the unique identifier for each respondent. This variable is used as the primary key for both the RAND and the Boston Fed datasets, and can be used to merge the raw, uncleaned data from RAND with the Boston Fed’s processed dataset. In addition, `prim_key` can be used to merge the SCPC dataset with any other RAND American Life Panel survey.

3 Questionnaire Changes

The SCPC questionnaire is written by the CPRC and is available to download at <http://www.bostonfed.org/economic/cprc/SCPC>. For the most part, the survey questions for the 2011 SCPC and the 2012 SCPC are the same or similar to those in the 2010 version, although every year changes are introduced either to collect new information or to collect the same information in a better way.

This section describes the changes to the economic definitions and the changes to the questionnaire design and methodology. The section also includes a detailed listing of all changes in the questionnaire content.

³<http://www.bostonfed.org/economic/cprc/SCPC>

3.1 Bank and Payment Accounts

In the 2010 SCPC, respondents were shown a screen with definitions of money market accounts and nonbank online payment accounts, and then asked to report the number of checking accounts, savings accounts, money market accounts, and nonbank online payment accounts (item pa001). For the 2011 SCPC, the definitions of money market accounts and nonbank online payment accounts were removed and replaced by detailed definitions of checking accounts and savings accounts. The 2011 and 2012 surveys no longer asked any questions about money market accounts (pa001_c).

The question about the number of nonbank online payment accounts (pa001_d) was moved to later in the survey and was changed to ask about adoption of these types of accounts instead of number of accounts. In addition, the 2010 SCPC asked only about a general category called “nonbank online payment accounts” and the 2011 SCPC asked the respondent to tell us if they had an account at any of the following services:

- PayPal (pa001_d1)
- Google Checkout (pa001_d2)
- Amazon Payments (pa001_d3)
- Other (specify) (pa001_d4)

In the 2012 SCPC, the questions about bank and payment accounts were exactly the same as those in the 2011 SCPC, except that “Google Checkout” was changed to “Google Wallet” because the name of the service changed.

The 2011 SCPC dropped two questions, pa045 and pa046, about the frequency of use and the typical dollar value of nonbank online payments. These questions were also removed from the 2012 SCPC. The 2011 SCPC added pa048, “Do you have any money deposited at a nonbank online payment service?” This question was changed for the 2012 SCPC, where respondents were asked how they fund their nonbank online payment account.

Finally, for item pa004 the ranges of interest rates in the response options were changed from the 2010 to the 2011 SCPC, and they were changed again for the 2012 SCPC.

3.2 Payment Instruments

The payment instrument is a central concept in any survey measuring consumer payment choice. Most of the questions measuring payment instrument adoption remained the same

from the 2010 SCPC through the 2012 SCPC. The following payment instrument questions had changes in their methodology.

3.2.1 Debit Cards

In 2011, item pa011, “Do any of your debit cards give rewards?” had response options Yes and No. A third response option of “I don’t know” was added in the 2012 SCPC.

For item pa034, in the 2011 SCPC, the response options were:

1. PIN
2. Signature
3. Either one is fine / I’m indifferent
4. Neither one / I prefer not to enter a PIN or give my signature

In the 2012 SCPC, the fourth response option was removed, leaving only the first three.

3.2.2 Credit Cards

From 2010 to 2011, the question that determines credit card adoption, pa053, was changed from “Do you have any credit cards?” to “Do you have any credit cards or charge cards?” Short definitions were given for both credit cards and charge cards. Finally, extra instruction text was added to the screen. These instructions asked the respondent to exclude cards used for business purposes only and to report cards that were owned jointly or for themselves, but not cards solely owned by a spouse or partner.

In addition, in 2010 the SCPC had follow-up questions (pa019, pa054) asking the respondent about three types of credit cards: general purpose, charge cards, and store branded cards. In 2011 this list was changed and expanded to the following:

- Visa, MasterCard, or Discover cards
- Company or store branded credit cards
- American Express charge cards
- American Express credit cards
- Diners Club or other charge cards

In 2012, the SCPC added a new question about the interest rate on the credit card with the highest balance (pu012).

3.2.3 Prepaid Card

The 2011 SCPC prepaid card section contained two versions of the prepaid card questions, which informed the design of the 2012 SCPC prepaid card section. In 2011, half the respondents received one version (version A: pa099, pa100, pa102) of the set of prepaid card questions, and half received a different version (version B: pa197, pa198, pa199). Version A had four categories of prepaid cards:

- Government issued
- Employer issued
- General purpose cards
- Specific purpose cards

and Version B presented the respondent with 12 categories of prepaid cards:

- Gift card
- General purpose
- Public transportation card
- Phone card
- Direct Express
- EBT
- Payroll card
- Incentive card
- Benefit card
- Remittance card
- Merchant rebate card
- Location specific card

For the exact wording and layout of the question, please refer to the questionnaire document. The follow-up questions about number of each type of card (version A: pa100, version B:

pa198) and dollar value of each type of card (version A: pa102, version B: pa199) have the same structure for both A and B, using four and 12 categories, respectively.

In the 2012 SCPC, the prepaid card section no longer split into two versions. The 12 categories were kept (version B, pa197, pa198, pa199), and one new category was added: “Other federal, state, or local government benefit card.” In addition, instead of asking pa039, “Are any of your prepaid cards reloadable?” and using that as a filter for follow-up questions, the survey goes straight to item pa022_extra, “In the past 12 months, did you load money onto any of your prepaid cards?”

Finally, in 2011, item pa101, about how the respondent reloads his or her prepaid card, had eight response options and in 2012 we added “other prepaid card” as a ninth response option.

For more detail on the prepaid card questions, please see (Hitczenko and Tai 2014).

3.2.4 Money Orders and Travelers Checks

The 2011 SCPC had two separate screens asking questions about using money orders and travelers checks in the past 12 months (items pa040 and pa042). In the 2012 SCPC these two payment instruments, plus two other types of “purchased” payment methods were presented in a table with four items (pa040). The rows of the table were:

- Money order (pa040_a)
- Travelers check (pa040_b)
- Cashier’s check (pa040_c)
- Certified check (pa040_d)

In addition, the definition for each type of payment instrument or method was presented above the table.

The 2011 SCPC dropped item pu008_c, which asked the respondents to report how many payments they make using travelers checks in a typical week, month, or year. In addition, the question about historical adoption of travelers checks, item pa043, “Have you ever used a travelers check, even once?” was dropped. The 2012 SCPC also omitted these items.

3.3 Mobile Banking and Mobile Payments

In 2010, the survey showed the respondent a definition of mobile banking and first asked whether the respondent has set up mobile banking (`pa026`). As a follow-up question, the survey asked whether the respondent has used mobile banking to access his or her account in the past 12 months (`pa033_c`). For the 2011 survey, the question about setting up mobile banking was removed. Instead, the 2011 survey asked a series of yes/no questions (`pa026`), and if the answer was “yes” to any of those, then the respondent was considered to be a mobile banking adopter. In addition, a “have you ever”-type question was added (`pa126`) to measure historical adoption. These questions were the same in the 2012 SCPC.

In 2011, the mobile payments question (`pa051`) was expanded from three categories to five categories. In the 2012 SCPC, an additional category was added for a total of six mobile payment categories.

In the 2010 SCPC, the survey asked several questions about features of smartphones (items `smartphone_a`–`smartphone_d`). These questions were removed for the 2011 SCPC, and replaced by one question, “Is your cell phone a smart phone?” (item `smartphone`). A historical adoption question (`evercell`) was added as a follow-up for those who did not report owning a cell phone.

The 2012 SCPC added a question about adoption of tablet devices, variable name `tablet`.

A question about using a mobile phone as a contactless payment technology was added to item `pa027` for the 2012 SCPC.

3.4 Characteristics of Payment Instruments

In the 2012 SCPC, groupings of the types of payment instruments were randomized. The random order was set on the first screen of the assessment of characteristics section (all `as003` items), and for each of the following screens the questions were presented in the same order. There was no randomization within each group. The groups were as follows:

- Paper (cash, check, money order)
- Card (debit, credit, prepaid)
- Electronic (bank account number payment, online banking bill payment)

For the 2012 SCPC, the respondent was presented with an increased number of categories for item `as004`. This question asks “How do you rate the security of the following means of

making a payment?” In 2011, there were five categories, and in 2012 there were 10 categories.

3.5 Bank Account Access

In 2010, item pa033 asked whether the respondent has used “online banking” to access his or her account. In 2011, “online banking” was split into the following:

- Online banking, using a computer or laptop, pa033_b
- Online banking using a mobile phone, pa033_c
- Online banking using other internet-connected device, pa033_d

In addition, an “other (specify)” open-ended response option was added to this question (item pa033_d_other).

The 2011 SCPC added a historical adoption question for telephone banking for those who said they did not currently have telephone banking set up (newtb).

The 2012 SCPC added two new questions about cash withdrawals, pa016_a and pa016_b. The first question is conditional on the respondent saying that ATM is their most common method for getting cash, and asks “What kind of plastic card do you use most often?” when getting cash from an ATM. The second question is conditional on cash back at a retail store being the most common method for getting cash, and asks “What method do you use most often?”

3.6 Financial Responsibility

From 2010 to 2011, the text for the household financial responsibility questions (fr001) changed. Here is the 2010 text:

In your household, how much responsibility do you have for these tasks?

- Budgeting and managing income (fr001_a)
- Paying bills (fr001_b)
- Shopping fr001_c)
- Investing and managing assets (fr001_d)

Here are the 2011 categories:

- Paying monthly bills (rent or mortgage, utilities, cell phone, etc) ([fr001_a](#))
- Doing regular shopping for the household (groceries, household supplies, pharmacy, etc) ([fr001_b](#))
- Making decisions about saving and investments (whether to save, how much to save, where to invest, how much to borrow) ([fr001_d](#))
- Making decisions about other household financial matters (where to bank, what payment methods to use, setting up online bill payments, filing taxes) ([fr001_e](#))

3.7 Fraud, Loss, and Theft

A set of questions about loss liability ([ph024](#)) was added to the 2012 SCPC. If the respondent said he or she had fraudulent activity on credit cards, debit cards, or checking accounts, the 2012 SCPC asks respondents “How much were you personally liable for?”

3.8 Detailed List of Questionnaire Changes

The questionnaire changes described in the preceding sections of this appendix were introduced primarily in three ways:

1. Deleting questions from the previous year’s survey. If a question was deleted for the 2011 SCPC, it is still deleted in the 2012 SCPC, unless stated otherwise. [Tables 1, 2, and 3.](#)
2. New questions in the 2011 or 2012 surveys, [Tables 4, 5, 6, and 7.](#)
3. Questions that were improved from one year to the next. If a question was changed from the 2010 SCPC to the 2011 SCPC, then that change remains in effect in the 2012 SCPC, unless stated otherwise. [Tables 8, 9, 10, 11, 12, 13, 14, and 15.](#)

Table 1: Deleted adoption questions.

Variable ID	Year deleted	Question description
pa001_c	2011	Please tell us the types of accounts you have that allow you to make payments. Number of money market accounts.
pa001_d	2011	Please tell us the types of accounts you have that allow you to make payments. Number of nonbank online payment accounts.
pa099	2012	Do you have any of the following types of prepaid cards? (four categories)
pa100	2012	Please tell us how many of each type of prepaid card you have. (four categories)
pa039	2012	Are any of your prepaid cards reloadable?
pa042	2012	In the past 12 months, have you used a traveler's check, even once?
pa043	2011	Have you ever used a traveler's check, even once?
smartphone_a	2011	Does your cell phone have any of the following features? Text/SMS with no texting plan
smartphone_b	2011	Does your cell phone have any of the following features? Text/SMS with texting plan
smartphone_c	2011	Does your cell phone have any of the following features? Web browsing
smartphone_d	2011	Does your cell phone have any of the following features? Smart phone such as iPhone, Android or BlackBerry
pa026	2011	Have you set up any of the following methods of accessing your current bank accounts? Mobile banking

Table 2: Deleted assets questions.

Variable ID	Year deleted	Question description
pa102	2012	What is the total dollar value of all cards in each type of prepaid card that you have? (four categories)

Table 3: Deleted use questions.

Variable ID	Year deleted	Question description
pa045	2011	In a typical period, how often do you use a nonbank online payment service such as PayPal to make a purchase or pay another person?
pa046	2011	When you make a purchase or pay another person using a non-bank online payment service such as PayPal, what amount do you spend most often?
pu008_c	2011	In a typical period (week, month, or year), how often do you use traveler's checks?

Table 4: New adoption questions.

Variable ID	Year added	Question description
pa001_d1	2011	Do you have an account at any of the following nonbank online payment services? PayPal
pa001_d2	2011	Do you have an account at any of the following nonbank online payment services? Google Checkout
pa001_d3	2011	Do you have an account at any of the following nonbank online payment services? Amazon Payments
pa001_d4	2011	Do you have an account at any of the following nonbank online payment services? Other (specify)
pa197	2011	Do you have any of the following types of prepaid cards? (12 categories)
pa198	2011	Please tell us how many of each type of prepaid card you have. (12 categories)
evercell	2011	Have you ever had a cell phone?
tablet	2012	Do you have a tablet device?
newtb	2011	Have you ever set up access to telephone banking?
pa026_a	2011	Do you currently have your bank's mobile banking app installed on your mobile phone?
pa027_f	2012	Do you have any of the following payment methods with contactless payment technology? Mobile phone

Table 5: New assets questions.

Variable ID	Year added	Question description
pa048	2011	Do you have any money deposited at a nonbank online payment service?
pu012	2012	What interest rate do you pay on the card where you have the largest balance?
pa199	2011	What is the total dollar value of all cards in each type of prepaid card that you have? (12 categories)

Table 6: New loss, theft, or fraud questions.

Variable ID	Year added	Question description
ph024_b	2012	Of the \$[ENTER NUMBER FROM PH023_b] of fraudulent charges on your credit card, how much of that were you personally liable for?
ph024_c	2012	Of the \$[ENTER NUMBER FROM PH023_c] of fraudulent charges on your debit card, how much of that were you personally liable for?
ph024_d	2012	Of the \$[ENTER NUMBER FROM PH023_d] of fraudulent activity on your checking account, how much of that were you personally liable for?

Table 7: New use questions.

Variable ID	Year added	Question description
pa016_a	2012	When you get cash from an ATM, what kind of plastic card do you use most often?
pa016_b	2012	When you get cash back at a retail store, what method do you use most often?
pa026_b	2011	Using your mobile phone, have you done any of the following in the past 12 months? Check a balance or check recent transactions
pa026_c	2011	Using your mobile phone, have you done any of the following in the past 12 months? Pay a bill
pa026_d	2011	Using your mobile phone, have you done any of the following in the past 12 months? Receive a text message alert from your bank
pa026_e	2011	Using your mobile phone, have you done any of the following in the past 12 months? Transfer money between two accounts
pa126	2011	“Have you ever . . . ? Yes/No” versions of the questions from pa026
pa033_d	2011	In the past 12 months, have you used the following methods to access your account? Online banking, using other internet-connected device.
pa051_d	2011	In the past 12 months, have you made any of the following types of mobile payments? Used your mobile phones web browser to make a mobile payment
pa051_e	2011	In the past 12 months, have you made any of the following types of mobile payments? Used a downloadable app to make a mobile payment
pa051_f	2012	In the past 12 months, have you made any of the following types of mobile payments? Swiped a credit, debit, or prepaid card in a device attached to the mobile phone

Table 8: Changed adoption questions, 2011.

Variable ID	Question description	Description of change
pa001	How many accounts do you have at any financial institution, including banks, credit unions, brokerages, or investment firms?	The categories for money market accounts and nonbank online payment accounts were removed. The definitions on the screen were replaced with definitions for checking accounts and savings accounts.
pa053	Do you have any credit cards or charge cards?	The words “or charge cards“ were added.
pa019	Do you have any of the following types of credit cards or charge cards?	The number of types of credit or charge cards was increased from three to five.
pa054	Please tell us how many cards you have of each type.	The number of types of credit or charge cards was increased from three to five.

Table 9: Changed adoption questions, 2012.

Variable ID	Question description	Description of change
pa001_d2	Do you have an account at any of the following nonbank online payment services? Google Wallet	The word “Checkout” was changed to “Wallet” because the name of the service changed.
pa011	Do any of your debit cards give rewards?	A third response option of “I don’t know” was added.
pa040	In the past 12 months, have you used any of the following payment methods, even once?	This question used to ask just about money orders, now it asks about money orders, traveler’s checks, cashier’s checks, and certified checks.
pa197, pa198	Questions about prepaid card adoption and number of cards	Added a new category, “Other federal, state, or local government benefit card.”

Table 10: Changed assets questions, 2011.

Variable ID	Question description	Description of change
pa004	What interest rate do you earn on the balance in your primary checking account?	Each year, the set of response options changed to show different interest rates.

Table 11: Changed assets questions, 2012.

Variable ID	Question description	Description of change
pa004	What interest rate do you earn on the balance in your primary checking account?	Each year, the set of response options changed to show different interest rates.
pa048	Please tell us how your nonbank online payment service is funded.	Changed from a Yes/No question asking if you have any money deposited at a nonbank online payment service to asking how the account is funded.
pa199	Questions about value on prepaid cards	Added a new category, "Other federal, state, or local government benefit card."
pa101	Thinking about the prepaid card that you load most often, what is the most common way that you load that card?	Added "other prepaid card" as a ninth response option.

Table 12: Changed use questions, 2011.

Variable ID	Question description	Description of change
pa033_b	In the past 12 months, have you used the following methods to access your account?	Changed from "Online banking" to "Online banking, using a computer or laptop"
pa033_c	In the past 12 months, have you used the following methods to access your account?	Changed from "Mobile banking" to "Online banking, using a mobile phone"

Table 13: Changed use questions, 2012.

Variable ID	Question description	Description of change
pa034	If you are given a choice while completing a debit card purchase, do you prefer to enter your PIN or give your signature?	A fourth response option, “Neither one,” was removed.

Table 14: Changed demographic questions, 2011.

Variable ID	Question description	Description of change
fr001	In your household, how much responsibility do you have for these tasks?	The text describing the different tasks was expanded and clarified.

Table 15: Changed assessment questions, 2012.

Variable ID	Question description	Description of change
as003	Assessment of characteristics questions	The payment instrument categories were randomized by groups of payment instruments (paper, card, electronic)
as004	How do you rate the security of the following means of making a payment?	There are 10 means of making a payment presented here, as004_a–as004_j. Some have changed from the 2011 version of the question, and others are new.

4 Data Collection

This section describes various aspects of the data collection for the SCPC, with a primary focus on the the 2011 and 2012 versions. Once the survey instrument is finalized, the collection of data involves two general steps: sample selection and administration of the survey. The strategies and philosophies adopted by the CPRC in each step are outlined below. In addition, summary statistics related to survey completion are detailed. Similar expositions focusing on the previous editions of the SCPC can be found in the official releases of the CPRC (Foster et al. 2011; Foster, Schuh, and Zhang 2012; Foster, Schuh, and Stavins 2014).

4.1 American Life Panel

As in previous years, all SCPC respondents in 2011 and 2012 are members of the RAND American Life Panel (ALP), an internet panel of individuals aged 18 and over. The ALP commenced in 2003 as a panel of approximately 500 members, with the original intent to study the methodological issues of internet-based surveys among the older population. As a result, until 2006 all recruits into the ALP were over the age of 40. Since then, the ALP has expanded to include individuals between the ages of 18 and 39 and has grown considerably in size. At the time of the 2012 SCPC sample selection (end of September 2012), there were roughly 4,500 panelists.

There are several pathways that lead individuals into the ALP, but from a survey methodological point of view these condense into two general recruiting strategies. The first strategy involves recruiting volunteers from social clusters that are not yet represented in the ALP. Traditionally, RAND has done this by gathering volunteers from other, already established panels, such as the University of Michigan Internet Panel Cohort (<http://www.sca.isr.umich.edu/>) and the National Survey Project Cohort (terminated in 2009). Potential subjects have also been recruited via address-based sampling. Most notably, in 2011, around 2,000 panel members from ZIP code areas with high percentages of Hispanics and low-income households were added to the ALP (referred to as the “Vulnerable Population Cohort”). The second strategy involves asking individuals already in the ALP to recommend acquaintances or fellow household members to participate in ALP-distributed surveys. As of 2012, such members represented under 10 percent of the ALP cohort.

ALP members remain in the panel, unless they formally ask to be removed or stop participating in surveys over a prolonged period of time. At the beginning of each year, RAND

contacts all members who did not take any survey for at least a year and removes them from the panel, unless they explicitly declare continued interest in participating. Since inactive members are removed only once a year, the pool of those invited to answer the survey at a given point in time may include inactive members. Nevertheless, the annual attrition rate is roughly 3 percent, so the proportion of such cases is likely to be small.

In its early stages, the ALP was, understandably, not demographically representative of the U.S. population of adults. First, due to its early research intentions, the panel prior to 2006 was composed exclusively of individuals above the age of 40. In addition, as the panel was expanded, members recruited directly from already existing panels were recruited on a voluntary basis, with recruitment rates ranging from around 30 percent to approximately 50 percent. Even if the source panels were representative, nonuniform eagerness to join the ALP across demographic strata could have easily produced a biased cohort. Finally, expanding the panel by inviting household members likely skewed the demographic composition further. Nevertheless, as the ALP has been growing in size, its overall representativeness relative to the Current Population Study (CPS) with respect to a variety of demographic variables has been improving. More information about the American Life Panel can be found at the website <http://mmic.rand.org/alp>.

4.2 SCPC Sample Selection

The SCPC was originally conceived as a longitudinal panel. The benefits of a longitudinal panel, namely the added power associated with tracking trends at the individual level, have been well discussed (Baltagi 2008; Duncan and Kalton 1987; Frees 2004; Lynn 2009). Thus, for many research agendas, it is advantageous to base results on a longitudinal panel, rather than on a sequence of cross-sectional studies. As a result, one of the primary goals of SCPC sample selection in each year of its existence has been the preservation of the longitudinal structure.

The planned sample size of the 2008 SCPC was 1,000 respondents. The limitations of the ALP size at the time of sample selection in 2008 (1,113 individuals) forced a virtual census of the ALP. In every year since 2008, in order to maximize the size of the longitudinal panel, an invitation to participate in the SCPC was extended to everyone who had participated in the previous years. In order to ensure a minimum number of yearly respondents, invitations were also sent out to individuals who had never taken the SCPC. Thus, in 2011, a year in which a minimum of 2,000 respondents was targeted, all 2,182 of respondents from previous years who had not attrited were selected for participation as were an additional 553 individuals. The

new individuals were chosen from demographics that were underrepresented in the existing SCPC panel.

In 2012, in addition to the SCPC, the CPRC administered the first, full-magnitude version of the Diary of Consumer Payment Choice (DCPC). The budget allowed for around 2,500 individuals taking the DCPC and around 3,000 individuals taking the SCPC. The goal of the CPRC in administering both surveys was, first, to make the subset of individuals who took the DCPC be as representative of the U.S. population as possible and, second, to maximize the number of individuals taking both surveys. To accomplish this, an optimal sample composition was first chosen for the 2012 DCPC. This meant designating the number of individuals to solicit from the entire ALP within each of several strata (discussed in Section 5) so that representativeness would be fulfilled under expected participation rates. To fulfill the second goal, as many individuals as possible within each stratum were taken from the existing SCPC panel, with preference given to those who had responded most recently. This set of SCPC panelists, along with 1,197 individuals who had never taken the SCPC, were asked to complete both surveys. In addition, the remaining members of the SCPC panel were asked to take the SCPC only. The result is that 3,670 individuals, of whom 2,473 had taken the SCPC at some prior point, were asked to take the 2012 SCPC.

ALP members who are selected for a survey receive an email message with a request to visit the ALP webpage and fill out the survey’s online questionnaire. Anyone who logs on to the survey is considered a participant in the survey, no matter how much of the survey he or she completes. Naturally, not everyone will participate. Table 16 provides the participation rates for individuals as new and existing SCPC panelists for both 2011 and 2012. It should be noted that the number of eligible survey participants reported consists only of active members.

2011 SCPC RECRUITMENT			
Respondent Type	# Eligible	# Participated	Participation Rate
Repeat	2,182	1,832	84.0
New	553	319	57.7
2012 SCPC RECRUITMENT			
Respondent Type	# Eligible	# Participated	Participation Rate
Repeat	2,473	2,065	83.5
New	1,197	1,111	92.8

Table 16: *The sources of the 2011 and 2012 SCPC respondents. “Repeat” refers to those who also participated in previous editions of the SCPC, while “New” refers to those who did not. All calculations are based on active members of the ALP.*

Table 16 indicates that retention rates among individuals who had taken the SCPC at some prior point is quite high. Around 84 percent of those who had participated before agree in each year, with the rate jumping to 89 percent among those who had participated in the previous year. The result is a “convenience panel” of considerable size. Indeed, as Figure 1 shows, there were 1,515 individuals in the four-year panel from 2009 to 2012 and 1,926 in the two-year panel from 2011 to 2012 (but not in 2010). In 2011, the participation rate among new respondents was 57.7 percent, finalizing the 2011 SCPC sample at 2,151 individuals. Interestingly, the participation rate among the 1,197 newly recruited individuals in 2012 was higher than among other sources (92.8 percent). This could be due to the fact that many of these individuals had only recently agreed to take surveys within the ALP, or to the fact that these individuals were all strongly encouraged to take the 2012 DCPC and SCPC as a pair.

Many of the 1,111 individuals who took the SCPC for the first time in 2012 represented sub-populations that were poorly represented in past SCPC samples. Specifically, many of these individuals come from the Vulnerable Population Cohort. The inclusion of these individuals drastically shifts the sample composition, making it difficult to compare across years. As a result, the 2012 SCPC analysis is based on the 2,065 individuals from the SCPC cohort⁴.

The longitudinal panel is an important aspect of the annual survey, and further development of its statistical properties is a high priority for future implementations. This process involves systematically addressing attrition and panel member replacement, as well as developing a methodology for creating longitudinal weights. While at the moment, only cross-sectional weights are provided with the dataset, a set of longitudinal weights, based on the methodology undertaken by the Panel Study of Income Dynamics (Gouskova et al. 2008), for the 2009–2013 panel is planned for release with the 2013 SCPC data.

4.3 Survey Completion

Each year, the SCPC is fielded in the fall with the goal of having most surveys completed in the month of October. The desire to standardize this response period is three-fold. First, from an analytical point of view, trends from year to year are more easily identified if differences in behavior are not attributable to seasonal behavioral variation. Second, from an economic point of view, the month of October is a reasonably representative month with respect to yearly payment behavior; there are no major holidays and it falls between summer

⁴Readers interested in data from the entire sample of 3,176 should contact Kevin Foster at: Kevin.Foster@bos.frb.org.

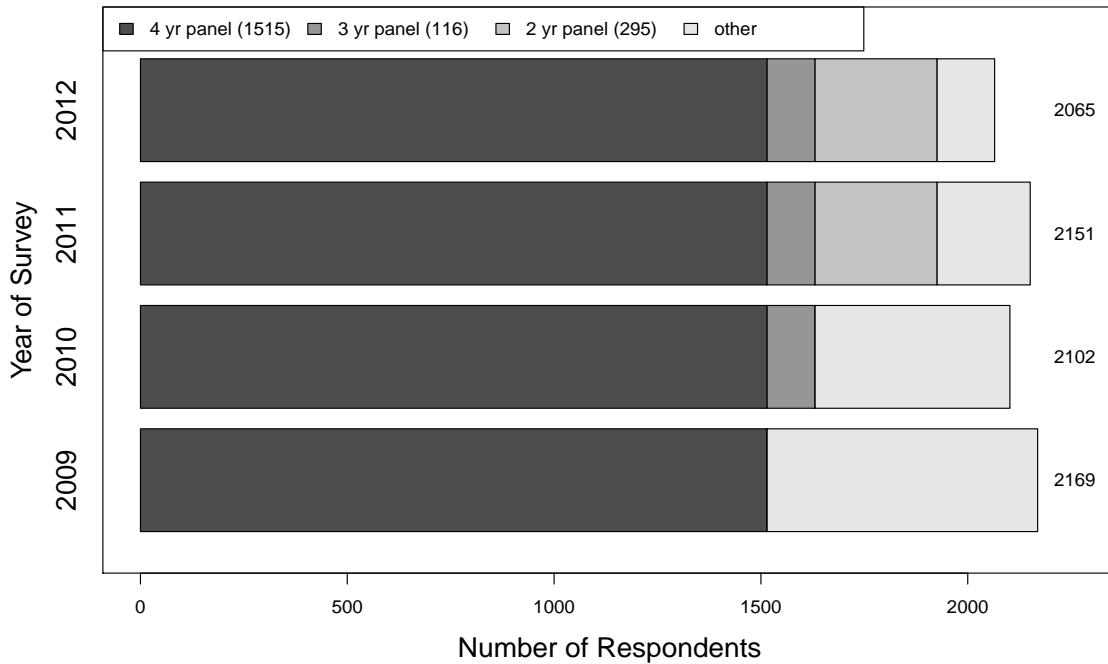


Figure 1: The annual composition of the SCPC respondents.

and winter. Although we ask respondents for responses in a “typical” month, it is possible that recent behavior influences responses. Finally, the DCPC is administered in October (a pilot version in 2010 and 2011 and the full version in 2012), and responses from both surveys can be linked more easily if they correspond to the same period of economic activity.

As mentioned previously, selected individuals receive an invitation to take the SCPC survey via email. The email is sent to everyone simultaneously, and the day on which this occurs is the “release date” of the survey. The respondent is offered a \$20 financial incentive to complete the survey. Each respondent can begin the survey at any point after receiving the invitation. The time of starting is defined as the time at which the individual first logs on to the survey, and the time of completion is defined to be the day on which the respondent logs off for the final time. It is important to note that logging off may not accurately reflect total completion of the survey, as it is possible to finish the survey without logging out. Other standards to define survey completion can be used. For example, individuals who reached the last screen, which asks individuals for feedback on the survey questionnaire itself, but did not log out also answered all of the SCPC questions. Indeed, reaching the last question is the minimum requirement for the respondent to receive the financial incentive. Because our analysis utilizes data from everyone who ever participated (logged on), these distinctions

are not vital to further analysis or results. Individuals who have not logged on after a few weeks are given reminders to do so with follow-up emails.

Figure 2 shows the proportion of surveys completed by each calendar day within each of the years from 2009 to 2012. This plot shows that, while in 2009 the survey was not released until the second week of November, the release date in the past three years has consistently been within a few days of the beginning of October. Specifically, the 2011 version was released on October 3, 2011, and the 2012 version was released on September 26, 2012. As a result, in the past three years, about 90 percent of surveys were completed in October, although at least 50 percent were completed by the end of the first week of October. In every year, only about 2 percent of individuals never log off.

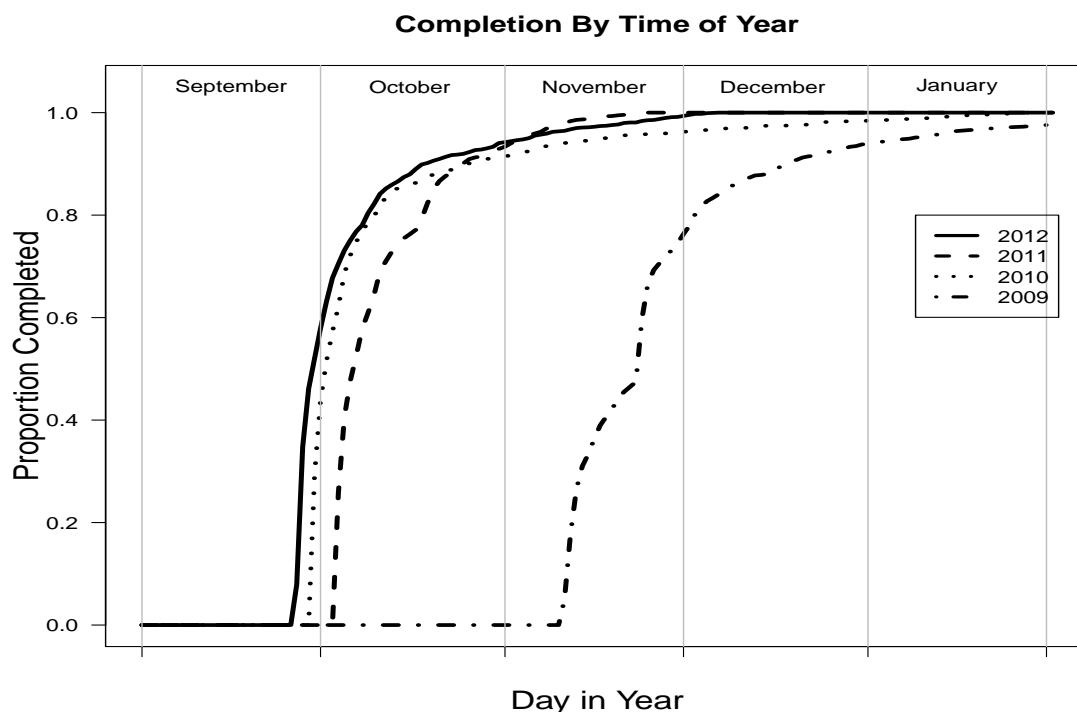


Figure 2: The proportion of respondents who completed the survey as a function of the date within the year.

Figure 3, which shows the proportion of surveys completed as a function of the number of days since the survey was distributed for the 2009–2012 versions, gives a better sense of the distribution of days until completion. Except for 2009, the distribution of completion rates from the time of release is very similar across years. From 2010 to 2012, over 50 percent of the respondents had completed the survey within two days of its being made available, and 91 percent had completed it within a month. In 2009, while 90 percent of the respondents

had completed the survey after a month, only about 18 percent had done so after a day.⁵

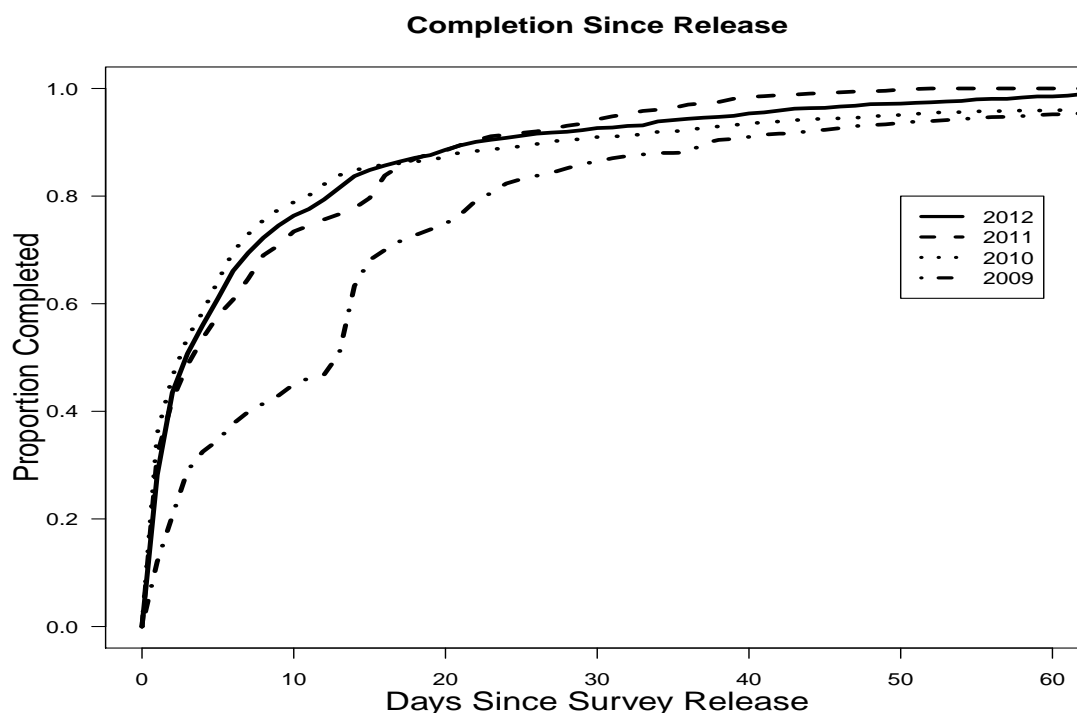


Figure 3: The proportion of respondents who completed the survey as a function of the number of days since the survey was received. The spike at 14 days for 2009 is likely the result of an email reminder sent out two weeks after the survey was distributed. This spike can be seen in Figure 2 as well.

An important aspect of the SCPC time-series data made evident by the completion data relates to the relatively wide range of dates within a year during which surveys are taken. Although approximately 80 percent of surveys are completed within two or three weeks of the release date, as Figure 3 makes clear, the range of completion dates for the remaining surveys spans a period of months. What is more, the later release of the 2009 survey ensures that there is little overlap in the completion periods for the SCPC in this and the following years. As a result, comparisons across years could be influenced by differences due to seasonal behavior as well as by general trends across years. For example, if typical behavior changes in November due to the ensuing holiday season, payment use responses in the 2009 SCPC may reflect this, while those in the other years will not. This type of temporal gap is even more extreme at the individual level, where a particular respondent might respond in October of

⁵The 2009 SCPC went into the field on Tuesday, November 10, 2009. The fact that the following day was a public holiday (Veterans Day on November 11, 2009) might explain why few respondents answered the survey after a day.

one year and as late as January in a different year. Again, this raises issues of comparability. An effort to minimize this seasonal effect has led to the consistent timing of the release in the past three surveys near the end of September.⁶

Figure 4 compares the distributions of the number of minutes it took respondents to complete the survey for the past four years of the SCPC⁷. The plot makes clear that the survey is getting longer with each passing year. Indeed, the median completion time ranges from 30 minutes in 2009 to almost 38 minutes in 2012. The increases in time of completion is due to the addition or expansion of survey questions, discussed in Section 3.

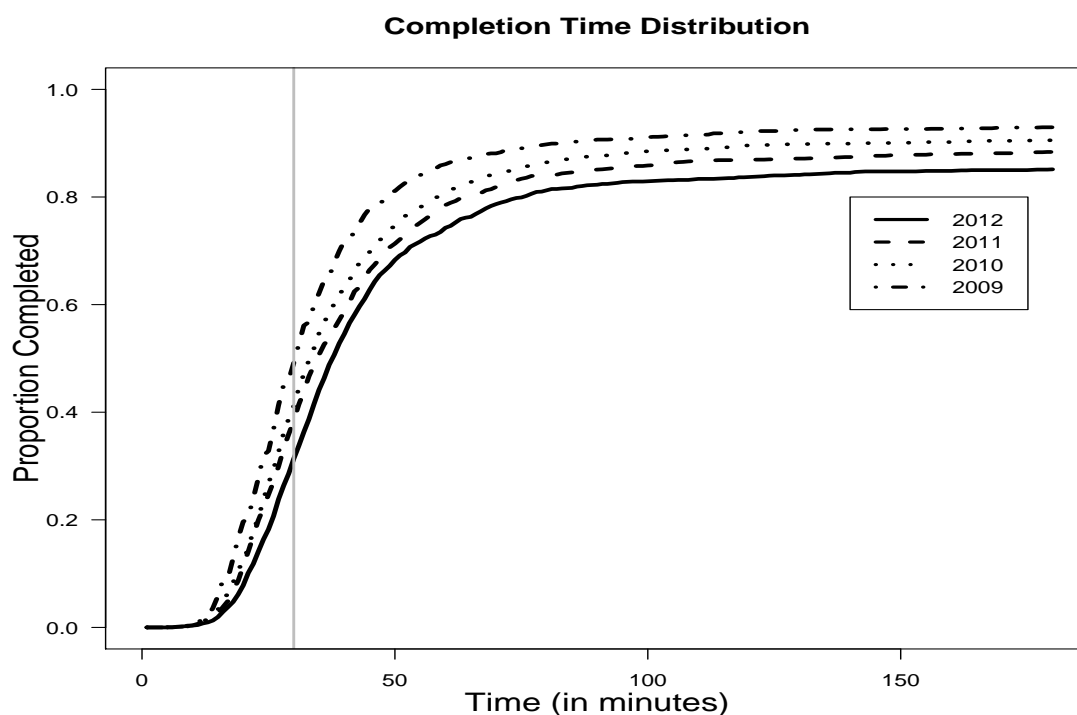


Figure 4: The proportion of respondents who completed the survey as a function of time. The vertical line at 30 minutes represents the intended average length of completion.

⁶The Diary of Consumer Payment Choice is administered over a strict calendar time period (September 29–November 2) and is linked to the SCPC, so the SCPC was consistently launched at the end of September or beginning of October from 2011 to 2013.

⁷The distribution is highly skewed to the right, since completion time is defined as the difference in minutes between the time of first log-in to the survey and the last log-out. A log-out requires responding to the very last question in the survey. Individuals who take breaks while taking the survey will thus have long completion times. In addition, as noted above, more than 1 percent of individuals never log out of the survey.

4.4 Item Response

For a survey to provide a valid picture of the overall population, it is very important that the item response rates for each question be high. High nonresponse rates not only mean there is less information on which to base estimates but also raise concerns about potential bias in the estimates. If the fact that an observation is missing is independent of the value of the observation, a condition referred to as “missing at random” (Little and Rubin 2002), imputation procedures can be used to generate estimates of sample statistics. However, if there is a confounding variable that relates to both the value of a variable and the likelihood of nonresponse, it is impossible to adjust for the effects on sample statistics. Certain economic variables, such as dollar worth or personal cash holdings, are potentially sensitive topics, and it is possible that there is a correlation between the true values and the willingness of respondents to provide these values. Naturally, variables with low nonresponse rates are less susceptible to this type of bias.

The 2011 and 2012 SCPC have roughly 200 survey variables, although the survey itself is administered with a relatively complicated skip logic so not everyone answers the same set of questions. However, there are 100 questions that are asked of everyone, and these are spread throughout the survey. The median response rate for these items is slightly above 99 percent, and the lowest response rate is about 95 percent. Although those who did not complete the survey are factored into these rates, there is no clear pattern of response rates dropping farther along in the survey. Overall, the response rate is very high within the SCPC, which may be partly attributable to the fact that respondents have volunteered to take surveys and are being paid to do so.

5 Sampling Weights

5.1 Post-Stratification

An important goal of the SCPC is to provide estimates of payment statistics for the entire population of U.S. consumers over the age of 18. As mentioned in Section 4, the ALP is a collection of volunteers from a variety of existing databases. A direct implication of this fact is that any SCPC sample will not be a probability sample, making probability-based weighting to generate population-wide inferences impossible. Nevertheless, recent work by Wang et al. (2009) suggests that nonrepresentative polling can provide relatively accurate estimates with appropriate statistical adjustments.

The aforementioned evolution of the ALP as well as the CPRC’s focus on preserving the longitudinal aspect of the sample suggests that the SCPC sample itself is not necessarily representative of the U.S. population of consumers. Table 17 shows the unweighted sample proportions for a set of chosen demographic categories along with the weighted ones for various renditions of the SCPC. It is clear that the SCPC panel tends to under-sample males as well as young people, minorities, people with lower levels of education, and those with lower income levels. In 2011, a concerted effort was made to improve representativeness by recruiting new respondents from under-represented strata. This can be seen in the slight improvement in the unweighted distributions in 2011 and 2012. This results in less variable sampling weights as well, with the standard deviation of the weights moving from 57.6 and 57.9 respectively in 2010 and 2011 to 41.9 and 44.8 in 2011 and 2012.

To enable better inference of the entire population of U.S. consumers, SCPC respondents are assigned post-stratified survey weights designed to align as much as possible the composition of the SCPC sample to that of a reference population. Specifically, each year the benchmark distributions against which SCPC surveys are weighted are derived from the Current Population Survey Annual Social and Economic Supplement, administered in March (CPS). This follows common practice in other social science surveys, such as the Consumer Expenditure Survey (CES).

5.2 Raking Algorithm

Sampling weights are generated by RAND, using a raking algorithm (Deming and Stephan 1940; Gelman and Lu 2003). This iterative process assigns a weight to each respondent so that the weighted distributions of specific socio-demographic variables in the SCPC sample match their population counterparts (benchmark or target distributions). The weighting procedure consists of two main steps. In the first part, demographic variables from the CPS are chosen and mapped onto those available in the SCPC. Continuous variables such as age and income are recoded as categorical variables by assigning each to one of several disjoint intervals. For example, Table 17 shows six classifications for age and seven classifications for income. The number of levels for each variable should be small enough to capture homogeneity within each level, but large enough to prevent strata containing a very small fraction of the sample, which could cause weights to exhibit considerable variability. Table 18 shows the variables used in weighting as well as the levels within each variable. In the second step, the raking algorithm is implemented and sample weights are generated by matching the proportions of predefined demographic groups in the SCPC to those in the CPS. More

Demographics		Unweighted 2010 SCPC	Unweighted 2011 SCPC	Unweighted 2012 SCPC	Weighted 2012 SCPC
Gender	Male	42.0	44.3	43.6	48.1
	Female	58.0	55.7	56.4	51.9
Age	18–24	3.3	4.3	3.0	6.2
	25–34	10.9	16.9	15.7	24.5
	35–44	14.2	12.6	13.1	15.5
	45–54	25.7	22.9	22.3	19.1
	55–64	27.6	25.7	26.0	16.4
	65 and older	18.2	17.5	20.0	18.3
	Race	White	88.2	86.0	85.5
Black		6.9	7.6	8.2	14.6
Asian		1.7	1.8	1.8	2.8
Other		3.2	4.6	4.4	9.0
Ethnicity	Hispanic	5.3	7.3	7.3	14.3
Education	No HS diploma	1.8	2.6	2.7	7.1
	High School	15.9	16.2	15.9	35.1
	Some College	37.2	37.1	36.8	28.8
	College	25.1	25.6	25.2	16.5
	Post-graduate	20.0	18.5	19.4	12.5
Income	< \$25K	15.5	17.8	17.0	24.4
	\$25K – \$49K	26.0	24.8	24.7	27.4
	\$50K – \$74K	24.6	21.9	21.6	21.1
	\$75K – \$99K	15.2	14.1	14.5	12.1
	\$100K – \$124K	8.2	8.9	9.7	7.4
	\$125K – \$199K	7.1	8.8	9.0	4.9
	≥ \$200K	3.4	3.6	3.5	2.7

Table 17: Unweighted percentages for various marginal demographics in the 2010, 2011, and 2012 SCPC sample as well as weighted percentages for the 2012 SCPC. The weighted values are based on CPS values.

precisely, the weighting algorithm is performed using the 31 pairs of demographic variables shown in Table 18.

The socio-economic variables chosen for the raking procedure result from recent research conducted by RAND regarding the sampling properties of weights based on different demographic factors. First, a new imputation algorithm for all possible socio-demographic variables was developed to allow for weights based on a wider range of consumer information. The procedure is sequential, so that variables with the least number of missing values are imputed first and, in turn, used as inputs to impute the variables with the most missing values. Imputations are performed by ordered logistic regression for ordered categorical variables,

Gender × Age				
M, 18 – 32	M, 33 – 43	M, 44 – 54	M, 55 – 64	M, 65+
F, 18 – 32	F, 33 – 43	F, 44 – 54	F, 55 – 64	F, 65+

Gender × Ethnicity	
M, White	M, Other
F, White	F, Other

Gender × Education		
M, High School or Less	M, Some College	M, Bachelor’s Degree or More
F, High School or Less	F, Some College	F, Bachelor’s Degree or More

Household Size × Household Income			
Single, < \$30K	Single, \$30K – \$59K	Single, ≥ 60K	
Couple, < \$30K	Couple, \$30K – \$59K	Couple, \$60K – \$99K	Couple, ≥ \$100K
≥ 3, < \$30K	≥ 3, \$30K – \$59K	≥ 3, \$60K – \$99K	≥ 3, ≥ \$100K

Table 18: The set of weighting variables. “M” stands for male, and “F” stands for female. The highest income brackets for single households were combined to avoid small cell sizes.

and by multinomial logistic regression for categorical variables. Sample weights produced by different combinations of variables were evaluated on the basis of how well they matched the distributions of demographic variables not used as raking factors (test variables). To assess the robustness and accuracy of different combinations of weighting variables, Monte Carlo samples were drawn and demographic distributions of the test variables were generated based on the weights for that particular sample. Mean deviation from the CPS-defined levels for test variables were estimated by averaging over the samples. The combination of variables in Table 18 consistently matched the target distributions of the CPS for a variety of different sample sizes.

The pairing of gender with other socio-demographic variables allows one to better correct for discrepancies between distributions within each gender, while avoiding the problem of small cell counts. In other words, implementing the raking algorithm on the set of pairs shown in Table 18 ensures that the distributions of age, ethnicity, and education in the SCPC are separately matched for men and women to their population counterparts in the CPS. Moreover, since bivariate distributions imply marginal distributions for each of the two variables, this approach also guarantees that the distributions of gender, age, ethnicity, and education for the entire SCPC sample are aligned with the corresponding benchmarks in the CPS. The same is true for household size and household income.

Because the ALP sample itself is not representative of the U.S. population, post-stratification is an important step in inference for the population. The fact that not all strata of interest are

represented in the sample makes raking the natural method for assigning weights. However, doing so introduces a few complications related to the statistical framework and analysis of the data. The first relates to the increased difficulty in calculating standard errors of population estimates, which are weighted averages of the sample values. In all tables and publications, the standard errors have been calculated by taking the weights as fixed values, thereby reducing the standard errors. The sampling weights, which are a function of the strata representation in the sample, are random variables, and their variation should be factored into the calculation of standard errors (Gelman and Lu 2003).

The second area of concern regards the effects of the sampling scheme on the weights and on the estimates they produce. In order for the raking algorithm to be appropriate, in the sense that the expected weights for each stratum equal those of the population, the sampling procedure must be such that, in expectation, each stratum is proportionally represented in the sample. To be precise, the expected proportion of the sample belonging to a specific stratum is directly proportional to the relative proportion of that stratum within the population. A sampling procedure that does not have this property is likely to consistently produce weights for certain strata that do not reflect the true representation in the entire population. If strata properties correlate with payment behavior, this could lead to biased population-wide estimates. In the case of a sampling procedure in which some strata tend to be over-represented and others under-represented, the raking algorithm, which strives to match marginal proportions rather than those of the cross-sections of all the variables, may generate sample weights with too wide a range of values in order to achieve the alignment between the sample composition and the one in the reference population. Work is currently being done to better incorporate CPS population proportions for strata into the sampling scheme in the hope of eliminating any potential bias from nonproportional stratum sampling.

Despite these issues, the results of the SCPC data and any observed changes from year to year based on these results are likely to be reliable. High response rates and targeted sampling (as described in Section 3.2) suggest that the variability in estimates attributable to the weights is relatively small. In addition, there is little evidence of very strong correlations between demographic variables and consumer behavior, with a lot of the variation seen in the data seemingly attributable to differences from person to person at the individual level. This suggests that mis-specification of weights would have a minor impact on any point estimates and likely result in conservative confidence intervals. Such intervals, in turn, make Type-I errors less likely, suggesting that any trends we do see in the data are real. A discussion of using the post-stratification weights to generate per-consumer as well as aggregate U.S. population estimates appears in Section 7.2.1.

6 Data Preprocessing

Prior to further statistical analysis, it is important to carefully examine the data and develop a consistent methodology for dealing with potentially invalid and influential data points. As a survey that gathers a large range of information from each respondent, much of it about a rather technical aspect of life that people may not be used to thinking about in such detail, the SCPC, like any consumer survey, is susceptible to erroneous input or missing values. This section describes the general types of data preprocessing issues encountered in the SCPC and outlines the general philosophy used in data cleaning.

Section 6.1 describes the methodology of imputing missing data, while Section 6.2 describes procedures used to identify and edit data entries that are likely to be erroneous (commonly referred to as “cleaning the data”). It should be noted that all procedures are applied retroactively to the data of previous years, so variables from 2008, 2009, and 2010 may have different values from those in previous data releases. The edited variables are used for analysis by the CPRC, most notably to generate population estimates provided in the SCPC tables. However, both edited and unedited data are released to the public. A guide on how to access each version of the variables is given in Section 6.3.

6.1 Data Imputation

The imputation strategy adopted by the CPRC is simple and relates mostly to categorical data variables. The types of categorical variables in the SCPC are diverse, ranging from demographic variables, to binary variables (answers to Yes/No questions), to polytomous response variables (multiple choice questions with more than two possible answers). The first line of data inspection consists of a basic range and consistency check for the demographic variables to ensure that reported values are logical and that they correspond to established categorical codes. Any response item that fails this check is considered to be missing data.

Treatment of demographic variables differs from treatment of all other categorical variables. In the case of many demographic variables, such as age group, gender, or race, missing information can be verified from other surveys taken within the context of the ALP. For household income and household size, both attributes that could easily change within a year, values are imputed through logistic regression models for the purpose of creating post-stratification weights by RAND.

Most of the data imputation performed on SCPC data relates to sequences of questions in

which respondents are asked binary questions, such as “Do you have an ATM card?” or are asked to enter numerical values for a set of related items. This latter form might relate to the number of credit cards owned for several credit card categories or the dollar value stored on different types of prepaid cards. In either of these cases, if at least one of the items features a non-missing response, we impute the values of all missing responses in the same sequence. Specifically, in the case of binary questions, missing variables are coded as “No,” while in the case of numerical values, they are coded as 0.

In some cases, data are imputed to missing values from numerical values, if an individual’s responses defy logic. An example of a question in which this can occur in the 2011 and 2012 SCPCs is that which first asks respondents whether or not they own various types of prepaid cards and then asks for the number owned for only the categories that were declared as owned. In such a case, it is technically possible for someone to claim that he or she is an adopter of a card, but, when prompted, say that he or she owns zero of such cards, a clear inconsistency. The CPRC takes the most liberal approach in that all responses are kept as given for as much of the sequence as possible. At all subsequent levels, inconsistent responses are marked as missing. Thus, in the case of prepaid card adoption, the hypothetical respondent would be recorded as an adopter, but with the number of prepaid cards owned missing.

At the moment, no other variables are imputed, although multiple imputation procedures are planned for future editions of the survey results. It is very difficult, without making strong assumptions, to identify irregular or erroneous data inputs, especially for multiple choice questions. Research conducted by the CPRC suggests that response bias in sequences of Likert scale questions introduced by a form of anchoring effects (Hitczenko (2013a), see Daamen and de Bie (1992); Friedman, Herskovitz, and Pollack (1994) for general discussion on anchoring effects) is present, but not of economic significance. Because the item response rates are high, the effect of missing values is not a major concern for the SCPC. Nevertheless, the CPRC is considering the development of multiple imputation techniques for missing numerical data entries.

6.2 Data Editing

The greatest challenge in data preprocessing for the SCPC comes in the form of quantitative variables, especially those that represent the number of monthly payments or dollar values. Measurement errors in such a context, defined as any incongruity between the data entry and the true response, can be attributed to a variety of sources ranging from recall error to

rounding errors to data entry errors or even to misinterpretation of the question. A data entry subject to measurement error can take many forms, but practically the only identifiable forms are those that lie outside the realm of possible values and those that fall in the realm of possibility, but take extreme values. The former, such as negative monthly payment counts, are easily identified by range checks. Identification of the latter is much more difficult, as it is important to recognize the heterogeneity of behavior within the population, especially for economic variables such as cash holdings and value of assets. In other words, it is possible that data entries that by some numerical evaluations are statistical outliers are actually accurate and valid.

This issue is not unique to the SCPC. Many consumer surveys, such as the Survey of Consumer Finances (SCF) and the Consumer Expenditure Survey (CES) must also tackle the cleaning of such fat-tailed variables. While the details of the preprocessing of outliers are not provided in either survey, the general approach mirrors that adopted in the SCPC (Bricker et al. 2012; Bureau of Labor Statistics 2013). First, all relevant information in the data particular to each variable is used to identify statistical outliers and inconsistent responses. Then, values that cannot be confirmed or reconciled are imputed. It should be noted that the SCPC does not benefit from in-person interviews (as does the SCF) or multiple phases and modes of interview for each respondent (as does the CES), making it more difficult to identify inconsistent responses.

It is important to distinguish conceptually between influential and potentially invalid data points. An influential point is one whose inclusion or exclusion in any inferential analysis causes a significant difference in estimates (Bollen and Jackman 1990; Cook and Weisberg 1982), and thus the influence of a point depends on the statistical procedure being performed. An invalid data entry is, technically, any entry that does not represent the truth. As mentioned above, data cleaning procedures predominantly focus on identifying invalid entries in the tails of the distribution (Chambers and Ren 2004). An invalid data point need not be influential and an influential point is not necessarily invalid. To the degree possible, the procedures adopted by the CPRC rely on economic intuition to identify potentially invalid data entries. Thus, the cleaning procedures for variables for which we have a higher degree of economic understanding seek to identify invalid entries and edit their value. For variables for which there is less economic intuition available, we rely more on raw statistical procedures such as matching known parametric distributions to the data or Cook's distance to identify influential points in the context of estimating weighted sample means (Cook 1977; Cook and Weisberg 1982).

Below we outline the considerations and economic motivations in cleaning several different

variables and provide adopted algorithms for each. The variables relate to the typical number of monthly uses of payment instruments, reported dollar amounts in various contexts, and the number of payment instruments or accounts owned. In certain cases, new data patterns have made previous editing strategies ineffective. In such cases, we update the algorithm or fall back on simpler strategies. As noted above, the raw (uncleaned) data are available, so researchers are free to preprocess the data as they see fit.

6.2.1 Preprocessing: Typical Monthly Payment Use

The number of typical payments in a month is an aggregate from data entries for 41 different combinations of payment method and transaction type. The SCPC delineates 10 payment methods, nine payment instruments plus income deduction, and seven transaction types. For example, the use of cash is reported in a series of questions about cash use in the context of paying for a service, for a bill, for a product, or as a payment to a specific person. All combinations of payment method and transaction type are listed in the SCPC User’s Guide (Foster 2014). In addition, for each of the 41 variables, the SCPC allows the respondent to answer on either a weekly, monthly, or annual frequency, so that recall periods better match natural frequencies of use. Since only “adopters,” defined as those people who claim to possess the payment method, are asked to provide information on use, missing entries for this question are assumed to be zero (for example, a person who has a credit card need not make use of it). Before preprocessing, all 41 payment number variables are standardized to a monthly frequency (multiplied by $\frac{52}{12}$ if reported by week and divided by 12 if reported by year).

The 10 payment methods are indexed by $j = 1, 2, \dots, 10$. For each payment method, there are a variety of potential transaction types, $k = 1, \dots, K_j$. In addition, each data entry is associated with an individual, labeled $i = 1, \dots, N$, and a year, labeled $t = 2008, \dots, 2012$. Therefore, Y_{ijkt} is the recorded number of typical monthly payments by individual i via payment method j of the k^{th} transaction type for that particular method in year t . Then, $Y_{ijt} = \sum_{k=1}^{K_j} Y_{ijkt}$ is the number of reported monthly payments by payment method j in year t and $Y_{it} = \sum_{j=1}^{10} Y_{ijt}$ is the number of total number of monthly payments reported in year t .

More economic intuition exists about the total number of monthly payments than about lower-level components of this variable. In addition, economic theories dictate that the number of payments made with a particular payment method depends on the payment methods adopted by the individual. The collection of adopted payment methods is called a “bundle.” The general cleaning procedure first identifies a hard threshold for the total

number of monthly payments and then, in turn, a bundle-dependent threshold for each payment method. For each payment method, if the reported value exceeds this threshold, the lower-level components are imputed. If an individual component stands out as an outlier, it is winsorized. Otherwise, all components are scaled down to bring the resulting number of payments with the method in question to the threshold, while preserving the relative shares within the payment method. The economic idea behind this latter adjustment is that the individual is likely consistently over-estimating use of the payment method.

Although the fundamental idea behind the adopted procedure is based on the common approach of using known distributions to identify potential invalid data points, the unique characteristics of payment choice require some additional assumptions. As a result, many aspects of the procedure are based on original ideas developed at the CPRC. This process is described in more detail below and is fully delineated in Algorithm 1.

An initial threshold for the total number of monthly payments was determined to be 300, representing 10 payments per day for 30 days. Figure 5 shows that this roughly corresponds to the 98th percentile of the raw SCPC data for each year, and is also where the yearly distributions seem to start diverging from each other. From a statistical point of view, the ability to pool data to estimate empirical distributions is a great advantage, as pooling enables estimates to be based on more information. In the future, other sources, such as the Diary of Consumer Payment Choices (DCPC), could also be used to inform this threshold.

Given a maximum number of monthly payments, the distribution of the numbers reported for each payment method quite naturally depends on which payment methods are adopted by the individual. A simple model assumes that the number of payments made with each instrument follows a multinomial distribution, conditional on the total number of payment instruments adopted. Thus, the model assumes that with each incoming payment, there is some set of probabilities $\{p_j\}$ that correspond to the probability of using payment j . The decision is assumed to be independent for each individual and for each of the necessary payments and to depend only on the individual's adoption choices. While this assumption may not hold completely (for example, the choice of payment method might depend on the dollar value of the transaction), it is a suitable approximation for the purposes of identifying likely invalid data points. To make this more concrete, for individual i in year t , let \mathcal{P}_{it} be the bundle adopted by individual i . For example, $\mathcal{P}_{it} = \{1, 2\}$ for an individual who adopts only cash and checks.

In order to account for the fact that certain payment methods are used much more often than others yet keep the calculations simple, the probabilities, $\{p_j\}$, are assumed to be

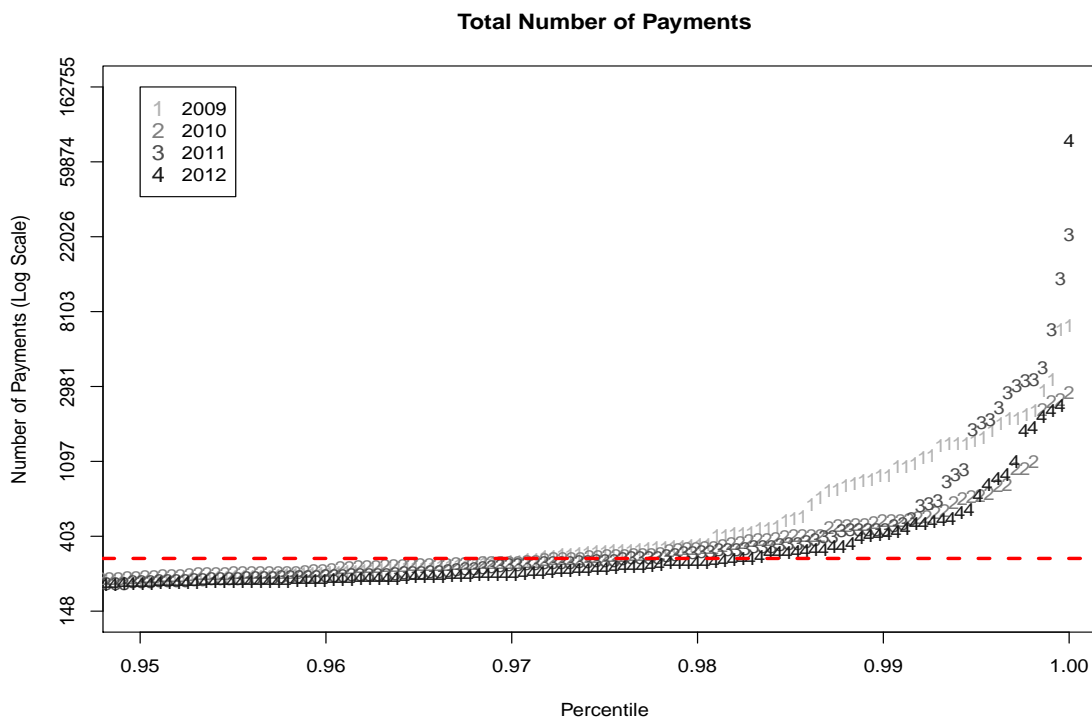


Figure 5: The log-values of the largest 5 percent of the total monthly payments data plotted against the percentiles for past three years of data.

proportional to the relative prevalence of the adopted payment methods to one another. Thus, for $j = 1, \dots, 10$, r_j is defined as the weighted mean of the bottom 95 percent of the number of monthly payments made by method j in the raw data. The 95th percentile is used to prevent undue influence of outliers, and changing this percentile does very little to change the relative prevalence. The intuition then is that r_j represents a prior sense of the typical monthly rate of use of payment method j among the population.

Based on the chosen r_j , the approximated proportion of payments made by individual i with payment method j in year t , defined as p_{ijt} will be

$$p_{ijt} = \frac{r_j}{\sum_{j' \in \mathcal{P}_{it}} r_{j'}} 1_{\{j \in \mathcal{P}_{it}\}}.$$

The value p_{ijt} is a probability and the distribution of these values will be the same for every individual with the same bundle of payment methods. It should be noted that calculations of p_{ijt} are dependent not only on the prior assumptions but also on the assumption that using one payment method does not influence the relative use rates of the other methods. As an example, this means that the relative use ratio of cash to check does not depend on

whether or not the individual uses credit cards. While this might be a strong assumption, it is one that avoids the need to make many assumptions about joint use rates for various bundles of payment methods.

The cutoffs for each payment method are then defined as the 98th percentile of the number of monthly payments, with 300 total payments and probability of use p_{ijt} . Therefore, if $Y_{ijt} \sim \text{Binomial}(300, p_{ijt})$, the cutoff c_{ijt} is defined to be such that

$$\text{Prob}(Y_{ijt} \leq c_{ijt}) = 0.98.$$

Based on this, y_{ijt} is flagged whenever $y_{ijt} > c_{ijt}$. This flag indicates that the reported value is unusually high when taking into account the payment methods adopted. It is only at this point that the lowest level of data entry, y_{ijkt} , is studied. Because little intuition exists about the distributions of the y_{ijkt} , comparisons of flagged values are made to the 98th percentile of the empirical distribution estimated by pooling data from all three years. Specifically, let q_{jk} be the 98th percentile of the pooled set of data comprised of the y_{ijkt} for $t = 2008, \dots, 2012$ among people for all (i, t) for which $j \in \mathcal{P}_{it}$. Then, for each flagged payment method, the flagged entry is imputed with the minimum of the calculated quantile and the entered value: $y_{ijkt}^* = \min(y_{ijkt}, q_{jk})$. This form of winsorizing means that extremely high reported numbers are brought down to still high, but reasonable levels. If none of the data entries at the lowest level is changed, all y_{ijkt} for the payment method j are scaled down proportionally in order to bring the total for the payment method down to the cutoff value c_{ijt} .

Once data at the lowest level of input are cleaned, aggregated values can naturally be reconstructed. Figure 6 shows the implied number of total monthly payments before and after preprocessing (on the log scale). It is evident that despite the use of 300 as cleaning parameter, the algorithm allows individuals to have more payments. In each year, there are individuals with as many as 400 monthly payments. Figure 6 also indicates that the smallest number of payments to be edited is around 50, although the changes to the number of payments made are relatively small.

6.2.2 Preprocessing: Cash Withdrawal

A second concept that requires a fair amount of attention in terms of preprocessing is that of cash withdrawal. Cash withdrawal since the 2009 SCPC is reported as a combination of four separate variables: frequency of withdrawal at primary and all other locations and typical dollar amount per withdrawal at primary and all other locations. Because reported dollar

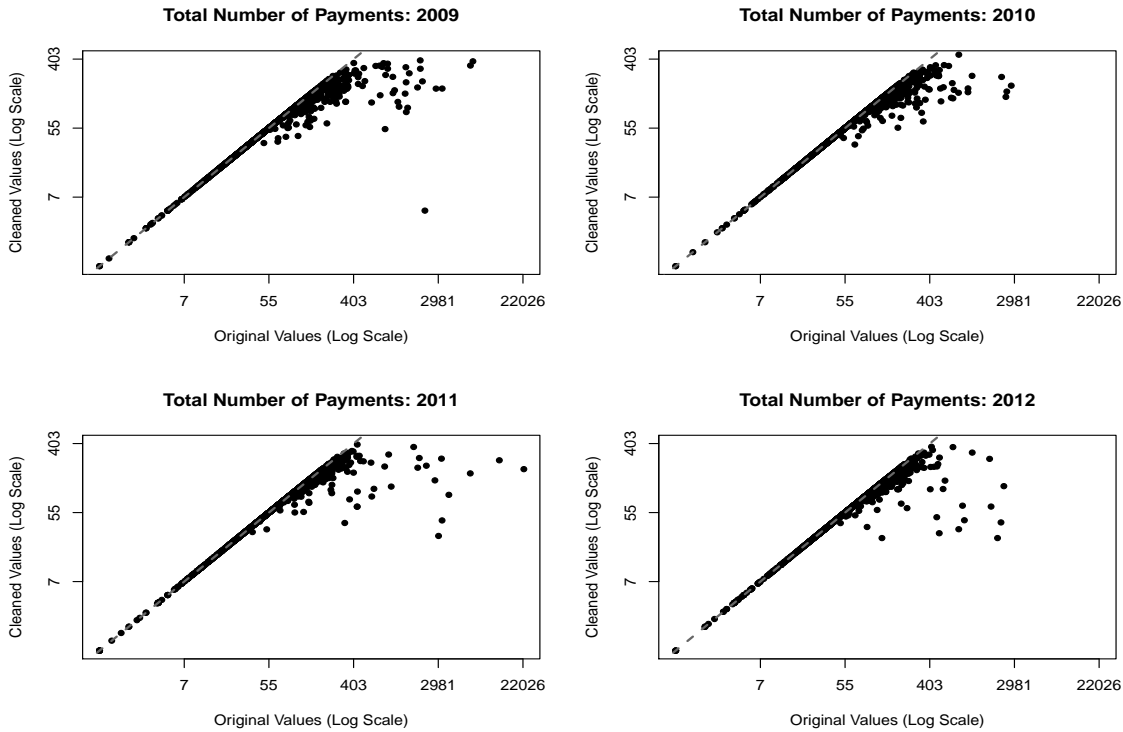


Figure 6: The log-values of the cleaned total monthly payments data plotted against the log-values of the original values.

amounts correspond to typical values, which could represent the mean, the median, or the mode, the value determined by multiplying the reported frequency and the dollar amount does not necessarily correspond to the average total cash withdrawal either for primary or for all other locations. In preprocessing the cash withdrawal values, data for primary and all other locations are treated separately.

With this release of the SCPC results, we are introducing a change to the existing preprocessing algorithm for cash withdrawal data and reapplying the new procedure retroactively to data from earlier years. The complete details of the previous methodology can be found in “The 2010 Survey of Consumer Payment Choice: Technical Appendix.” While the overall framework remains the same, less confidence in the validity of certain tail observations in the 2011 and the 2012 SCPC has motivated an adjustment to the procedure.

Table 19 shows six different sample percentiles for the dollar amounts per withdrawal and the number of withdrawals per month at both the primary source and all other sources for the 2009–2012 SCPC. There is some evidence that the dollar amount per withdrawal is increasing, although the changes are relatively modest. On the other hand, while the lower percentiles of the frequencies are consistent across the four years, the top 2 percent

Algorithm 1 Preprocessing: Number of Monthly Payments

```
for  $i = 1 : N$  do
  Determine  $\mathcal{P}_{it}$ 
  for  $j \in \mathcal{P}_{it}$  do
    Calculate  $p_{ijt}$  and then  $c_{ijt}$ 
    if  $y_{ijt} > c_{ijt}$  then
      Set change.subtotal = 0 {used to keep track if  $y_{ijkt}$  are changed}
      for  $k = 1 : K_j$  do
        if  $y_{ijkt} > q_{jk}$  then
          Set  $y_{ijkt} = q_{jk}$ 
          Set change.subtotal = 1
        end if
      end for
    if change.subtotal = 0 then
      for  $k = 1 : K_j$  do
        Set  $y_{ijkt} = y_{ijkt} \times \frac{c_{ijt}}{y_{ijt}}$ 
      end for
    end if
  end if
end for
end for
```

exhibit very large increases, particularly in 2012. After careful analysis of these extreme observations, we find that there is reason to believe that many, if not all, are inaccurate.

From an economic point of view, a change in behavior of this magnitude, even in the tail, seems much too drastic given the lack of comparable changes in the economic climate from 2010 to 2012. In most of the instances in which a very high frequency was reported, the total dollar value of cash withdrawn each month was also very high. Even if one allows that a fraction of the population is withdrawing much more cash than in previous years, one might expect to observe cases in which this is done with few withdrawals but a large dollar value per withdrawal, a more efficient way of accumulating cash. However, as the lack of a significant increase in the amounts in Table 19 attests, there is no evidence of such a phenomenon in the data. Perhaps more importantly, for many of the people with high reported values, we have access to other information, such as income, net worth, and in most cases, responses from previous years. Examining these variables further suggests that many of the reported values in the tail are likely to be erroneous. For example, for many individuals, the monthly cash flow is vastly inconsistent with income levels. While we cannot explain this change in the yearly results (the survey question did not change), the evidence as a whole introduces doubt as to the validity of these observations.

Amount: Primary Source (\$)							Amount: All Other Sources (\$)						
	Percentile							Percentile					
Year	50	75	95	98	99	Max	Year	50	75	95	98	99	Max
2009	60	120	400	600	930	3500	2009	10	40	200	500	672	3000
2010	60	120	400	600	800	5000	2010	10	40	200	481	631	2500
2011	60	150	500	700	1000	6000	2011	20	50	200	500	731	5770
2012	60	150	500	672	1000	4850	2012	20	50	200	500	700	4200

Frequency: Primary Source							Frequency: All Other Sources						
	Percentile							Percentile					
Year	50	75	95	98	99	Max	Year	50	75	95	98	99	Max
2009	2	4	9	13	17	217	2009	0.3	1	4	9	10	100
2010	2	4	9	13	22	435	2010	0.3	2	4	9	13	130
2011	2	4	9	17	26	435	2011	0.4	2	4	9	17	217
2012	2	4	9	22	49	2167	2012	0.5	2	5	17	50	5600

Table 19: Percentiles for the four cash withdrawal variables for the 2009–2012 SCPC samples. Amounts refer to the dollar amount per withdrawal, and frequencies refer to the number of withdrawals per month.

The previous preprocessing procedure relied on iteratively comparing the most extreme pair of amount and frequency to the expected properties of such a pair from a bivariate Log-Normal distribution, with parameters defined by all observations. By comparing one observation to all of the rest, the presence of several extreme values makes it more difficult to identify the point in question as being inconsistent with the data. As a result, the procedure is less likely to identify the cluster as erroneous. The new procedure first designates a confidence region for all observations, and then winsorizes all pairs beyond that region. This allows the cleaning to better deal with the observed cluster of outliers. The details of the new procedure are given below.

Assuming that N independent individuals report positive cash withdrawal in a typical month, let $C_{it} = A_{it}F_{it}$, where A_{it} is the reported amount per visit in year t and F_{it} is the reported frequency of monthly visits in year t . In the case of cash withdrawals, because stronger distributional assumptions apply, statistical power from pooling data across years is not necessary. As a result, the subscript corresponding to year t is dropped for simplicity.

If $C_i \sim \text{Log-Normal}(\mu_W, \sigma_W)$ with independence across individuals, then it follows that

$$\log(C_i) = \log(A_i) + \log(F_i)$$

has a normal distribution, which in turn means that $\log(A_i)$ and $\log(F_i)$ are also normally

distributed. The fact that individuals who withdraw a larger value of cash will likely need to do so fewer times than those who take out smaller values suggests a negative correlation between the two variables. Thus, the joint distribution will take the form

$$\begin{bmatrix} \log(A_i) \\ \log(F_i) \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mu_A \\ \mu_F \end{bmatrix}, \begin{bmatrix} \sigma_A^2 & \rho_{AF} \\ \rho_{AF} & \sigma_F^2 \end{bmatrix} \right),$$

with ρ_{AF} likely to be negative. For simplicity of notation, let $W_i = [\log(A_i) \ \log(F_i)]^T$, where the superscript T refers to a matrix transpose, and let μ and Σ represent the respective mean and covariance of W_i .

In order to determine distributional outliers, consider that if Λ is such that $\Lambda^T \Lambda \Sigma = \mathbf{I}_2$, the 2×2 identity matrix (in other words, Λ is the cholesky decomposition of Σ^{-1}), then the set of $Z_i = \Lambda^T (W_i - \mu)$ will be independent draws from a two-dimensional standard normal distribution. For the bivariate standard normal, $D_i = \|Z_i\|$ is the Euclidean distance of the i^{th} draw, Z_i , to the point $(0,0)$. Also, if $f(\cdot \mid \mathbf{0}, \mathbf{I})$ is the density function of the bivariate standard normal distribution then $D_i^2 > D_{i'}^2$ implies $f(Z_i \mid \mathbf{0}, \mathbf{I}) < f(Z_{i'} \mid \mathbf{0}, \mathbf{I})$. This implies that if $D_i^2 = D_{i'}^2$ then the density at Z_i is equal to that at $Z_{i'}$, which is why the bivariate standard normal curve has circular contour lines. The contour lines of a bivariate normal distribution with mean μ and variance Σ will be an ellipse centered at μ with points W_i and $W_{i'}$ having the same densities if and only if

$$(W_i - \mu)^T \Sigma^{-1} (W_i - \mu) = (W_{i'} - \mu)^T \Sigma^{-1} (W_{i'} - \mu).$$

Transforming the N independent draws from the true distribution to N independent draws of the bivariate distribution makes it easier to work with the data. This transformation preserves the sense of distance from the mean with respect to the assumed density (which is lower for less likely points and decreases as one moves away from the mean). Therefore, if W_i and $W_{i'}$ are such that $D_i^2 > D_{i'}^2$ then $f(W_i \mid \mu, \Sigma) < f(W_{i'} \mid \mu, \Sigma)$. So, the extremity of each of the N points can be measured by comparing the distances D_i^2 .

It is known that D_i^2 are independent and identically distributed random variables from the $\text{Exp}(0.5)$ or equivalently a Chi-Square(2) distribution. Therefore, we can easily determine the 98th percentile for D_i^2 , which we call $q_{.98}$.

For all observation pairs for which $D_i^2 > q_{.98}$, the procedure reassigns the data entry to a point more consistent with the fitted distribution but a minimum distance from the original value. Specifically, the data point is reassigned so that its new distance is exactly $\sqrt{q_{.98}}$.

Algorithm 2 Preprocessing: Monthly Cash Withdrawal

Let $w_i = (\log(a_i), \log(f_i))$ for all $i = 1, \dots, N$
Estimate $\hat{\mu} = \text{mean}(w_i)$ and $\hat{\Sigma} = \text{var}(w_i)$ from sample statistics of the w_i
Calculate $\hat{\Lambda}$ such that $\hat{\Lambda}^T \hat{\Lambda} = \hat{\Sigma}^{-1}$
Calculate $q_{.98}$ based on $\hat{\mu}$ and $\hat{\Sigma}$
for $i = 1, \dots, N$ **do**
 Calculate $z_i = \hat{\Lambda}^T (w_i - \hat{\mu})$
 Calculate $d_i^2 = \|z_i\|^2$
 if $d_i^2 \leq q_{.98}$ **then**
 Calculate z_k^{new}
 Calculate $w_k^{new} = \hat{\mu} + \hat{\Lambda}^{-T} z_k^{new}$
 Replace w_k with w_k^{new}
 end if
end for
Keep changes to w_i only if $\log(a_i) < \hat{\mu}_A$ and $\log(f_i) < \hat{\mu}_F$.

The imputation procedure is exactly the same as in previous years. First, Z_i is reassigned to Z_i^{new} , which corresponds to a well-known constrained optimization problem. Namely, Z_i^{new} is such that $\|Z_i^{new} - Z_i\|$ (the distance between the old and new points) is minimized, subject to the condition $\|Z_i^{new}\|^2 = q_{.98}$. Optimization programs for this paradigm are available for most computational packages (Press et al. 2007). The new value, Z_i^{new} , is then converted from the standard normal distribution to a corresponding value on the bivariate normal distribution defined by μ and Σ by letting

$$W_i^{new} = \mu + \Lambda^{-T} Z_i^{new}.$$

In practice, μ and Σ are not known and must be estimated from the data. We use lower-case notation, such as $w_i = (\log(a_i), \log(f_i))$, to represent the actual values observed in any given survey year, and estimate the bivariate mean and covariance with $\hat{\mu}$, the sample mean, and $\hat{\Sigma}$, the sample covariance. The entire procedure is outlined in Algorithm 2. In addition, Figure 7 shows the result of the heretofore outlined cleaning algorithm applied to the 2012 cash withdrawal data from the primary source. The plot shows an ellipse corresponding to the 98 percent confidence interval for any observation from the Log-Normal distribution defined by the parameters estimated from the sample. Via the preprocessing, all points outside this region are moved to the nearest point on the ellipse.

This procedure results in the editing of observations which are extreme with respect to the general mass of the sample data, even if the total monthly dollar value is reasonable. For example, if a person reports an amount of 1 dollar per withdrawal and a frequency of 0.25

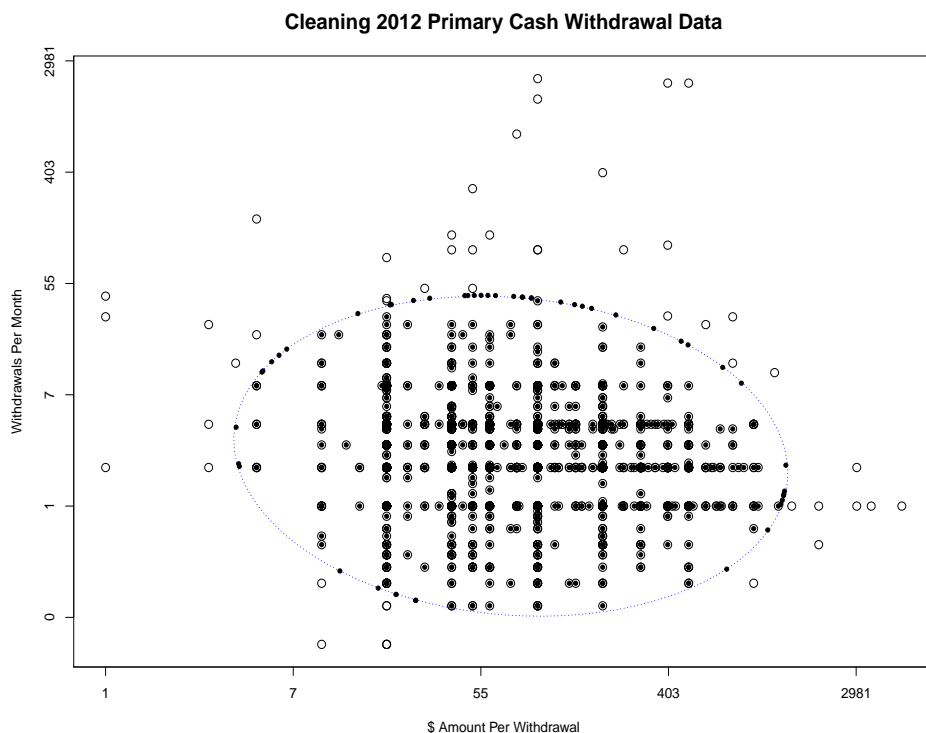


Figure 7: A diagram of the cleaning algorithm for cash withdrawal data. Circles represent original data and filled-in points represent the cleaned data (both plotted on the log-scale).

withdrawals per month, the corresponding pair on the log-scale will be $(0, -1.38)$, which could be determined to be extreme given the much higher average values of frequency and amount. Thus, additional rules to exclude points from the editing procedure above may be desired. One option is not to edit any pairs for which the implied monthly dollar total is below some threshold. A second option is to consider outliers by the quadrant they lie in. For the SCPC data, a rule is imposed so that no changes are made to data for which $\log(a_i) < \hat{\mu}_A$ and $\log(f_i) < \hat{\mu}_F$.

6.2.3 Preprocessing: Cash Holdings

The SCPC also collects the dollar value of cash holdings. This concept is collected as two variables: the value of cash holdings on person and the the value of cash holdings stored at home (or other locations). We treat each variable separately, as there is no clear relationship that one would expect to exist between the two. For the dollar values, we adopt the one-dimensional version of Algorithm 2 used to clean the cash withdrawal variables. Because other than in dimension, the algorithm is identical, we do not provide more information for

the procedure or delve into any details.

Figure 8 shows the distribution of the right tails of cash holdings for each of the two variables. As indicated, this cleaning procedure results in no edits to the cash holdings on person. The maximum reported values for the four years range from \$2,000 to \$5,000. These values are large, and it is certainly plausible that an input error caused \$20.00 to be coded as \$2,000. At the same time, the reported values are plausible and the presence of other observations of this magnitude suggests that there is not enough evidence to edit these values.

With respect to cash holdings at home, a datapoint corresponding to \$600,000 in 2012 was winsorized to \$100,000, which was the next highest value and the highest reported value in the other years.



Figure 8: Boxplots of right tails of cash holdings. The asterisk represents the only edited value.

6.2.4 Preprocessing: Prepaid Card Reloading

A variable that is collected with a similar methodology to the value of cash withdrawal is that of value reloaded onto prepaid cards. Much like the former, prepaid card reloading is characterized as a combination of the frequency of reloading with the typical amount

reloaded each time. Consequently, we apply the algorithm outlined in Section 6.2.2 above. From a practical point of view, the main difference is that there are fewer observations for prepaid card reloading, as one must not only be an adopter of reloadable prepaid cards, but also actively reload them.

The cleaning algorithm is depicted in Figure 9 for the 2011 and 2012 SCPC data. Both figures reveal a few edits to the data, predominantly relating to high dollar values per reloading. Effects on the summary statistics are minimal. In fact, in both 2011 and the 2012, the mean frequency of reloading is not changed up to the first decimal place by the cleaning.

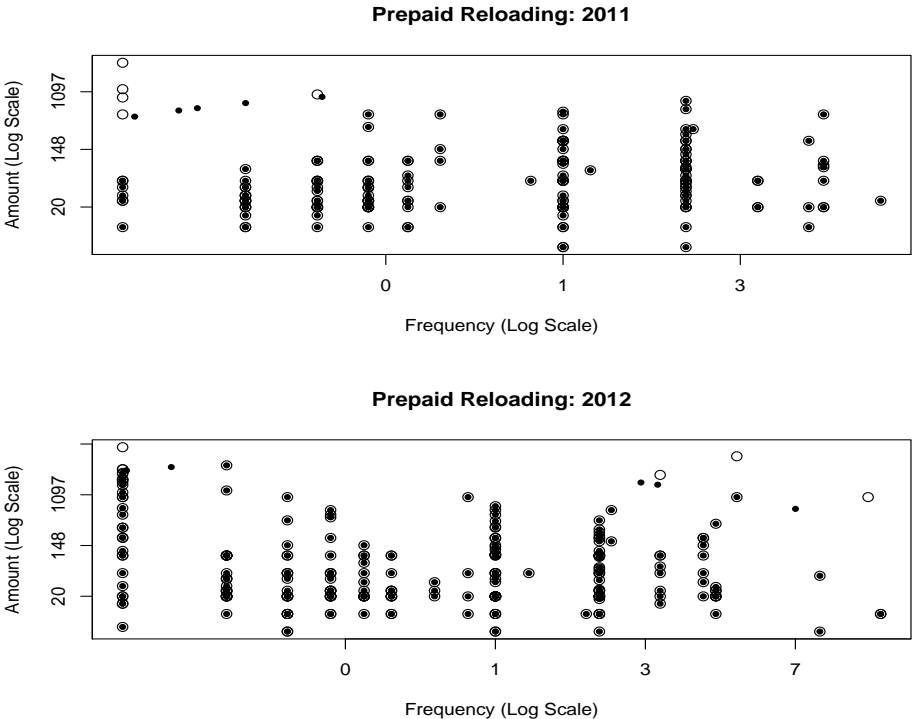


Figure 9: A diagram of the cleaning algorithm for prepaid card reloading data. Circles represent original data and filled-in points represent the cleaned data (both plotted on the log-scale).

6.2.5 Preprocessing: Value Stored on Prepaid Cards

A fourth variable for which dollar values are reported is the total dollar value stored on prepaid cards. In different years, this variable is collected in different ways: in some years, such as 2010, it is reported outright, while in other years it is an aggregate of the reported total for different sub-categories of prepaid cards. Because we are mostly interested in the total value, we are interested in cleaning the aggregated variable.

As these data are in the form of a dollar amount similar to cash holdings, it would seem that a one-dimensional version of Algorithm 2 would be well-suited for cleaning these data. However, this turns out not to be the case. Figure 10 shows the reported dollar values stored on prepaid cards by year. The aspect of the plot that stands out the most is the fat tail in 2010, which is significantly heavier in the right-tail than that in other years. While in all other years, fewer than 1 percent of values were over \$6,000, in 2010, almost 13 percent of values were above this threshold. As a result, the log-normal cleaning used for the other cash variables does not work well in this situation. There is simply too much weight in the tails of the 2010 data to recognize these values as outliers. At the same time, it seems unlikely that the distribution for this year is so different from those of the remaining years.

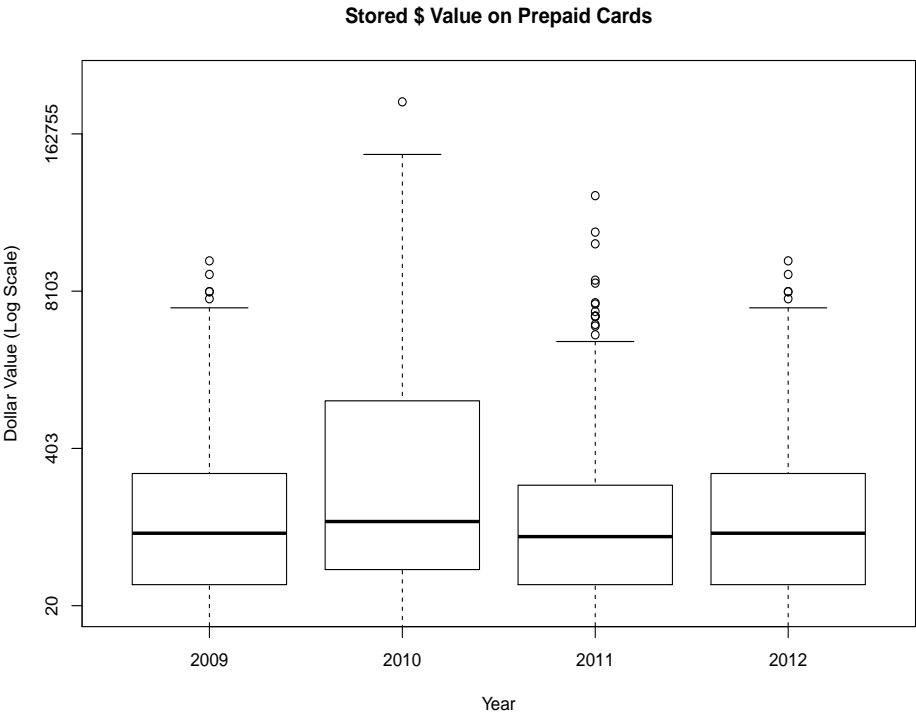


Figure 10: Boxplots of total value stored on prepaid cards.

Because of the complication resulting from the heavy tail, we resorted to a simpler methodology. The reported value of \$6,000 roughly corresponds to a Cook’s distance of 0.1 in 2009, 2011, and 2012, when considering unweighted, yearly means. Such a Cook’s distance is often considered to be the threshold for an influential point. Based on this, the CPRC bases all analysis only on values under \$6,000, treating all values above it as missing.

6.3 Summary of Edited Variables

In this section, we summarize the variables that are edited by the CPRC. In most cases, the edited variables are created by the CPRC as a function of various survey variables, which are any variables directly measured in the SCPC. In such cases, the underlying survey variables and any other underlying created variables that define the concept of interest are left unedited. The exceptions are the payment use variables, where the frequency-converted survey variables are edited. The original payment use survey variables remain unedited and are still reported in weekly, monthly, or yearly frequencies.

Any variables that are defined as functions of edited variables are created using edited data. Perhaps most importantly, all variables relating to payment use from “csh_typ,” which defines the number of cash payments, to “paper_typ,” which defines the number of payments made with cash, check, or money order, to “tot_pay_typ,” which defines the total number of monthly payments, are aggregates of the lowest-level entries for payment use. All statistics for such variables are created using the cleaned versions of data for each combination of payment method and transaction type. Thus, researchers who are interested in comparing the unedited variables must reconstruct any created variables themselves. All unedited variables are available, and are classified by an “_unedited” or “_unedit” (in order to keep variable names below a certain number of characters) at the end of the variable name. For example, “csh_amnt_1st” holds all edited entries for the dollar value of cash withdrawn from the primary location, while “csh_amnt_1st_unedited” defines the unedited version of the data. Table 20 lists all variables that are edited by the CPRC.

Variables Cleaned (Description of Algorithm)	Notes
<i>Payment Instrument Use</i> (Section 6.2.1) pu002_a, pu002_b, pu002_c, pu002_d, pu002_e, pu003_a, pu003_b, pu003_c, pu003_d, pu004_a, pu004_b, pu004_bmo, pu004_c, pu004_d, pu004_e, pu005_a, pu005_amo, pu005_b, pu005_c, pu005_d, pu005_e, pu006a_a, pu006a_b, pu006a_bmo, pu006a_c, pu006a_d, pu006a_e, pu006c_a, pu006c_b, pu006_bmo, pu006c_c, pu006c_d, pu006c_e, pu021_a, pu021_b, pu021_bmo, pu021_c, pu021_d, pu021_e, pu021_f, pu008_c	Variables based on these variables use edited data.
<i>Cash Withdrawal Value</i> (Section 6.2.2) csh_amnt_1st, csh_freq_1st, csh_amnt_2nd, csh_freq_2nd	Underlying variables remain unedited.
<i>Cash Holdings Value</i> (Section 6.2.3) csh_wallet, csh_house	Underlying variables remain unedited.
<i>Prepaid Reloading Value</i> (Section 6.2.4) svc_reload_freq, svc_reload_amnt	Underlying variables remain unedited.
<i>Prepaid Value Stored</i> (Section 6.2.5) svc_value	Underlying variables remain unedited.

Table 20: Summary of edited variables. “Underlying variables” are any survey or created variables that define some created variable.

7 Population Parameter Estimation

An important goal of the data collection in the SCPC is to produce estimates of consumer payment behavior for the entire population of U.S. consumers, including changes from one year to the next. This section details the model that provides a framework for achieving both of these goals. The model is presented in a general way so that it can easily be applied to a variety of measured variables, ranging from binary measurements of payment instrument adoption to count data such as typical number of monthly payments. Let Y_{ijt} be the measurement for person i , for category $j = 1, \dots, J$ in year $t = 1, \dots, T$. In the context of the number of monthly payments, for example, j could correspond to the number of payments made with payment method j .

Within the entire population, the identifier i will range from 1 to the total number of consumers over the years in question. However, within the sample, the respondent identifier i ranges from 1 to N , where N represents the total number of unique respondents in all three years. Let w_{it} designate the survey weight of person i in year t . J will naturally vary with the area of application and, for the 2012 SCPC, $T = 5$, with the years counted starting from 2008. Taking the function $1_{[t=x]}$ to be 1 when $t = x$ and 0 otherwise, a natural model for the population means is

$$Y_{ijt} = \mu_{j1}1_{[t=1]} + \mu_{j2}1_{[t=2]} + \dots + \mu_{jT}1_{[t=T]} + \epsilon_{ijt}, \quad (1)$$

where ϵ_{ijt} are mean 0 random variables with $\text{Var}(\epsilon_{ijt}) = \sigma_{jt}^2$ and $\text{Cov}(\epsilon_{ijt}, \epsilon_{i'j't'}) = \rho_{jtt'}$ for $i = i'$ and $j = j'$. This model is focused on estimating the population means, $\mu_j = [\mu_{j1} \mu_{j2} \dots \mu_{jT}]^T$, and it can correspond to a variety of underlying processes on the microeconomic scale. For example, in the context of typical monthly payments, such a model could correspond to a process in which each person conducts a random number of total transactions, where the totals are statistically dependent for each consumer across years. Then, the payment option used for each transaction is chosen independently according to some set of probabilities that are also allowed to vary from year to year.

In order to provide the formulas for estimating the population parameters as a function of the observed sample, we introduce the following variables. Let N_{jt} represent the number of responses obtained for category j in year t , and let $N_{jtt'}$ represent the number of respondents who gave responses for category j in both year t and year t' . Defining $N_j = \sum_{t=1}^T N_{jt}$, let \mathbf{Y}_j be the $N_j \times 1$ vector with all of the responses relating to category j over all T years. In addition, let \mathbf{X}_j be a $N_j \times T$ matrix defined as follows. The (k, t) th element of the matrix,

$\mathbf{X}_j[k, t]$, will be 1 if the k^{th} element of \mathbf{Y}_j was observed in year t , and 0 otherwise. Finally, \mathbf{W}_j is an $N_j \times N_j$ diagonal matrix such that the k^{th} element of the diagonal corresponds to the weight of the individual corresponding to the k^{th} element in \mathbf{Y}_j in the year when that observation was made. Then, according to established theory (Lohr 1999), the estimates of the population vector μ_j will be

$$\hat{\mu}_j = (\mathbf{X}_j^T \mathbf{W}_j \mathbf{X}_j)^{-1} \mathbf{X}_j^T \mathbf{W}_j \mathbf{Y}_j. \quad (2)$$

Before we proceed, note that the population estimates calculated from the model, given in (2), correspond to the natural, design-based estimates given by the SURVEYMEANS procedure in SAS (SAS Institute Inc. 1999). Namely, if we define $\mathcal{S}_{jtt'}$ to be the index of all respondents who provided a valid data entry for category j in year t and t' , then

$$\hat{\mu}_{jt} = \frac{\sum_{i \in \mathcal{S}_{jtt}} w_{it} y_{ijt}}{\sum_{i \in \mathcal{S}_{jtt}} w_{it}}.$$

It should also be noted that although the point estimates of the μ_j are the same as those in a weighted least squares, we are conceptually fitting a regression model with weights designed to scale the sample data to generate estimates for a finite population (see Lohr 1999, section 11.2.3). Therefore, unlike in the weighted-least squares case, the covariance of the estimates, $\mathbf{\Lambda}_j = \text{Cov}(\mu_j)$ will be estimated by

$$\hat{\mathbf{\Lambda}}_j = (\mathbf{X}_j^T \mathbf{W}_j \mathbf{X}_j)^{-1} \mathbf{X}_j^T \mathbf{W}_j \hat{\mathbf{\Sigma}}_j \mathbf{W}_j \mathbf{X}_j (\mathbf{X}_j^T \mathbf{W}_j \mathbf{X}_j)^{-1},$$

where $\hat{\mathbf{\Sigma}}_j$ is the Huber-White sandwich estimator of the error variances, $\text{Var}(\mathbf{Y}_j)$ (Eicker 1967; Huber 1967; White 1980). In this context, this means that

$$\hat{\sigma}_{jt}^2 = \frac{1}{N_{jt} - T} \sum_{k \in \mathcal{S}_{jtt}} (y_{kjt} - \hat{\mu}_{jt})^2$$

and

$$\hat{\rho}_{jtt'} = \frac{1}{N_{jtt'} - T} \sum_{k \in \mathcal{S}_{jtt'}} (y_{kjt} - \hat{\mu}_{jt})(y_{kjt'} - \hat{\mu}_{jt'}).$$

7.1 Standard Errors and Covariances

In addition to the important population means $\hat{\mu}_j$, the analysis above gives the estimates' covariances $\hat{\mathbf{\Lambda}}_j$. The square roots of the diagonal entries of $\hat{\mathbf{\Lambda}}_j$ correspond to the standard errors of the yearly mean estimates. The standard errors for the population estimates corresponding to the 2010–2012 SCPC are available at <http://www.bostonfed.org/economic/cprc/SCPC>.

The standard errors themselves give a sense of how much faith we have that the estimates are accurate given the stratum weights. Larger standard errors will denote more uncertainty in the true population values. As the standard error tables show, it is generally true that the standard errors in the year 2008 are considerably higher than those of the later years. This is so primarily because the sample size grew considerably from 2008 to 2009, giving a more accurate picture of the average behaviors.

The off-diagonal elements of $\hat{\mathbf{\Lambda}}_j$ correspond to the $\text{Cov}(\hat{\mu}_{jt}, \hat{\mu}_{jt'})$, which, when divided by $\sqrt{\text{Var}(\hat{\mu}_{jt})\text{Var}(\hat{\mu}_{jt'})}$, yield a correlation. This correlation reflects the extent to which estimates based on the samples within the assumed sampling scheme relate to one another. If the samples for two years did not include any of the same individuals, independence across individuals would imply that the correlations would be zero. However, as there is overlap, one expects positive correlations between estimates for two different years.

As an example, consider the results for the population average number of typical weekly debit card uses conditional on debit card adoption (*dcu*) and the proportion of the population that are debit card adopters (*dca*). For the three years of data collection, the correlation matrices for the two statistics are given by

$$\text{Corr}(dcu_{10,11,12}) = \begin{bmatrix} \mathbf{1.4} & 0.21 & 0.25 \\ 0.21 & \mathbf{0.9} & 0.52 \\ 0.25 & 0.52 & \mathbf{0.8} \end{bmatrix} \quad \text{and} \quad \text{Corr}(dca_{10,11,12}) = \begin{bmatrix} \mathbf{0.016} & 0.36 & 0.33 \\ 0.36 & \mathbf{0.013} & 0.55 \\ 0.33 & 0.55 & \mathbf{0.013} \end{bmatrix},$$

where the diagonal values in bold represent standard errors. In general, the correlations are higher for adoption values. This might be expected, as ownership of a payment instrument is more likely than the degree of use of that instrument to be the same in two consecutive years. The noticeably lower correlations between estimates from the earlier two years than those from the later two years can be partially explained by a lower level of overlap in respondents and a higher variance of estimates in 2010.

7.2 Functions of Population Means

While the most interesting population parameters are the μ_{jt} in (1) themselves, we are also interested in some variables that are functions of these population parameters. Perhaps the two most insightful functions from an economic standpoint are the growth rates and the shares. In this work, we choose to work with the macroeconomic definition of each, meaning that we consider the growth rate of the averages rather than the average of the individual growth rates. We thus let

$$g_{jt} = \frac{\mu_{j,t+1} - \mu_{jt}}{\mu_{jt}} \quad (3)$$

be the growth rate of category j from year t to $t + 1$, and

$$s_{jt} = \frac{\mu_{jt}}{\sum_{k=1}^J \mu_{kt}} \quad (4)$$

be the share of category j in year t .

The macroeconomic definitions used in (3) and (4) should be contrasted with their microeconomic alternatives. The former involve defining individual shares for each category, $s_{ijt} = \frac{y_{ijt}}{\sum_{k=1}^J y_{ikt}}$ and estimating s_{jt} by applying (1) and (2) to this individual variable. The macroeconomic approach is statistically sounder, as, under most models that treat individuals as independent, it will give the maximum likelihood estimates of the parameters in question. For example, if the total number of payments for person i at time t is Y_{it} modeled as a Poisson random variable and the number assigned to category j , Y_{ijt} is a binomial distribution conditional on Y_{it} with probability p_{jt} , then the maximum likelihood estimates for the p_{jt} will be given by $\frac{\sum_i Y_{ijt}}{\sum_i Y_{it}}$ rather than $\sum_i \frac{Y_{ijt}}{NY_{it}}$ (in this example, we have made all weights equal to simplify the equations). Thus, throughout this analysis, we generally use the macroeconomic definitions.

7.2.1 Generating U.S. Aggregate Estimates

The term μ_{jt} in (1) represents a population mean in year t . For example, if the variable of interest is the number of payments made in a typical month with cash, then μ_{jt} represents the average of this value with respect to all U.S. adult consumers. In theory, if $\hat{\mu}_{jt}$ is an estimate of this mean, then a corresponding estimate for the aggregate number among the entire population would be $\hat{\mu}_{jt}$ multiplied by the size of the population. However, such calculations must be taken with caution. The estimates of μ_{jt} from the SCPC are likely to be fairly

variable due to the relatively small sample size and variation in the post-stratification weights. Thus, while the estimates might be unbiased, any one estimate based on a particular sample is potentially a relatively poor estimate of μ_{jt} . Any difference between $\hat{\mu}_{jt}$ and μ_{jt} is magnified when multiplied by the U.S. population, making the resulting estimate a potentially poor estimate of the population aggregate. The high degree of error in these aggregate estimates is the reason we recommend that such methodologies be taken with caution. Issues of bias in the estimates could arise as a result of the sampling instrument and potential measurement errors. For example, the SCPC asks respondents for their personal rather than household payment choices. Inability to clearly delineate all payments related to the household, such as bills, could lead to systematically inaccurate responses.

7.2.2 Data Suppression

Many population estimates in the SCPC are based on a subset of the sample. For example, estimates for adopters of payment instruments are naturally based only on respondents who claimed to be adopters of the payment instrument in question. In some cases, the set of eligible respondents can be quite small, resulting in an unreliable estimate. As a result, in the data tables found in the 2011–2012 SCPC report (Foster, Schuh, and Stavins 2014), estimates that are based on a small number of responses are suppressed.

The CPRC uses two thresholds: one for categorical data and one for numerical data. The threshold for categorical data is 20 while that for numerical data is 50. That is, if the number of respondents is lower than the corresponding threshold, the estimated population average is not reported in the tables. Numerical data are given a higher threshold because many of the variables, such as those relating to dollar amounts or number of uses, are heavy-tailed and thus highly variable. Thus, a larger number of responses are required to produce reasonably reliable estimates. As can be seen in Klein et al. (2002), which details rules for suppression in various surveys, the thresholds adopted by the CPRC are comparable to those adopted by other U.S. government agencies.

8 Hypothesis Tests for Temporal Changes in Consumer Payments

Knowledge of $\hat{\mu}_j$ and $\hat{\Lambda}_j$ for all $j = 1, \dots, J$ also allows one to make inferences and test hypotheses about the population across the different years. In the following subsections, we

delineate and conduct a variety of hypothesis tests with the general goal of assessing changes in population estimates across years.

Sections 8.1–8.3 provide the methodology for three different types of hypothesis tests. The applications for the SCPC data are found below in Section 10. Hypothesis tests are made comparing 2010 to 2012 as well as 2011 to 2012. Many tests are performed, and they are organized by subject matter.

8.1 Hypothesis Tests for Means

Perhaps the most basic assertion one would like to make is the degree to which the population means change over time. Therefore, in the context of the model outlined above, we consider the following hypotheses:

$$H_o : \mu_{jt} = \mu_{jt'} \quad H_a : \mu_{jt} \neq \mu_{jt'}.$$

In order to do so, we need to estimate $\text{Var}(\mu_{jt'} - \mu_{jt})$, which we do by estimating the identity:

$$\text{Var}(\mu_{jt'} - \mu_{jt}) = \text{Var}(\hat{\mu}_{jt'}) + \text{Var}(\hat{\mu}_{jt}) - 2\text{Cov}(\hat{\mu}_{jt'}, \hat{\mu}_{jt})$$

with

$$\hat{\text{Var}}(\mu_{jt'} - \mu_{jt}) = \hat{\Lambda}_j[t', t'] + \hat{\Lambda}_j[t, t] - 2\hat{\Lambda}_j[t, t'].$$

Now, under the null hypothesis, the test statistic

$$Z = \frac{\hat{\mu}_{jt'} - \hat{\mu}_{jt}}{\sqrt{\hat{\text{Var}}(\mu_{jt'} - \mu_{jt})}}$$

is approximately distributed as a standard normal distribution. This fact allows us to calculate p-values and accordingly accept or reject the null hypotheses.

8.2 Hypothesis Tests for Growth Rates

In addition to changes in population means, tests for the significance of the change in the growth rates of the means from one year to the next are developed. With the growth rate in a given year t defined as in (3), $\Delta_{jt} = g_{j,t+1} - g_{jt}$ is the change in growth rates over two

consecutive years, which, written in terms of the means, takes the form

$$\Delta_{jt} = \frac{\mu_{j,t+1}}{\mu_{jt}} - \frac{\mu_{jt}}{\mu_{j,t-1}}.$$

Of course, Δ_{jt} is a nonlinear function of the means, which means that conducting a hypothesis test is no longer as simple. However, the delta method (Casella and Berger 2002) allows one to approximate the distribution of $\hat{\Delta}_{jt}$ by approximating the relationship between Δ_{jt} and the μ_{jt} through linearization. Since $\hat{\mu}_{jt}$ are close to normally distributed, a linear function of these variables will also be normally distributed. Let $f_{jt}(\cdot)$ be the function that maps the vector μ_j to Δ_{jt} and let $[\partial \mathbf{f}_{jt}]$ be the 1×3 vector such that the i^{th} element is $\frac{\partial f(\mu_j)}{\partial \mu_{ji}}$. Then, if the $\hat{\mu}_j$ are asymptotically normally distributed, the delta method tells us that

$$\hat{\Delta}_{jt} \rightarrow_D N(f(\hat{\mu}_{jt}), [\partial \mathbf{f}_{jt}] \hat{\mathbf{\Lambda}}_j [\partial \mathbf{f}_{jt}]^T),$$

where \rightarrow_D indicates a convergence in distribution as the sample size gets larger.

With this result, the test for the null hypothesis

$$H_o : \Delta_{jt} = 0 \quad H_a : \Delta_{jt} \neq 0,$$

relies on calculating the statistic

$$z = \frac{\hat{\Delta}_{jt}}{\sqrt{[\partial \mathbf{f}_{jt}] \hat{\mathbf{\Lambda}}_j [\partial \mathbf{f}_{jt}]^T}}$$

and using the normal distribution to calculate a p-value. While the assumption of normality of the resulting Δ_{jt} is only an approximation, it is likely to be a poor one if μ_{jt} or $\mu_{j,t-1}$ is small (near 0). In this case, the approximation of local linearity used in the delta method is not a good one, and the assumed distribution of Δ_{jt} does not match the real one, which will be more skewed than a normal density curve. This means that the p-value calculated from the above process might be a poor approximation to reality.

8.3 Hypothesis Tests for Shares

From an economic standpoint, it is not just the level of use of each payment method but also the relative prevalence of payments made by a particular payment method that matters. The relative prevalence, in many ways, most directly gets at the heart of a consumer's choice of

payment method. One can view each individual as needing to make some (random) number of payments over the course of a period of time, including for bills, groceries, and other fairly regular payments, along with other, less predictable payments. Given these necessary payments, it is up to the consumer to decide how to execute each transaction. The decision reflects a variety of factors such as convenience, cost, and acceptance of the payment method, which is why the prevalence of payments is important to economists. The level of use or growth rate will not reflect these aspects of the decision, since a decrease of use in terms of frequency per month could actually correspond to an increase in prevalence if the total number of payments decreased.

There are two statistics that can be used to measure prevalence. The first statistic is the relative growth differential (RGD), which measures the difference between the growth rate in the use of a particular payment option and the overall growth rate in the total number of payments. After some simple algebra, the RGD for payment option j from year t to t' is

$$G_{jtt'} = \frac{\mu_{jt'}}{\mu_{jt}} - \frac{\sum_{k=1}^J \mu_{kt'}}{\sum_{k=1}^J \mu_{kt}}. \quad (5)$$

The second commonly used statistic is the share differential (SD), defined to be the difference in the percentage of all payments made by payment option j in two years. The mathematical form is

$$S_{jtt'} = \frac{\mu_{jt'}}{\sum_{k=1}^J \mu_{kt'}} - \frac{\mu_{jt}}{\sum_{k=1}^J \mu_{kt}}. \quad (6)$$

In each case, the statistics of interest are nonlinear functions of the μ_{jt} and are evidently dependent, making hypothesis testing more complicated. Again, the delta method is used, although now it involves a joint, multi-variable hypothesis test. As mentioned above, normal approximations to growth rates can be poor when the means are close to 0. The share differential will not have this problem in this scenario, because the denominator, as the mean number of monthly payments, will be large, making the linear approximation inherent in the delta method a good one. For this reason, share differential is adopted as a preferred measure of relative prevalence.

Below, the methodology for the multivariate delta method hypothesis test (Casella and Berger 2002), as applied to the share differentials, is explained. For simplicity of notation, let S_j stand for $S_{jtt'}$ in the following paragraphs. The necessity of a multivariate test is due to the clear dependence between S_j and $S_{j'}$. In fact, $S_J = -\sum_{j=1}^{J-1} S_j$. This issue of

dependence means that the joint hypothesis test takes the form

$$H_o : S_1 = S_2 = \dots = S_{J-1} = 0 \quad H_a : S_j \neq 0 \text{ for at least one } j.$$

Now, let $\hat{\mathbf{S}} = [\hat{S}_1 \hat{S}_2 \dots \hat{S}_J]^T$, and let $\mathbf{h}(\mu_t, \mu_{t'})$ be the function that maps the population means to the share differential statistics with $[\partial \mathbf{h}(\mu_t, \mu_{t'})]$, the matrix of partial derivatives $\frac{\partial h(\mu_t, \mu_{t'})}{\partial \mu_{j,k}}$ for $k = t, t'$ and $j = 1, \dots, J$. Now, letting $\hat{\mathbf{\Lambda}}_{tt'}$ be the data estimate of the covariance of $[\mu_{1t} \dots \mu_{Jt} \mu_{1t'} \dots \mu_{Jt'}]^T$, the multivariate version of the delta method tells us that

$$\hat{\mathbf{S}} \rightarrow_D N \left(\mathbf{h}(\hat{\mu}_t, \hat{\mu}_{t'}), [\partial \mathbf{h}(\mu_t, \mu_{t'})] \hat{\mathbf{\Lambda}}_{tt'} [\partial \mathbf{h}(\mu_t, \mu_{t'})]^{-1} \right).$$

For simplicity of notation, let

$$\mathbf{C}_{tt'} = [\partial \mathbf{h}(\mu_t, \mu_{t'})] \hat{\mathbf{\Lambda}}_{tt'} [\partial \mathbf{h}(\mu_t, \mu_{t'})]^T.$$

The matrix $\mathbf{C}_{tt'}$ estimates the variances and covariances of the sample statistics $S_{jtt'}$ for $j = 1, \dots, J$. Given this approximate multivariate normal distribution of dimension J , it is known that under the null hypothesis, the statistic

$$Z = \hat{\mathbf{S}}_{tt'}^T \mathbf{C}_{tt'}^{-1} \hat{\mathbf{S}}_{tt'}$$

will be approximately Chi-square distributed with $J-1$ degrees of freedom. Therefore, $Z \sim \chi_{J-1}^2$, a fact that can be used to calculate a p-value corresponding to the hypothesis.

Of course, such a test provides insight only into whether the collection of share differentials is significantly different from the vector $\mathbf{0}$, but it is impossible to attribute the cause of the rejection to any particular payment method. However, one can consider whether the exclusion of any choice would make the relative share differentials of the remaining $J - 1$ choices consistent with the null hypothesis. Determining the joint 95 percent confidence intervals under the null hypothesis and studying the range of values observed within this interval for each payment choice provides some insight into this. In the case of a normal distribution and a null hypothesis that $S_j = 0$, this turns out to correspond to the one-dimensional 95 percent confidence interval for each option.

In addition to the one-dimensional 95 percent confidence intervals, it is useful to calculate the one-dimensional p-value for each observed share differential under the hypothesis that $S_j = 0$. While there is no straightforward way to determine which choice will result in the most similar set of all possible $J - 1$ share differentials based on the calculated p-values and

confidence intervals, choices corresponding to lower p-values and larger distances from the center of the confidence intervals, especially as they correspond to higher shares in the two years, are good candidates.

9 Future Work

Much work is currently being done at the CPRC and RAND to improve the SCPC. The overall goal is to improve the accuracy of estimates for various statistics relating to the population of U.S. consumers. This work involves modifying the questionnaire in order to elicit more reliable answers as well as improving the statistical methodology used in the data collection and data analysis. General areas of research and goals for future versions of the SCPC are as follows:

- Develop questions to capture trends in prepaid card use and mobile banking.
- Edit the survey instrument to collect more reliable information. This includes work on selecting optimal reporting periods for the number of payments, re-framing questions for improved recall, and incorporating instantaneous error-checking and data confirmation measures into the survey.
- Refine sample selection procedures to balance the extension of the longitudinal panel with better representativeness of the overall sample.
- Develop multiple imputation procedures for missing values, and incorporate these imputations into the estimation of population parameters.

10 Hypothesis Test Results

In this section, we provide in tabular form the results of various hypothesis tests, the methodology of which is detailed in Section 8. The tests are organized according to concept, namely adoption of instruments, use of payment instruments, and miscellaneous tests. As discussed previously, the SCPC considers payments in terms of payment instruments and type of transaction. Because certain instruments are naturally grouped together due to similarity, with the same going for transaction types, some hypothesis tests are related to broader groups of each. Specifically, we consider instruments as paper (cash, check, and money order), plastic (credit, debit, and prepaid cards), or online (online banking bill payment and bank account

number payments). In addition, we consider transactions as bills (automatic bill payments, online bill payments, in-person bill payments), online payments, or in-person nonbill payments (retail payments, payments for services, and person-to-person payments).

10.1 Adoption of Payment Instruments

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Cash	1.00	1.00	-0.00	-0.71	0.48
Check	0.87	0.85	-0.02	-0.95	0.34
MO	0.24	0.22	-0.02	-1.06	0.29
TC	0.06	0.01	-0.05	-6.49	0.00
Debit	0.78	0.78	0.00	0.03	0.98
Credit	0.70	0.72	0.02	0.89	0.37
Prepaid	0.38	0.52	0.14	6.69	0.00
OBBP	0.49	0.55	0.07	3.49	0.00
BANP	0.65	0.63	-0.02	-1.02	0.31
Income	0.17	0.16	-0.01	-0.72	0.47

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Cash	1.00	1.00	0.00	0.76	0.45
Check	0.85	0.85	-0.00	-0.08	0.94
MO	0.22	0.22	-0.01	-0.55	0.58
TC	0.02	0.01	-0.01	-2.89	0.00
Debit	0.77	0.78	0.02	1.49	0.14
Credit	0.70	0.72	0.02	1.96	0.05
Prepaid	0.51	0.52	0.01	0.58	0.56
OBBP	0.52	0.55	0.03	2.38	0.02
BANP	0.66	0.63	-0.03	-1.89	0.06
Income	0.21	0.16	-0.05	-3.54	0.00

Table 21: Adoption rates of payment instruments.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Paper	1.00	1.00	-0.00	-1.41	0.16
Card	0.94	0.97	0.03	2.14	0.03
Electronic	0.76	0.78	0.02	0.94	0.34

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Paper	1.00	1.00	0.00	0.76	0.45
Card	0.95	0.97	0.02	1.78	0.08
Electronic	0.78	0.78	-0.01	-0.38	0.70

Table 22: Adoption rates of payment instrument groups.

10.2 Use of Payment Instruments

10.2.1 Changes in Mean Number of Uses

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Cash	20.57	18.43	-2.14	-1.99	0.05
Check	7.37	6.55	-0.82	-2.56	0.01
MO	0.61	0.52	-0.08	-0.68	0.50
Debit	22.52	20.62	-1.90	-1.31	0.19
Credit	13.09	14.90	1.81	2.49	0.01
Prepaid	0.68	0.85	0.17	1.03	0.30
OBBP	3.15	3.21	0.07	0.34	0.73
BANP	3.33	3.26	-0.07	-0.34	0.74
Income	0.57	0.54	-0.03	-0.36	0.72
Total	71.89	68.89	-2.99	-1.15	0.25

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Cash	19.50	18.43	-1.07	-1.15	0.25
Check	6.93	6.55	-0.38	-1.32	0.19
MO	0.34	0.52	0.18	1.50	0.13
Debit	21.58	20.62	-0.95	-1.11	0.27
Credit	14.35	14.90	0.55	0.90	0.37
Prepaid	0.59	0.85	0.26	1.98	0.05
OBBP	3.26	3.21	-0.04	-0.27	0.79
BANP	3.38	3.26	-0.12	-0.76	0.45
Income	0.74	0.54	-0.20	-2.56	0.01
Total	70.67	68.89	-1.77	-0.95	0.34

Table 23: Mean number of payments per month by instrument.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Auto. Bill	6.03	6.12	0.09	0.19	0.85
Online Bill	5.79	6.68	0.89	2.40	0.02
Other Bill	9.20	9.17	-0.03	-0.06	0.95
Online	3.58	4.10	0.52	1.57	0.12
Retail	25.06	24.12	-0.94	-0.98	0.33
Service	18.03	15.37	-2.66	-3.55	0.00
P2P	4.19	3.34	-0.85	-2.74	0.01
Total	71.89	68.89	-2.99	-1.15	0.25

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Auto. Bill	6.55	6.12	-0.43	-1.32	0.19
Online Bill	6.19	6.68	0.49	1.63	0.10
Other Bill	9.83	9.17	-0.66	-1.21	0.23
Online	3.49	4.10	0.61	2.02	0.04
Retail	25.58	24.12	-1.46	-1.78	0.07
Service	15.71	15.37	-0.34	-0.58	0.56
P2P	3.32	3.34	0.02	0.08	0.93
Total	70.67	68.89	-1.77	-0.95	0.34

Table 24: Mean number of payments per month by instrument group.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Paper	28.55	25.50	-3.05	-2.55	0.01
Card	36.29	36.37	0.08	0.05	0.96
Electronic	6.47	6.47	0.00	0.00	1.00
Total	71.89	68.89	-2.99	-1.15	0.25

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Paper	26.77	25.50	-1.27	-1.19	0.24
Card	36.52	36.37	-0.14	-0.13	0.90
Electronic	6.64	6.47	-0.16	-0.68	0.50
Total	70.67	68.89	-1.77	-0.95	0.34

Table 25: Mean number of payments per month by transaction type.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Bill	21.01	21.96	0.95	0.85	0.40
Online	3.58	4.10	0.52	1.57	0.12
In Person	47.28	42.83	-4.45	-2.69	0.01
Total	71.89	68.89	-2.99	-1.15	0.25

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Bill	22.56	21.96	-0.60	-0.74	0.46
Online	3.49	4.10	0.61	2.02	0.04
In Person	44.61	42.83	-1.78	-1.37	0.17
Total	70.67	68.89	-1.77	-0.95	0.34

Table 26: Mean number of payments per month by groups of transaction types.

10.2.2 Changes in Growth Rates

	Growth Rate 2009 – 2010	Growth Rate 2010 – 2012	Difference	z-stat	p-value
Cash	3.35	-10.41	-13.75	-1.58	0.11
Check	-8.56	-11.09	-2.53	-0.38	0.70
MO	-8.99	-13.73	-4.74	-0.18	0.86
Debit	17.71	-8.43	-26.14	-1.99	0.05
Credit	15.85	13.84	-2.01	-0.21	0.83
Prepaid	-9.75	25.20	34.95	0.78	0.44
OBBP	0.24	2.17	1.93	0.18	0.86
BANP	21.94	-2.02	-23.95	-1.87	0.06
Income	20.94	-4.96	-25.90	-0.99	0.32
Total	8.65	-4.16	-12.81	-1.89	0.06

	Growth Rate 2010 – 2011	Growth Rate 2011 – 2012	Difference	z-stat	p-value
Cash	-5.21	-5.49	-0.28	-0.03	0.97
Check	-5.96	-5.45	0.51	0.07	0.94
MO	-43.34	52.26	95.60	2.06	0.04
Debit	-4.20	-4.41	-0.22	-0.03	0.98
Credit	9.61	3.86	-5.75	-0.70	0.49
Prepaid	-12.78	43.55	56.33	1.52	0.13
OBBP	3.59	-1.38	-4.97	-0.55	0.58
BANP	1.53	-3.49	-5.02	-0.57	0.57
Income	29.64	-26.69	-56.33	-2.57	0.01
Total	-1.70	-2.51	-0.81	-0.15	0.88

Table 27: Growth rates of monthly use by instrument.

	Growth Rate 2009–2010	Growth Rate 2010–2012	Difference	z-stat	p-value
Auto. Bill	26.61	1.53	-25.07	-1.46	0.15
Online Bill	11.87	15.39	3.51	0.26	0.79
Other Bill	13.61	-0.33	-13.94	-1.21	0.23
Online	-25.17	14.41	39.58	2.92	0.00
Retail	-7.92	-3.76	4.16	0.69	0.49
Service	39.99	-14.74	-54.74	-4.99	0.00
P2P	29.55	-20.31	-49.86	-3.05	0.00
Total	8.65	-4.16	-12.81	-1.89	0.06

	Growth Rate 2010–2011	Growth Rate 2011–2012	Difference	z-stat	p-value
Auto. Bill	8.71	-6.60	-15.31	-1.43	0.15
Online Bill	6.86	7.98	1.12	0.11	0.91
Other Bill	6.83	-6.70	-13.53	-1.15	0.25
Online	-2.64	17.51	20.15	1.48	0.14
Retail	2.06	-5.71	-7.76	-1.30	0.19
Service	-12.84	-2.18	10.66	1.63	0.10
P2P	-20.75	0.55	21.31	2.02	0.04
Total	-1.70	-2.51	-0.81	-0.15	0.88

Table 28: Growth rates of monthly use by transaction type.

	Growth Rate 2009–2010	Growth Rate 2010–2012	Difference	z-stat	p-value
Paper	-0.30	-10.68	-10.38	-1.48	0.14
Card	16.37	0.23	-16.14	-1.72	0.09
Electronic	10.33	0.02	-10.31	-1.08	0.28
Total	8.65	-4.16	-12.81	-1.89	0.06

	Growth Rate 2010–2011	Growth Rate 2011–2012	Difference	z-stat	p-value
Paper	-6.24	-4.74	1.50	0.21	0.83
Card	0.62	-0.39	-1.01	-0.16	0.87
Electronic	2.53	-2.45	-4.99	-0.73	0.47
Total	-1.70	-2.51	-0.81	-0.15	0.88

Table 29: Growth rates of monthly use by instrument groups.

	Growth Rate 2009–2010	Growth Rate 2010–2012	Difference	z-stat	p-value
Bill	16.54	4.53	-12.01	-1.06	0.29
Online	-25.17	14.41	39.58	2.92	0.00
In Person	9.12	-9.42	-18.53	-2.92	0.00
Total	8.65	-4.16	-12.81	-1.89	0.06

	Growth Rate 2010–2011	Growth Rate 2011–2012	Difference	z-stat	p-value
Bill	7.38	-2.65	-10.03	-1.20	0.23
Online	-2.64	17.51	20.15	1.48	0.14
In Person	-5.64	-4.00	1.65	0.31	0.76
Total	-1.70	-2.51	-0.81	-0.15	0.88

Table 30: Growth rates of monthly use by groups of transaction types.

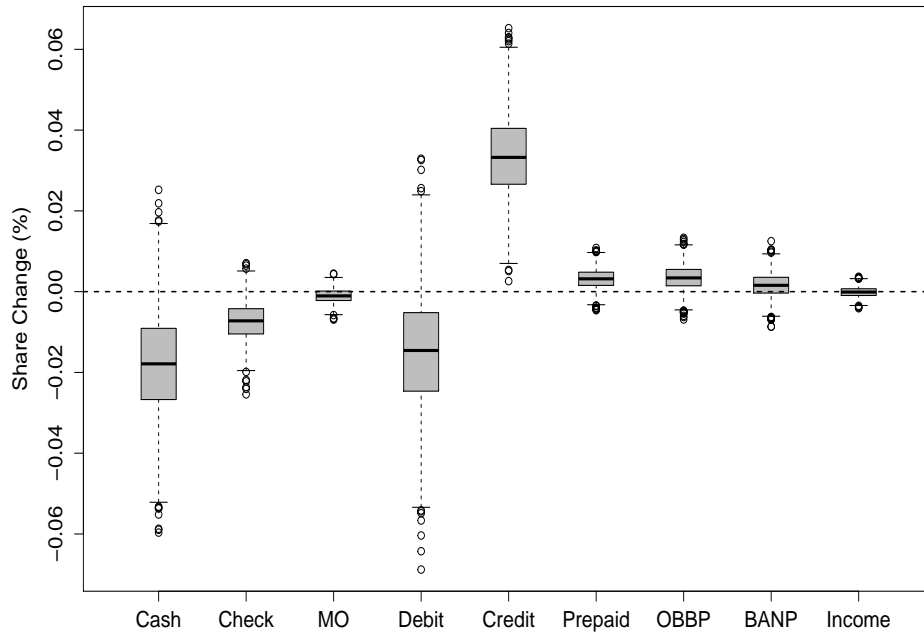
10.2.3 Changes in Share

	Shares in 2010	Shares in 2012	Difference
Cash	28.62	26.76	-1.87
Check	10.25	9.51	-0.74
MO	0.84	0.76	-0.08
Debit	31.33	29.93	-1.40
Credit	18.21	21.63	3.42
Prepaid	0.94	1.23	0.29
OBBP	4.38	4.66	0.29
BANP	4.63	4.73	0.10
Income	0.79	0.79	-0.01
Chi-stat			18.58
p-value			0.02

	Shares in 2011	Shares in 2012	Difference
Cash	27.60	26.76	-0.84
Check	9.80	9.51	-0.30
MO	0.49	0.76	0.27
Debit	30.53	29.93	-0.60
Credit	20.31	21.63	1.33
Prepaid	0.84	1.23	0.40
OBBP	4.61	4.66	0.05
BANP	4.78	4.73	-0.05
Income	1.05	0.79	-0.26
Chi-stat			16.01
p-value			0.04

Table 31: Share of monthly payments by instrument. See Figure 11 for marginal distributions.

Share Differences: 2010 – 2012



Share Differences: 2011 – 2012

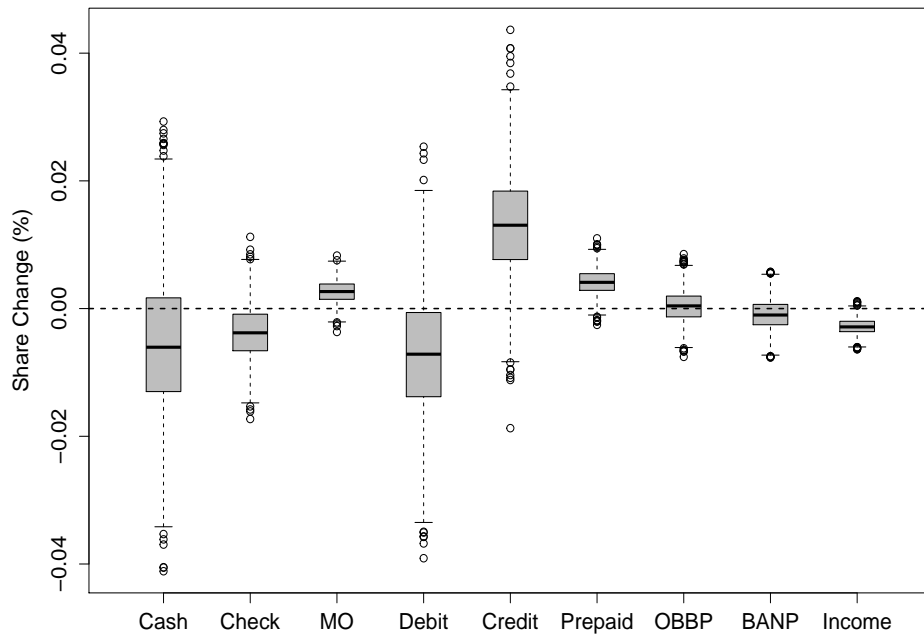


Figure 11: Share of monthly payments by instrument.

	Shares in 2010	Shares in 2012	Difference
Auto. Bill	8.38	8.88	0.50
Online Bill	8.05	9.70	1.64
Other Bill	12.80	13.31	0.51
Online	4.99	5.95	0.97
Retail	34.87	35.01	0.14
Service	25.08	22.31	-2.77
P2P	5.83	4.85	-0.98
Chi-stat			27.10
p-value			0.00

	Shares in 2011	Shares in 2012	Difference
Auto. Bill	9.27	8.88	-0.39
Online Bill	8.75	9.70	0.94
Other Bill	13.90	13.31	-0.60
Online	4.94	5.95	1.01
Retail	36.20	35.01	-1.19
Service	22.24	22.31	0.07
P2P	4.70	4.85	0.15
Chi-stat			12.53
p-value			0.05

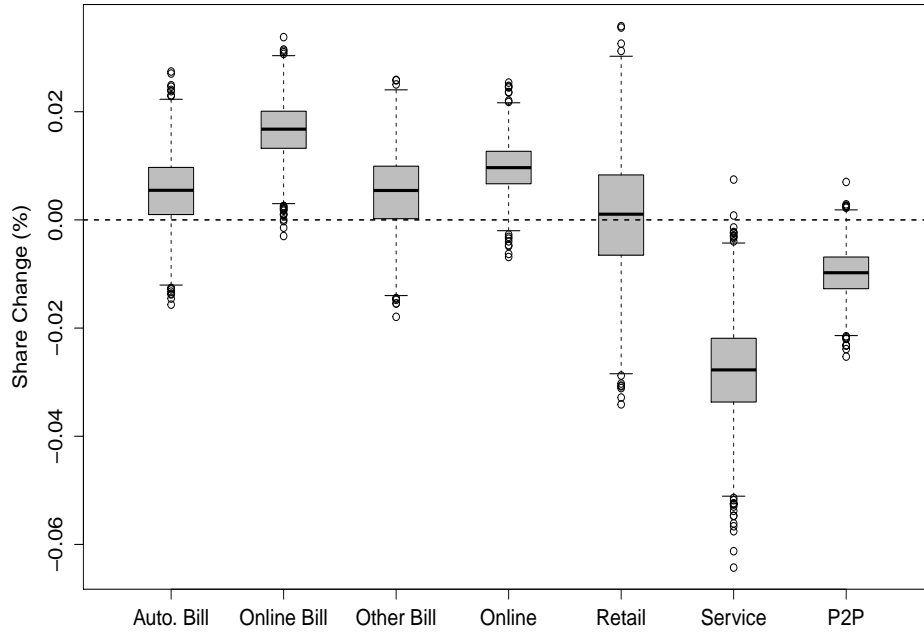
Table 32: Share of monthly payments by transaction type. See Figure 12 for marginal distributions.

	Shares in 2010	Shares in 2012	Difference
Paper	40.04	37.31	-2.73
Card	50.88	53.22	2.33
Electronic	9.08	9.47	0.40
Chi-stat			4.25
p-value			0.12

	Shares in 2011	Shares in 2012	Difference
Paper	38.29	37.31	-0.97
Card	52.22	53.22	0.99
Electronic	9.49	9.47	-0.02
Chi-stat			0.80
p-value			0.67

Table 33: Share of monthly payments by instrument groups. See Figure 13 for marginal distributions.

Share Differences: 2010 – 2012



Share Differences: 2011 – 2012

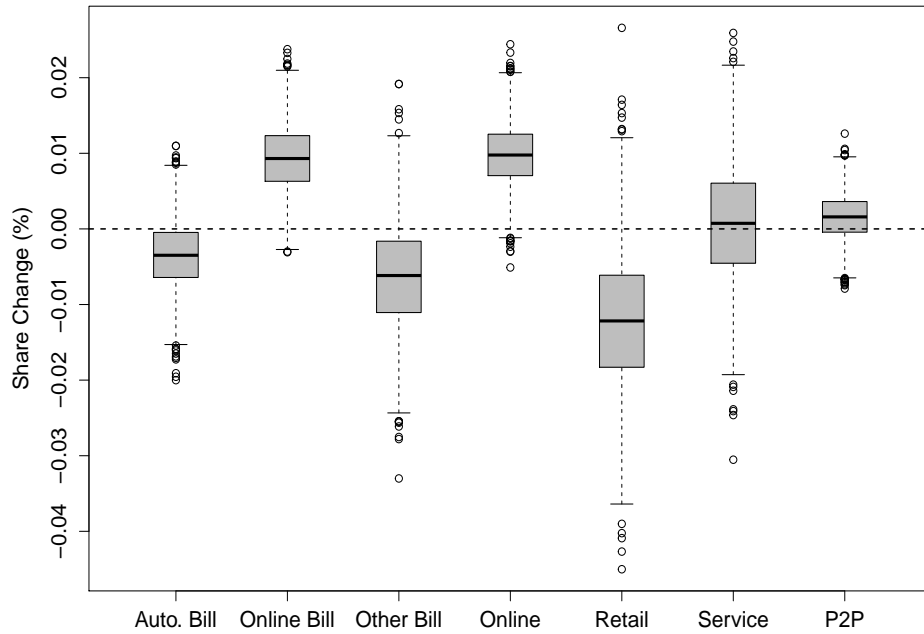
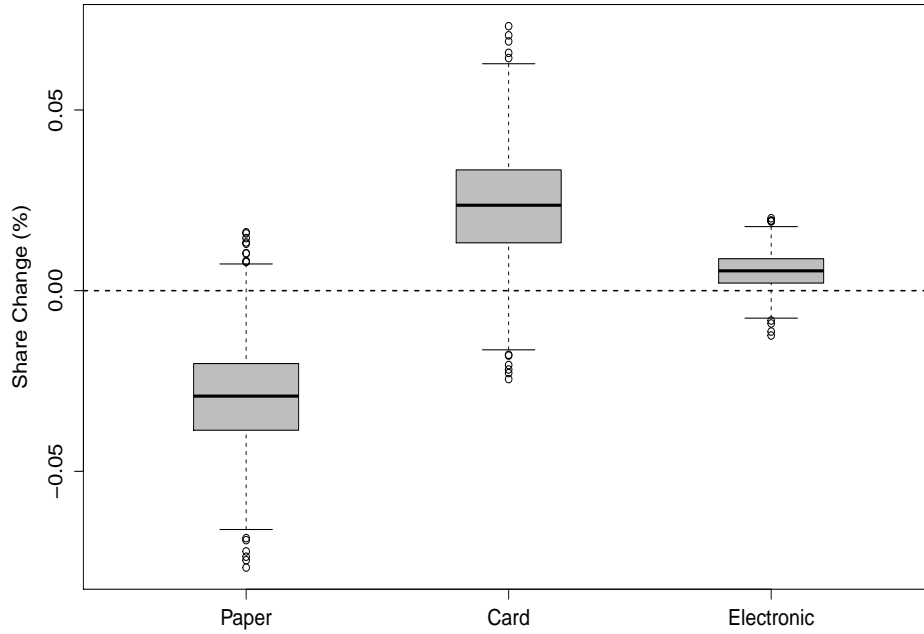


Figure 12: Share of monthly payments by transaction type.

Share Differences: 2010 – 2012



Share Differences: 2011 – 2012

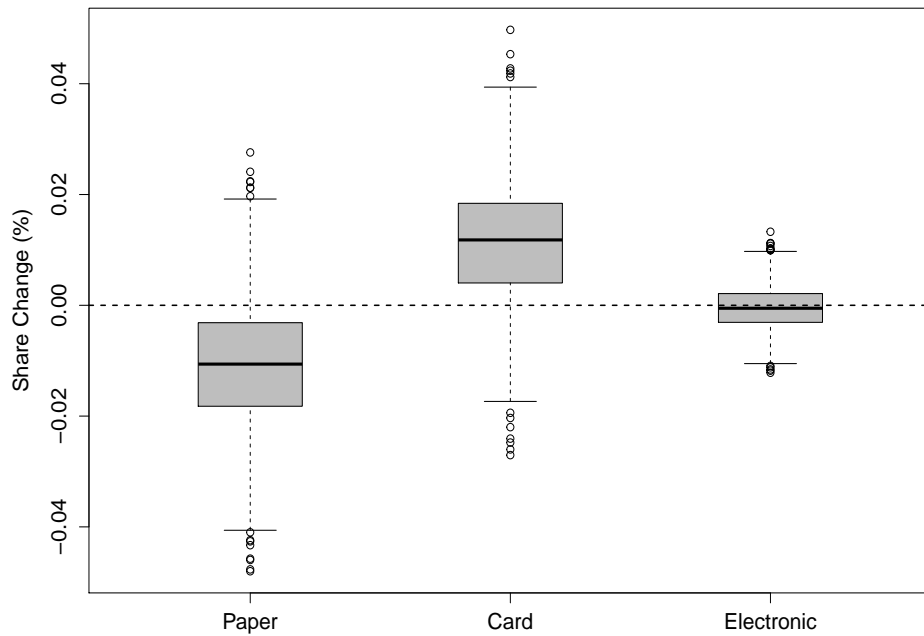


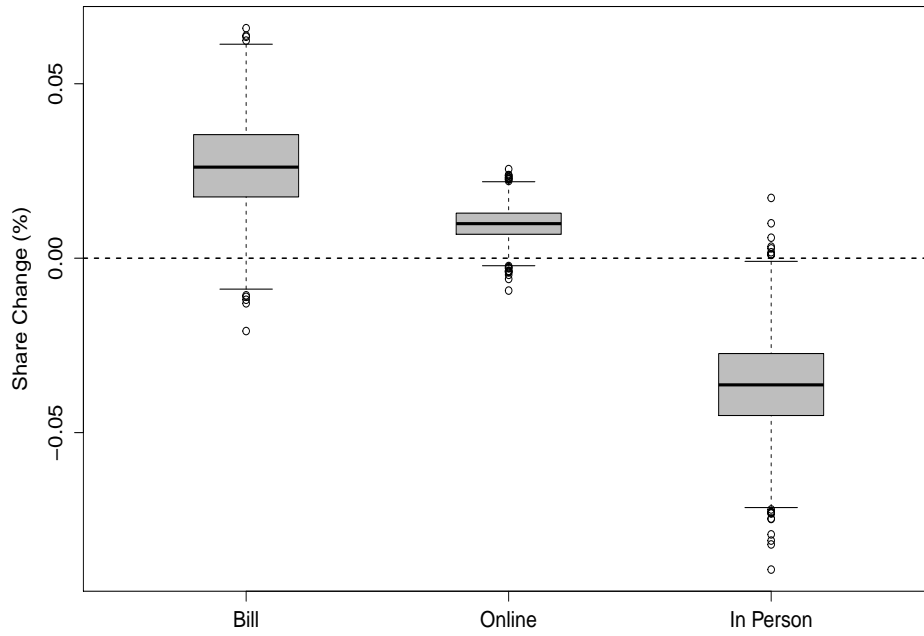
Figure 13: Share of monthly payments by instrument groups.

	Shares in 2010	Shares in 2012	Difference
Bill	29.23	31.88	2.65
Online	4.99	5.95	0.97
In Person	65.78	62.17	-3.61
Chi-stat			9.26
p-value			0.01

	Shares in 2011	Shares in 2012	Difference
Bill	31.93	31.88	-0.05
Online	4.94	5.95	1.01
In Person	63.13	62.17	-0.97
Chi-stat			5.64
p-value			0.06

Table 34: Share of monthly payments by groups of transaction types. See Figure 14 for marginal distributions.

Share Differences: 2010 – 2012



Share Differences: 2011 – 2012

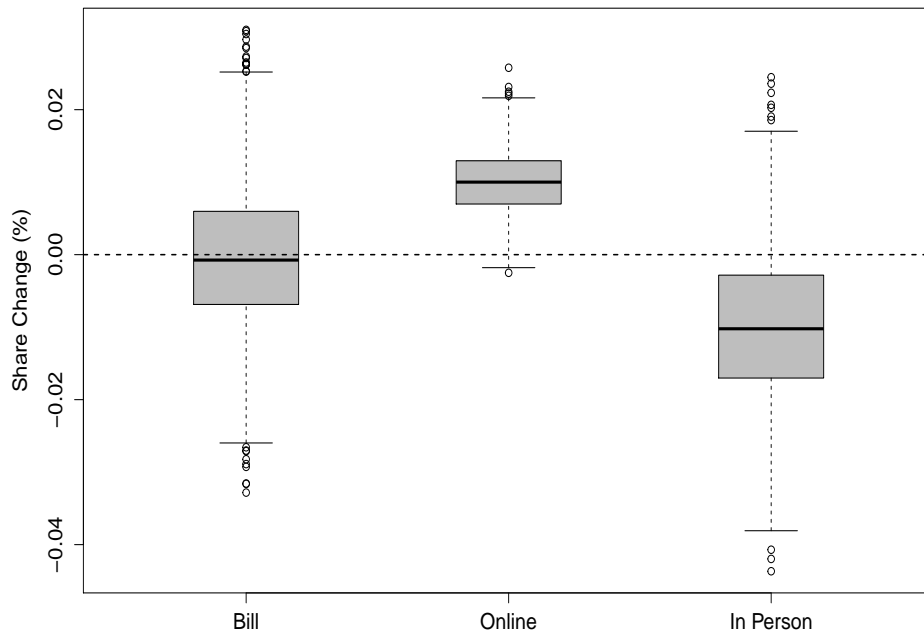


Figure 14: Share of monthly payments by groups of transaction types.

10.3 Miscellaneous Variables

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Cell Adoption	0.92	0.95	0.03	2.67	0.01
Mobile Banking Adoption	0.12	0.36	0.24	14.12	0.00
Mobile Banking Incidence	0.10	0.34	0.24	14.10	0.00
Test/SMS Payments	0.03	0.03	-0.00	-0.31	0.75
Contactless Payments	0.01	0.01	-0.00	-0.07	0.94
Barcode Scan	0.01	0.02	0.01	3.12	0.00
Bank Account Access	0.91	0.89	-0.01	-0.85	0.39

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Cell Adoption	0.93	0.95	0.02	3.24	0.00
Mobile Banking Adoption	0.30	0.36	0.06	3.87	0.00
Mobile Banking Incidence	0.29	0.34	0.05	3.43	0.00
Test/SMS Payments	0.02	0.03	0.01	0.95	0.34
Contactless Payments	0.01	0.01	-0.00	-0.64	0.52
Barcode Scan	0.02	0.02	-0.00	-0.28	0.78
Bank Account Access	0.89	0.89	0.01	0.51	0.61

Table 35: Adoption and incidence (unless otherwise stated) of mobile banking.

	Shares in 2010	Shares in 2012	Difference
Prefer Pin	47.86	53.59	5.73
Prefer Signature	31.71	23.51	-8.21
Indifferent	20.43	22.90	2.47
Chi-stat			21.81
p-value			0.00

	Shares in 2011	Shares in 2012	Difference
Prefer Pin	54.38	53.59	-0.79
Prefer Signature	22.96	23.51	0.54
Indifferent	22.66	22.90	0.25
Chi-stat			0.27
p-value			0.87

Table 36: Preferred method of authorization of debit cards.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Used in Past Year (Adopters)	0.32	0.34	0.02	0.58	0.56
Reloaded in Past Year	0.06	0.12	0.06	4.26	0.00

	Level in 2011	Level in 2012	Difference	z-stat	p-value
% Who Used in Past Year (Adopters)	0.37	0.34	-0.03	-1.13	0.26
% Who Reloaded in Past Year	0.08	0.12	0.04	4.06	0.00

Table 37: Use statistics of prepaid cards.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
% with Stolen/Lost	0.13	0.16	0.02	1.44	0.15

	Level in 2011	Level in 2012	Difference	z-stat	p-value
% with Stolen/Lost	0.15	0.16	0.00	0.33	0.74

Table 38: Percentage of consumers who experienced loss or theft of payment instrument in past year.

	Level in 2010	Level in 2012	Difference	z-stat	p-value
All Sources					
Value	468.23	654.58	186.34	3.42	0.00
Amount	128.80	131.42	2.62	0.31	0.76
Frequency	4.81	6.37	1.56	3.81	0.00
Primary Source					
Value	380.09	470.34	90.25	2.43	0.02
Amount	129.37	138.29	8.92	0.97	0.33
Frequency	3.56	4.13	0.57	2.20	0.03
Secondary Sources					
Value	90.96	189.19	98.23	3.45	0.00
Amount	48.79	58.44	9.65	1.33	0.18
Frequency	1.27	2.28	1.01	3.95	0.00
Cash Holdings	141.84	173.99	32.14	3.17	0.00

	Level in 2011	Level in 2012	Difference	z-stat	p-value
All Sources					
Value	526.19	654.58	128.39	2.70	0.01
Amount	129.09	131.42	2.34	0.42	0.67
Frequency	5.39	6.37	0.97	2.26	0.02
Primary Source					
Value	425.87	470.34	44.47	1.55	0.12
Amount	134.01	138.29	4.28	0.75	0.45
Frequency	3.92	4.13	0.21	0.83	0.41
Secondary Sources					
Value	104.94	189.19	84.25	2.97	0.00
Amount	50.79	58.44	7.65	1.24	0.21
Frequency	1.53	2.28	0.76	3.03	0.00
Cash Holdings	158.01	173.99	15.98	1.65	0.10

Table 39: Use of cash. “Value” refers to the total dollar value of withdrawals per month, “Amount” refers to the amount withdrawn per withdrawal, and “Frequency” refers to number of monthly withdrawals. Cash holdings are excluding large value holdings (top 95 percent).

	Level in 2010	Level in 2012	Difference	z-stat	p-value
Cash	2.67	2.78	0.11	1.62	0.11
Check	2.95	3.05	0.10	2.01	0.04
Debit	3.09	3.20	0.11	2.14	0.03
Credit	3.11	3.31	0.21	3.90	0.00
Prepaid	2.76	2.86	0.10	1.90	0.06
OBBP	3.18	3.30	0.13	2.38	0.02
BANP	2.58	2.77	0.19	3.27	0.00

	Level in 2011	Level in 2012	Difference	z-stat	p-value
Cash	2.61	2.78	0.16	2.97	0.00
Check	3.00	3.05	0.05	1.30	0.19
Debit	2.99	3.20	0.21	4.77	0.00
Credit	3.11	3.31	0.21	4.63	0.00
Prepaid	2.72	2.86	0.14	2.95	0.00
OBBP	3.20	3.30	0.10	2.32	0.02
BANP	2.63	2.77	0.14	2.82	0.00

Table 40: Mean security ratings of payment instruments. Possible ratings are integers from one to five.

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