Anticipatory Spending*

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Abstract

We leverage exogenous income changes from various state and federal transfer policies to demonstrate that U.S. consumers tend to increase spending in advance of income arrival. These anticipatory increases (pre-MPCs) are small compared to the substantial increases observed following income receipt (post-MPCs), but respond to the salience of the payment event. Individuals exhibit significant heterogeneity in anticipatory spending responses and these responses are persistent within individuals over time, suggesting that much of the correlation between MPCs and financial characteristics like liquidity is driven by personality traits. Utilizing this additional dimension of consumption response across multiple policy-induced income changes per individual, we cluster individuals into distinct types. These types' behavior and characteristics correspond roughly to rational (about 45%), mental accounting (24%), rationally inattentive (21%), and present-biased consumers (9%). We find that a number of untargeted characteristics are well captured by this clustering, with present-biased and mental accountants having much lower levels of liquidity, income, and financial market participation than rational and rationally inattentive individuals. Moreover, increases in available financial resources increase the smoothness of consumption surrounding these transfer payments, with present-biased individuals most strongly pulling spending from the post-payment period into the pre-payment period.

JEL classification: D12, D14, E21, G51

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1 Introduction

Measuring anticipation effects in consumption is crucial yet challenging. Leading consumption theories, such as variants of the permanent income hypothesis and the buffer stock model, predict that in the absence of credit frictions, consumers respond to anticipated income changes ahead of time – not when the money arrives. The primary mechanism driving responses to anticipated income changes in these models is the presence of borrowing constraints. These constraints therefore lead to two distinct testable predictions about consumer behavior: unconstrained consumers react in advance of anticipated income changes but not at the point of receiving the predictable income, while constrained consumers are unable to respond to news about positive future income and only adjust their consumption upon receiving the income.

Policymakers are also particularly concerned with anticipation effects, as most fiscal transfer policies are debated and announced well before their implementation. This lag provides consumers with ample opportunity to adjust their behavior in advance of the arrival of income. Not accurately capturing anticipation effects leads to biased estimates of the total response to the policy, and potentially to misjudgment of its effectiveness as policy tool and its welfare implications. Therefore, quantifying the entire trajectory of intertemporal consumption responses, including anticipation effects, is essential for the design of optimal policy (e.g., Auclert et al. 2024).

A substantial body of literature estimates marginal propensities to consume (MPCs) or to spend (MPXs) in response to exogenous income changes using detailed household-level microdata. However, few studies employ similar data and methodologies to measure the extent of household responses *in anticipation* of these income changes and how such anticipatory changes relate to subsequent consumption responses when the income is finally received. One key challenge in this area is identifying instances where exogenous income changes are predictable and where the timing of announcements or periods during which consumers likely become aware of these forthcoming changes can be pinpointed. Fiscal transfer policies, ranging from one-time stimulus payments to more regular transfers, are well suited to study anticipatory effects as they typically meet these criteria. Nonetheless, analyzing these policies requires high-frequency microdata, as announcements and awareness typically occur only days or weeks before implementation, rather than months or years. Access to such high-frequency spending data has become feasible only in the past decade. Moreover, the extent to which such theoretically anticipated income transfers are actually known or salient to individuals is important to measure. Variation in the salience or news-worthiness of a given income transfer may vary across geographies and events, leading to systematic differences in spending responses.

Additionally, examining anticipation effects necessitates a large sample size to ensure sufficient statistical power to detect the potentially small anticipatory effects predicted by the leading consumption theories. To discriminate between different models of consumer behavior, the dataset should ideally feature an extended panel dimension to facilitate the estimation of both pre-payment and post-payment responses across multiple policy changes within the same individual. This enables a more nuanced analysis to determine whether behavioral responses are primarily driven by circumstances (e.g., temporary low liquidity) or by persistent consumer characteristics (e.g., present bias or mental accounting).

This paper uncovers novel and robust consumption patterns that deviate from the predictions of standard models, but are consistent with leading alternatives. Its contributions can be summarized by the three main findings. First, using high-frequency account-level data and examining a variety of income changes stemming from U.S. federal and state transfer policies from 2012–2023, we find small, positive, but statistically significant anticipatory spending responses to these predictable income payments. Prior research, including our own, has found mostly insignificant results and has typically interpreted this as a failure of canonical macroeconomic models of consumption dynamics. Instead – and in line with these canonical models –, our estimates of pre-payment MPCs in anticipation of the policy-induced payments is small, around 0.5 to 1.5% in the week prior to the payment. This anticipatory response is typically an order of magnitude smaller than the average MPC in the week following the payment. Importantly, these anticipation effects are a robust feature of the data. We find them for all payments we study, ranging from one-off events, such as each of the three rounds of COVID stimulus or the expansion of the Child Tax Credit, to repeated payments, such as those from the annual Alaska Permanent Fund Dividend or from annual federal and state tax refunds.[1] While the spending responses to these events differ somewhat depending on certain characteristics of the payments, such as more salient events featuring slightly larger pre-payments and smaller post-payment responses, our main finding is that the spending dynamics look remarkably similar: Small anticipatory spending responses are followed by a second round of substantially larger responses after the arrival of income.

The post-payment responses are much easier to detect in the data as their event date is directly observable in transaction data, and often also in survey data, and because the payments loosen borrowing constraints immediately. Our estimates of post-payment MPCs are in line with those of a substantial prior literature related to excess sensitivity tests; see for example Jappelli and Pistaferri (2010); Fuchs-Schündeln and Hassan (2016); Carroll et al. (2017); Havranek and Sokolova (2020); Sokolova (2023) for surveys and discussions of these estimates. Moreover, to demonstrate the representativeness of our sample, we validate five studies of such 'quasi-natural experiments'. All five replications consistently use the same set of individual transaction data and are able to reproduce the main result of those papers closely. Our post-MPC estimates also shed light on why previous studies might not have found anticipatory spending effects: The t-statistic of the typical post-MPC estimate is more than four times larger than that of the pre-MPC for the same payment event, making it difficult to observe anticipation effects in conventional datasets.

Second, we follow a recent literature and estimate MPCs at the individual level. Relative to this literature, we estimate the novel pre-payment MPCs for each individual in addition to its

[1] We also find qualitatively similar but quantitatively larger pre- and post-MPCs in response to regular paychecks, consistent with previous research (e.g., Olafsson and Pagel 2018; Gelman 2022). However, as this literature has documented, those pre-paycheck MPCs are often the result of individuals timing their regular bill payments (e.g., Gelman et al. 2014; Baker and Yannelis 2017; Gelman et al. 2020, 2022). The income payments we study in this paper are not as regular or frequent and therefore do not lend themselves to this type of liquidity management.

post-payment MPCs, and importantly, doing this for all payment events observed for each individual in the data. Observing multiple payment events per individual allows us to characterize the marginal distributions of pre- and post-MPCs in more detail. Consistent with recent studies (e.g., Misra and Surico 2014; Lewis et al. 2024; Boehm et al. 2025), we find substantial heterogeneity in post-MPCs. Our novel contribution to this literature is that we also document similar heterogeneity in the pre-MPCs. Both marginal distributions show a relatively wide dispersion around the average treatment effect. Leveraging the fact that we observe multiple MPCs for each individual, we show that while the dispersion of the marginal distributions of within-person average pre- and post-MPCs is smaller than that of the corresponding individual-by-event MPCs, these individual average MPCs still have a wide distribution, consistent with persistent personal traits playing an important role in determining consumption responses.

Our main finding from analyzing the unconditional distributions of MPCs, however, comes from studying the *joint* distribution of pre- and post-MPCs. The comparison of pre- and post-MPCs is economically powerful because canonical macroeconomic models, such as buffer stock models or the permanent income hypothesis mentioned above, impose strong restrictions on this joint distribution. In those models, the set of consumers who respond in anticipation of future income should be distinct from those who respond when the payments occur. The large average post-payment MPCs and the small but statistically significant average pre-payment MPCs are in principle consistent with these canonical models of rational consumption decisions under uncertainty. But if excess sensitivity to predictable income payments was mainly a product of liquidity constraints as in those models, we would expect to see a *negative* relationship between pre- and post-payment MPCs, with constrained individuals unable to increase spending prior to the arrival of income. For the same individual and for the same payment event, a positive pre-MPC should indicate that this consumer is not credit constrained and thus that its post-MPC should be zero. And vice versa, a positive post-MPC in response to a predictable payment should imply a zero pre-MPC, indicating that this consumer is up against her borrowing constraint. However, when regressing pre- on post-MPC for the same individual and the same event, we instead find a significant and robustly positive correlation. Hence, many consumers who respond in anticipation of an income payment also respond to its arrival, which is inconsistent with canonical models in macroeconomics.

Third, and motivated by the evidence of the importance of persistent traits in explaining individuals' consumption dynamics – which is consistent with previous studies (e.g., Parker 2017; Gelman 2022) – we use k-means clustering, a computationally efficient unsupervised machine learning algorithm to group individuals into four consumer types based on their pre- and post-MPCs. Sorting consumer types from high to low pre-MPCs and studying auxiliary variables that were not targeted by the clustering algorithm, such as financial characteristics, we find that the characteristics and spending behavior of consumers in these clusters are well described by four leading consumption theories: present-biased consumers (representing about 9% of the sample), rational consumers behaving according to the canonical macroeconomic models (45%), mental accountants (24%), and near-rational or inattentive consumers (21%).[2]

Present-biased consumers are characterized by having both large pre- and post-MPCs. The large pre-MPC is driven by being highly impatient, and the large post-MPC reflects time-inconsistency in their consumption plans, say due to hyperbolic discounting, or difficulties with sticking to a plan more generally. Consistent with their pre- and post-MPCs used by the clustering algorithm, these consumers also have characteristics based on unused auxiliary variables one would expect from present-biased individuals, such as low liquidity, frequent overdraft fees, and a high average propensity to consume (APC) and high spending sensitivity to predictable paychecks as pointed out by recent studies (e.g., Kuchler and Pagel 2021; Gelman 2022; Aguiar et al. 2025).

Rational consumers, on the other hand, have small positive pre- and post-MPCs. The small pre-MPCs reflect the desire to smooth consumption changes over long periods, while the small post-MPCs reflect occasionally binding credit constraints. In contrast to present-biased consumers, they have relatively high levels of liquidity on average, incur few if any overdrafts, and have a low APC.

Mental accountants are reluctant to pull spending forward (Thaler 1985; Shefrin and Thaler 1988). They are characterized by having a pre-MPC close to zero and a sizable post-MPC. Based on observable characteristics, such as various measures of liquidity, they resemble present-biased or temporarily but severely liquidity-constrained rational consumers. This could explain why many studies have typically categorized these individuals as liquidity constrained, while more recent studies have concluded that such households might alternatively also be described as exhibiting being engaged in mental accounting.

This discussion shows the usefulness of including the new concept of pre-MPCs when classifying consumer types. While income and measures of illiquidity correctly predict sizable post-MPCs for the first three consumer types, these observable characteristics do not help to predict pre-MPCs at the individual level, which differ substantially across these types. This may explain why prior studies failed to find subgroups with high anticipatory MPCs, given the relatively small average pre-MPC across the entire population. Latent variables on the other hand, like the APC or the average spending response to paychecks, help explain both pre- and post-MPCs as they better reflect persistent personal traits of consumers.

The anticipatory pre-MPC is thus key in separately identifying hyperbolic discounters from mental accountants. Both types have high post-MPCs, but only mental accountants have low pre-MPCs. The theory is typically agnostic on what observable characteristics are associated with mental accountants. Traditionally, low liquidity has been used to identify those who are impatient (i.e., low delta in the model of Laibson 1997) or are hyperbolic discounters (low beta). By definition, these individuals will have a low pre-MPC because they are constrained. Our analysis finds that there is a group of individuals who have low liquidity relative to other groups, but are not so constrained that they cannot pull spending forward and thus have an elevated

[2] Even with more than four clusters, the data always identifies two clusters, one that has low pre-MPC and high post-MPC (consistent with mental accountants or rational but liquidity-constrained consumers) and one with both high pre- and post-MPC (consistent with hyperbolic discounters).

anticipatory pre-MPC. We find that using the anticipatory pre-MPC appears less constricting than using typical measures of liquidity.

Finally, near rational consumers have pre- and post-MPCs that are close to zero or even negative. This reflects either inattention to events that have a small effect on their life-time resources, or an unwillingness to change consumption plans in response to relatively small income payments more generally. On average, these households have relatively high incomes and ample liquidity, and they thus rarely incur overdraft fees. In addition to having financial characteristics one would expect from individuals that closely but imperfectly follow the prescriptions of the canonical models, they also show behavior consistent with theses models. They are least affected by the salience of events, respond little to changes in news coverage, but their consumption response is most sensitive to the relative payment size as predicted by models of near rationality (Akerlof and Yellen 1985; Cochrane 1989; Kueng 2018).

Literature.— This paper contributes to three main strands of literature on dynamic consumer behavior. First, it provides evidence on spending responses prior to future income increases. While there is a smaller and older literature that tests for anticipation effects, it mostly relies on macroeconomic times series data (e.g., Blinder 1981; Flavin 1981; Deaton 1986; Poterba 1988; West 1988; Campbell and Deaton 1989). This literature has coined the term *excess smoothness* to describe the pattern that (aggregate) consumption responds too little to new information. Based on the permanent income hypothesis, people should respond to future income changes when they learn about them, and survey-based studies show that individuals react to hypothetical future income events (e.g., Fuster et al. 2021; Colarieti et al. 2024).[3] However, empirical findings on anticipatory spending behaviors in response to future income changes using observational microdata are mixed (e.g., Agarwal and Qian 2014; Broda and Parker 2014; Baugh et al. 2021; Caldwell et al. 2023; Thakral and Tô 2024; Graham and McDowall 2025).

The differences may occur due to variations in events or samples. Using detailed transaction-level data, we estimate households' anticipatory spending behaviors for several income events that differ in amounts, timing, and frequency. One noteworthy difference among events is their "salience" (i.e., the amount of attention households pay to the events respectively the amount of information that is supplied by the news media). We develop measures of event salience using newspaper mentions and Google searches to quantify the differences in salience across events and over time. Understanding how households respond before the income payment (or at the announcement of a future payment) in addition to their responses following the arrival of income provides a more complete picture of household spending behaviors and allows us to test models of household consumption dynamics. Furthermore, the results of this paper should be of interest to those studying the effects of fiscal policies on household spending.

Second, this paper also relates to the much larger modern literature which estimates MPCs out of exogenous and predictable income changes and tests for *excess sensitivity* relative to

[3]Other work has also shown that households may respond in advance to anticipated non-income events such as future tax changes. For instance, households pull spending forward prior to anticipated sales tax increases (Baker et al. 2018, 2021; Angelucci et al. 2024) and prior to federal income tax changes (Kueng 2014).

the canonical models' null hypothesis of full consumption smoothing. While previous studies, including our own, mostly focused on a single event at a time, this study examines numerous events with varying characteristics, including differently spaced announcement dates and salience, and analyzes how households' responses vary across different events using high-frequency data. It thereby contributes to the large literature explaining household heterogeneity in MPCs from anticipated income changes (see the survey articles mentioned above as well as more recent studies such as Andreolli and Surico 2021; Crawley and Kuchler 2023; Commault 2024; Indarte et al. 2024; Koşar et al. 2024 and many more). We test various characteristics that contribute to heterogeneity in MPCs with detailed information on household financial situations and spending behaviors.

Finally, this paper contributes to a fast-growing recent literature that incorporates behavioral frictions into dynamic models of individual consumption, such as near-rationality, inattention, mental accounting, present bias and hyperbolic discounting (e.g., Parker 2017; Kuchler and Pagel 2021; Maxted forthcoming; Lee and Maxted 2023; Mijakovic 2023; Gelman and Roussanov 2024; Hamilton et al. 2024; Indarte et al. 2024).

The rest of the paper proceeds as follows. Section 2 describes the data and measurements and provides institutional background for the different fiscal interventions. Section 3 discusses the empirical strategy and presents estimates of average pre- and post-payment MPCs and their joint distribution. Section 4 uses individual-level pre- and post-MPCs to classify consumers into types and characterizes these types using variables not targeted by the clustering algorithm. Section 5 concludes.

2 Data and Events

2.1 Transaction Data from Linked Financial Accounts

We mainly use de-identified proprietary account-level financial transaction data from a major U.S. financial aggregation and analytics firm to construct our dataset. Primarily contracting with financial institutions, our data provider aggregates financial information across users' accounts and assists these institutions in offering personal financial management services. We use the terms user, individual and household interchangeably. As part of 'open banking,' the platform's data access is based on agreements with bank and non-bank partners rather than consumers, ensuring comprehensive coverage and mitigating selection biases when consumers must opt-in to data sharing. Consequently, no additional selection bias occurs among the population of individuals with financial accounts once users' financial institutions form an agreement.

The data enable us to track bank, credit card, and debit card account transactions. For each transaction, we observe the precise date and amount, the transaction category (from one of 43 categories), and a transaction description. Additionally, we capture the merchant's name and its location for most transactions. Although we do not observe the user's demographic information (age, gender, and race), we can infer the user's residence at the zip code level, along with detailed financial characteristics (e.g., balances and overdrafts).

The data cover the complete financial flows across millions of Americans. Due to the platform's rapid increase in clients during the first two years, we focus on the period from January 2012 to September 2023. The dataset covers numerous financial institutions, allowing us to observe income and spending for a given user, potentially across several separate financial institutions. However, it is still possible that these accounts do not represent the totality of users' total income and spending, as some customer accounts may be excluded if held at institutions not contained within our database. Therefore, we follow Aiello et al. (2023a) to construct a representative sample of high-quality users based on the quality measure of the data provider and the tenure of the account. For computational convenience, we work with a 2% random sub-sample of households from January 2012 to September 2023.[4]

Table 1, panel A, reports the summary statistics for the spending households in the final dataset, which is made up of the daily spending and income transactions of over 50,000 users. We define consumption based on the categories of consumption, as described in Appendix Table A.1, and aim to follow the definition of other studies (Kueng, 2018; Di Maggio et al., 2022; Graham and McDowall, 2025). Our main consumption variable is spending in non-durable and service categories, while total spending combines spending on non-durable goods and services, durable goods, and other expenditures such as charitable giving and gifts as well as ATM withdrawals and check payments.

Panel B shows monthly income of households. We define income as including not only salary but also other types of income, such as pensions, bonuses, and interest income. In addition, it presents several household financial characteristics (at the household-by-event level) related to liquidity and credit constraints: bank account balances, the amount of credit available across credit cards, and the number of bank overdrafts. Balance and credit data are obtained via snapshots of accounts for a subset of users. For each account, a maximum of four snapshots are available: May 2022, November 2022, May 2023, and September 2023. Bank balances and available credit levels before and after these dates are imputed on the basis of total transaction flows within the accounts. Bank overdrafts are identified from transaction description strings within bank accounts that describe an overdraft fee being charged.

Given that the announcement and occurrence of income changes from fiscal policy events are close in time, it is essential to use transaction-level data to measure anticipatory spending effects. However, one concern is the representativeness of the transaction data. To address this, previous studies that use the same dataset for different settings compare it to the Census Retail Sales Surveys and demonstrate its representativeness (e.g., Balyuk and Williams (2021); Di Maggio et al. (2022); Aiello et al. (2023a,b)).[5] Except for households without bank accounts, our sample broadly represents U.S. customers in terms of income, spending, and geography. Additionally, we compare our dataset to those used in other studies employing different transaction-level and

[4]To obtain an adequate sample size for our estimates of the spending response to the Alaska Permanent Fund Dividend, we oversample residents of the state of Alaska. Since the population of Alaska is less than 0.25% of the total U.S. population, this does not affect the estimation of the responses to other income transfers.

[5]See Baker and Kueng (2022) for a review of recent studies that use transaction-level data.

survey data to demonstrate its representativeness (see Table 3). We discuss the results of these replications of prior MPC estimates in Section 3.1.

2.1.1 Google Search Data

We use Google Trends to obtain information about Google search queries. After providing a search term and a date window, Google Trends returns a daily metric called relative search volume, which ranges from 0 to 100. It is not an absolute search count, but rather a normalized metric that represents the proportion of searchers for a term relative to the total search volume within a specified time frame.[6]

Prior work, such as Da et al. (2011), Choi and Varian (2012), Baker and Fradkin (2017), and Baker et al. (2021) demonstrate the utility of using Google Trends to measure contemporaneous attention across households for a wide range of economic and financial topics.

2.1.2 Newspaper Data

We use the Access World News Newsbank database to obtain information on newspaper articles. We use the same search term and date window as the Google search data to find relevant articles for each event that we study. We then normalize the daily number of articles by the total number of articles published in all states for national level events like the COVID stimulus programs and the Child Tax Credit. For the Alaska Permanent Fund Dividend events we only normalize the measure by total articles published in Alaska.

2.2 Policy-Induced Income Changes

Table 2 lists several types of fiscal income transfers we recognize to estimate anticipatory spending effects. We select events discussed in prior literature that are observable in our data during the sample period 2012–2023. The various transactions are identified within the data based on the description field, and if necessary also merchant and payment size.

The first COVID-19 stimulus has a description denoting a generic tax refund, so additional restrictions are employed based on the precise dollar amounts of the stimulus check. For the second and third COVID-19 stimulus checks, transaction descriptions are more precise, identifying the relevant transactions as 'TAXEIP2' or 'TAXEIP3', and dispensing with the need for utilizing other filters. The Child Tax Credit has a description denoting each transaction as a 'CHILDCTC' payment. Federal tax refunds and payments are identified based on merchant and description, allowing for transactions of any size (e.g., 'USATAXPYMT' or 'IRS TREAS 310 TAX REF'). The Alaska Permanent Fund Dividend disbursements typically are denoted as a 'PFD' payment, but in some years this description is absent, necessitating us to identify the transactions based on the precise dollar amount of the dividend in a given year (e.g., multiples of $1,884.00 for 2014).

Finally, regular salary transactions are identified as those categorized as "Salary/ Regular Income." For replicating existing MPC estimates, we utilize all transactions. However, for our main specifications, we focus on periods during which households receive income as monthly

[6] The search terms are stimulus, child tax credit, ctc, permanent fund, pfd, and tax refund.

payments instead of bi-weekly or weekly payments, ensuring that the pre- and post-periods of regular income payments do not overlap and have sufficient gaps between them.

Panel C of Table 1 shows the distribution of each income transfer. The transfers differ in their magnitude and also in their frequency and periodicity. This heterogeneity allows us to examine how individuals respond to different income magnitudes and to the salience of each event. Additionally, by observing multiple events for each individual, we can analyze responses both across and within individuals.

2.2.1 Announcement and Payment Dates

Table 2 shows the payment date indicating the date at which the payments are distributed to most households, the announcement date based on occurrences such as the passing of a legislative bill or the official announcement of the policy, and the predicted announcement date according to two different salience measures together with the two salience measures. We define the predicted anticipation date as the date prior to the payment date that has the highest value of our coverage metric.

The table shows that of the 15 official announcement dates, the earliest of the two predicted announcement dates based on Google searches and newspaper mentions identifies nine events exactly and three events within two weeks of the official announcement. There are two events that are off by over a month.[7] The average absolute difference between official and predicted announcement date is three days once we exclude the two large outliers. This alignment provides credibility to our salience measure.

As described above, our newspaper-based salience measure consists of the number of articles that mention the event, normalized by either a national or state measure based on the event. For example, newspaper articles related to COVID stimulus payments are normalized by the total number of articles in all states while newspaper articles related to the Alaska Permanent Fund Dividend are normalized only by the number of articles in Alaska.

In terms of news salience, the COVID stimulus payments have the largest measures reflecting the very publicized nature of the events. The child tax credit has the smallest measure, suggesting it is not as widely reported as the other events. Looking at the Alaska Permanent Fund Dividend, the largest values for search occur in 2018 and 2019 while the the largest values for news occur in 2021 and 2022. These were all years in which the dividend amount was higher relative to the surrounding years (see Appendix Figure A.1).

The table also shows that, excluding the two outliers, there are on average 13 days between announcement and payment dates. The relatively short time between announcement and pay-

[7] The two events are the child tax credit and the 2018 Alaska Permanent Fund Dividend. For the Child Tax Credit, the mismatch is likely related to the fact that the official announcement was four months ahead of the disbursement. Furthermore, the Child Tax Credit was jointly announced with COVID Stimulus 3 as part of the American Rescue Plan. It is likely that most of the consumer and media attention focused on the stimulus payments rather than the child tax credit. For the Alaska Permanent Fund Dividend, 2018 was an anomaly as the dividend amount was announced in May rather than the typical September timing although the disbursement was consistent with previous years. The early announcement was tied to special legislation that was passed regarding the use of the Alaska Permanent Fund.

ment dates highlights why high frequency data is essential for estimating anticipation effects. Furthermore, this relatively short timeline means that we have to limit the estimation of the anticipation effects to one week or two in most cases.

2.2.2 Salience of Events

One precondition to any anticipatory spending response is the extent to which consumers are aware of the upcoming payments. We measure salience of these events using three different methods. The first uses Google search data regarding a particular event and is a more active measure of what information individuals are actively seeking out. One drawback of this measure is that it is a relative measure across time within a search term. This feature makes it difficult to compare salience across events.

To address this concern, we also use the number of newspaper articles that mention a particular event. This is a more passive measure of what information is available to individuals without knowing if this information is processed by consumers. However, it allows us to better compare salience across events. Finally, we are able to observe whether a given consumer has had experience with a particular event type previously. For instance, whether a consumer has previously received an Alaska Permanent Fund Dividend. We use an indicator for being a repeat event as a final measure of salience at an consumer-specific level.

We consider these methods complementary. Google search data captures the demand for information and newspaper article data the supply of information about an event. Moreover, Google search data can be thought of as measuring salience within events and newspaper articles measuring salience across events. For example, a high Google search data value leading up to the payment date of an event shows that individuals are actively seeking information about the payment before it occurs. On the other hand, newspaper article data can provide insight into how well-covered different events are relative to each other.

The final two columns of Table 2 show the two salience measures for each payment event. As expected, our newspaper salience values are higher for the various COVID stimulus payments compared to the child tax credit as the stimulus was widely reported on in the news media. Similarly, we find that the Alaska Permanent Fund receives more newspaper coverage in years where its dividend payment is larger.

3 Pre- and Post-MPCs

Because our primary goal is to study consumer behavior and discriminate between different theories or models, we estimate marginal propensities to consume (MPCs) by focusing on spending on nondurables and services. In other specifications, we use total consumer expenditures by adding in spending on durable goods to estimate marginal propensities to spend (MPXs), because they are typically the object of interest for policymakers managing aggregate demand (Laibson et al. 2022).

3.1 Replication of Prior Post-MPC Estimates

While the focus in this paper is on understanding the anticipatory behavior of consumers in response to forecastable income payments, the consumption response *following* the particular income payments (i.e., following the 'cash flow date') used in this paper – what we call the post MPC in the next section – has been previously estimated by researchers in a range of studies. Partly to demonstrate the external validity of our estimates and representativeness of our sample, we first show that, when following the relevant methodologies of the prior studies, our data can recover these 'post' MPCs documented by these researchers.

Table 3 shows that we can replicate the results of these previous papers when mirroring the specifications those authors laid out. For each fiscal transfer, we chose a leading published article that also uses transaction-level data, except for the Child Tax Credit, where we use an unpublished study using the Consumer Expenditure Survey (CEX) as our benchmark (Schild et al. 2023), because we are not aware of published articles that study this policy using transaction-level data. For consistency, if available, we replicate the monthly MPCs or MPXs and the papers' main specification otherwise. We match the sample periods of each study when it is available. We are able to replicate previous estimates closely, despite the fact that the data source, sample, and even time span are often quite different between our paper and these other studies. Moreover, while we closely followed the data cleaning and sample selection processes of these papers, the consumption measures could differ slightly due to variations in how the datasets categorize transactions.

For example, previous studies used various private transaction-level and public survey datasets, as well as different sample periods (e.g., periods earlier than January 2012). Graham and McDowall (2025), for instance, utilize transaction-level data from a single U.S. financial institution to estimate the post-payment of tax refund arrival on household spending across the liquidity distribution. We mirror their approach, calculating the MPC across all expenditures in the three-months after refund arrival. While they find an MPC of approximately 0.42 across 2014 and 2015, we recover an estimate of 0.37 in our own data.

Schild et al. (2023), in contrast, utilize data from the CEX to investigate the post-payment of the Child Tax Credit on both overall and child-related spending. While we cannot precisely mirror their specification given the differences in measurement inherent to the CEX as compared to our transaction data, we recover MPXs ranging from 0.21–0.40, depending on the categories included in our measure of consumption, as compared to their estimate of 0.44.

Finally, we replicate three of our own studies which estimate the MPC out of regular paycheck income (Gelman et al. 2014), out of the annual Alaska Permanent Fund Dividend (Kueng 2018), and out of the first COVID stimulus payments in 2020 (Baker et al. 2023).[8] Despite using a differ-

[8] We are aware of only two working papers that study the spending response to Stimulus 2 or Stimulus 3, and their estimates diverge somewhat. Karger and Rajan (2021) use transaction-level data and report an MPC out of Stimulus 2 of 39% over a two-week period. Their sample over-represents lower-income households, which potentially leads to a higher estimate than in the full population. Parker et al. (2022) use the nationally-representative CEX to study the response to all three COVID stimuli and report relatively low MPCs over a three-month period, although the estimates' standard errors are very large because of the

ent source for the transaction-level income and spending data, we obtain very similar estimates, 0.06 vs. 0.07 for the MPC during the first day after receiving a regular paycheck, 0.10 vs. 0.11 for the monthly MPC out of the Alaska dividend, and we match the monthly MPX of 0.22 out of the first COVID stimulus payments exactly despite using a different source of transaction-level data.

Overall, we take these results as evidence for the broad utility of this data source in providing reliable and externally valid measurements of individual consumption behavior.

3.2 Pre- and Post-Payment MPCs

Moving beyond these replication exercises, we next provide standardized MPCs for each income transfer, holding constant our specification rather than mirroring the disparate approaches for each prior study. We estimate post-payment MPCs using the following regression specification:

$$c_{i,t} = \beta_{post} \frac{Post_{i,t} \times Amount_i}{D_{i,t}} + \alpha_{i,d(t)} + \alpha_t + u_{i,t}, \tag{1}$$

where $c_{i,t}$ is daily non-durable (respectively total) spending of individual i in date t, $Post_{i,t}$ is an indicator that equals one if date t is after individual i receives the income transfer and zero otherwise, $Amount_i$ is the amount of the income transfer, $D_{i,t}$ is the total time period, in days, over which we estimate the MPC (respectively MPX), e.g., 7 days for the one-week and 30 days for the one-month MPCs. $\alpha_{i,d(t)}$ are individual-by-day of month fixed effects and α_t are date fixed effects. We use $\alpha_{i,d(t)}$ to account for regular spending patterns that occur on a specific day of the month (e.g., utility bills or rent and mortgage payments). Standard errors are clustered at the level of individual accounts.

The coefficient of interest, β_{post}, estimates cumulative MPCs after receiving an anticipated income transfer by including indicators for the days after the income transfer, where each day's indicator is equal to 1 times the amount of the transfer divided by the number of days in the relevant period. It flexibly captures the excess spending for a given period following the arrival of the income. We scale by the size of the income transferred to each individual to allow responses to vary with the amount of money received. We can examine the cumulative MPC over different time periods by including more or fewer daily indicators before or after the event.

Similarly, to estimate pre-payment MPCs, β_{pre}, we use the following regression specification:

$$c_{i,t} = \beta_{pre} \frac{Pre_{i,t} \times Amount_i}{D_{i,t}} + \alpha_{i,d(t)} + \alpha_t + u_{i,t}, \tag{2}$$

small sample of CEX respondents and the considerable measurement error. They find MPCs of 0.102 and 0.083 out of Stimulus 1 and 2, receptively, and only 0.009 for Stimulus 3. However, the authors document substantial under-reporting of payment receipt by survey respondent, which has a large effect on the point estimates. After imputing payment receipt and size using the government's distribution rule, these three MPCs increase to 0.250, 0.262, and 0.126, respectively. These corrected estimates closely align with our estimates of three-months MPCs reported in Table 4 of 0.241 and 0.159 for Stimulus 1 and 3. Because Stimulus 2 occurred only 11 weeks before Stimulus 3, we do not estimate the three-month MPC. However, the one-month MPCs out of all three COVID stimuli are similar, suggesting that a three-month MPC of 0.262 for Stimulus 2 is plausible.

where $Pre_{i,t}$ is an indicator that equals one if date t is before individual i receives transfer payment $Amount_i$ and zero otherwise.

Specifications (1) and (2) employ several sources of identifying variation in both the receipt, timing, and amount of income transfers conditional on receipt. Each of the events are only received by a subset of individuals, many of the event types have substantial variation in the amount of income received, and several events also have substantial variation in when precisely the income was received by an individual (see for example Figure 2 in Parker et al. (2022) for the variation generated by the three COVID Stimulus programs, reproduced in Appendix Figure A.8 for convenience).[9]

3.2.1 Excess Sensitivity: Post-Payment MPCs

Table 4 lays out the nondurables MPCs out of the listed income transfers for three different post-payment periods: (i) the week, (ii) the month, and (iii) the three months following the income transfer. For each of these post-payment MPCs, we find broadly consistent consumption responses across payment events. MPCs generally range from 0.03 to 0.11 in the week following the income's arrival to approximately 0.15 to 0.39 during the first three months after the transfer.[10] These ranges of post-payment MPCs are in line with those of a substantial prior literature related to excess sensitivity tests, which test the prediction of the canonical models such as the permanent income hypothesis that consumption of individuals with sufficient liquidity should not systematically respond to predictable income changes (e.g., Jappelli and Pistaferri 2010; Fuchs-Schündeln and Hassan 2016; Carroll et al. 2017; Havranek and Sokolova 2020; Sokolova 2023).

3.2.2 Anticipatory Spending: Pre-Payment MPCs

Table 4 also examines the pre-payment MPCs for one week prior to income arrival. We do find that households increase spending in the week prior to the arrival of income, but that magnitudes for most events that are are 70%–90% smaller than their spending responses following arrival.

To the best of our knowledge, we are the first to document small but statistically significant anticipatory spending effects on average, and robustly across different income transfers. The majority of studies report insignificant anticipatory spending effects (Broda and Parker, 2014; Baugh et al., 2021; Graham and McDowall, 2025), and only very few document significant effects (Agarwal and Qian, 2014; Kueng, 2014; Caldwell et al., 2023).[11] A likely reason is that even if individuals' spending behavior follows that of canonical consumption models, it is empirically

[9]As an alternative estimation approach, following the recent literature on two-way fixed effects models with staggered treatment (e.g., Borusyak et al. 2024), we also estimate a fully dynamic distributed lag specification at daily frequency surrounding each event date. We then cumulate the daily responses to a one-week (see Appendix Figure A.2), one-month, and three-month MPCs respectively MPXs, finding results consistent with our more aggregated approach outlined above.

[10]Differences between MPCs reported in Table 3 and post-payment MPCs in Table 4 stem from following each previous paper's main specification in Table 3 (including sample selection, data cleaning, variable definition (e.g., MPC vs. MPX), etc.) while using a common specification across all events in Table 4.

[11]Thakral and Tô (2024) notes a relationship between a post-payment MPCs and the duration of time between annoucement and receipt of income, but does not find evidence for any sizable anticipatory spending.

challenging to estimate the anticipatory spending results, as the theoretically predicted response size is small, even for responding households, because the annuity value of income changes is typically very small, leading to spending responses that would be even smaller due to consumption smoothing (Kaplan and Violante, 2014). Furthermore, there is heterogeneity in the salience of events and it is likely that individuals differ in their ability to acquire and process information. They also differ in the subjective probability that they assign to the event occurring. Measuring this individual heterogeneity is very difficult, which makes it empirically challenging to estimate these anticipation effects, requiring data with a large sample size and with observations recorded at high frequency and with minimal measurement error.

Appendix Table A.2 reports the corresponding MPXs by looking at total spending rather than nondurable spending responses, finding similar patterns of smaller, but non-zero, anticipatory spending responses (pre-MPXs) and sizable responses following income arrival (post-MPXs). Magnitudes of MPXs are mechanically larger given the larger absolute dollars that we track across total spending relative to non-durable spending.

Appendix Table A.3 shows the response of spending in the week before and after the public announcement of a future income transfer. Overall, we find small and often insignificant spending responses in anticipation of these announcements, though the the post-announcement period often features a spending response on the order of 0.01–0.03.

3.3 Event-Specific Individual MPCs

To understand how consumption responses vary across events and individuals, and to identify the determinants of these heterogeneous responses, we estimate MPCs at the individual-event level by leveraging the dataset's structure, in particular its long panel dimension and the fact that all individuals experience multiple events. Specifically, we estimate individual event-level pre- and post-payment MPC using the following regression specification:

$$c_{i,t} = \beta_{post,i} \frac{Post_{i,t} \times Amount_i}{D_{i,t}} + \alpha_{i,d(t)} + \alpha_t + u_{i,t}, \tag{3}$$

$$c_{i,t} = \beta_{pre,i} \frac{Pre_{i,t} \times Amount_i}{D_{i,t}} + \alpha_{i,d(t)} + \alpha_t + u_{i,t}, \tag{4}$$

where $\beta_{pre,i}$ and $\beta_{post,i}$ are allowed to vary across individuals and payment events and thus estimate heterogeneous cumulative MPCs for each individual and each event separately.

3.3.1 Unconditional and Within-Person Distributions of MPCs

Figure 1(a) plots the distribution of coefficients at an individual-by-event level for both the consumption response in the week prior to (pre-MPCs) as well as the week following the payment (post-MPCs), allowing for multiple observations per individual. Some fiscal policies have multiple payments across years, such as tax refunds or the Alaska dividends. We treat each annual payment as a separate event.

In line with previous studies, we find that the individual consumption response coefficients exhibit a relatively wide dispersion around their mean. The distribution of post-payment MPCs has a much more pronounced positive skew relative to the distribution of pre-payment MPCs, consistent with the much larger average MPC seen in Table 4 for the post-payment period.

The individual-by-event coefficients exhibit very thick tails, similar to the post-payment MPCs out of the 2001 and 2008 stimulus checks computed from CEX survey data in Misra and Surico (2014) and Lewis et al. (2024). The distribution of post-MPCs in Figure 1(a) supports these previous findings and shows that measurement error in survey data is unlikely the main driver of this dispersion. Similarly, the distribution of individual post-payment MPCs estimated in Boehm et al. (2025) based on a randomized controlled trial (RCT) with customers of a French bank – and also using transaction data as in this paper – shows similar dispersion even after constraining the distribution to have only positive support.

In Figure 1(b) we extend this analysis by leveraging the fact that we observe multiple MPCs for each individual, one for each event. Averaging coefficients across events within individual removes much of the noise contained in the unconditional distribution of single-event MPCs. The resulting two distributions of averaged MPCs display much thinner tails, and the distribution of post-payment MPCs is more clearly positively skewed. Nevertheless, the distribution of within-person average pre- and post-MPCs shows large dispersion, consistent with persistent personal traits playing an important role in determining consumption responses.[12]

3.3.2 The Joint Distribution of Pre- and Post-Payment MPCs

The large average post-payment MPCs and the small but statistically significant average pre-payment MPCs shown in Table 4 across several fiscal transfers events is consistent with canonical macroeconomic models of rational consumption choice under uncertainty, such as one- and two-asset buffer stock models (e.g., Carroll 2001; Kaplan and Violante 2014).

If excess sensitivity of consumption to predictable income payments was mainly a product of credit and liquidity constraints as in those models, we would expect to see a *negative* relationship between pre- and post-payment MPCs, with constrained individuals unable to increase spending prior to the actual arrival of income. That is, the canonical models impose strong testable restrictions on the joint distribution of pre- and post-MPCs: For rational forward-looking consumers $\beta_{pre,i} > 0$ and $\beta_{post,i} \approx \beta_{post,i}$ due to the desire to smooth consumption over time, while for rational but credit-constrained consumers, $\beta_{pre,i} = 0$ due to the constraint and $\beta_{post,i} \gg 0$.

Figure 2 plots the relationship between these two objects across individuals. Figure 2(a) uses nondurable MPCs, which are the relevant concepts to test the theory, and Figure 2(b) shows the corresponding relationship between MPXs. There is a strong *positive* relationship between the average pre-payment MPC for an individual and their average post-payment MPC, and the same holds for pre- and post-MPX. We see that post-payment MPCs are highest for those who also have high levels of spending in the week before income arrival, contrary to the predictions of the canonical consumption models.

Appendix Table A.4 displays results of regressions of one-week pre-payment MPCs on one-week and one-month post-payment MPCs, confirming this graphical relationship while account-

[12] Figure A.3 displays the same results for MPX's rather than MPCs.

ing for event and household fixed effects, as well as other time-varying individual financial characteristics such as bank balances, available credit, income, recent overdrafts, and after controlling for the person's average propensity to consume (APC) and average salary MPCs.

3.3.3 Predictive Power of Pre- and Post-MPCs Across Events

Table 5 examines the persistence of these pre- and post-payment MPCs within household across events. We regress pre- and post-payment MPCs on lagged values from prior events, including event specific fixed effects and household-level financial characteristics.

In columns 1 and 3, We find that there is a significant persistence in the size of a households' consumption response, both prior to income arrival and following arrival. That is, households that increase spending in advance of (or following) income arrival for one event tend to do so in the context of the following event, as well.

Columns 2 and 4 add interactions of the lagged MPC value with two measures of the salience of these payments. 'High News' indicates that both a given event and the preceding event were in the top quartile of news coverage across all events, as measured by the fraction of newspaper articles in the household's state that discussed the payment. 'Repeat Event' denotes an event type with which the household had prior experience and thus was more familiar with. For both of these interactions, we find that higher levels of salience or familiarity tended to increase the persistence of the observed Pre- and Post-MPCs approximately doubling the magnitude of the relationship. Intuitively, households need to be aware of the income shock in order for persistent characteristics to drive similarity in spending responses.

3.4 Income, Liquidity, and MPC Heterogeneity

We now turn to a more in depth examination of factors that can explain variation in MPCs across and within individuals. Estimating MPC heterogeneity is crucial for both policy and macroeconomic modeling. For policy, it enables targeting households with high MPCs to maximize aggregate demand responses. For macroeconomic models, matching the observed heterogeneity in MPCs is key to validate model predictions, potentially falsify certain frameworks (e.g., Kaplan and Violante 2022; Auclert et al. 2023, 2024). The distribution of MPC can even serve as a sufficient statistic for evaluating the welfare effects of policy changes in a manner robust to different specifications in a class of supporting structural models (Auclert 2019).

Table 6 examines the relationship between both pre- and post-payment MPC and the two main drivers of MPC heterogeneity in the canonical models, liquidity and income, which many previous papers have studied. This wide ranging literature includes both empirical contributions (Baker 2018; Gelman 2021; Baker et al. 2023; Crawley and Kuchler 2023) and theoretical contributions (Deaton 1991; Carroll 2001; Kaplan and Violante 2014; Gelman et al. 2022; Kaplan and Violante 2022) examining the interactions of financial resources and consumption behavior. Overall, a major finding is that a strong relationship exists between financial resources and MPC.

We advance this literature by leveraging the fact that we observe the same individual over several distinct payment events. This allows us to decompose the explanatory power of liquidity into the within-person variation that reflects changes in liquidity due to temporary circumstances, such as transitory low income or large expenditure shocks, and permanently low liquidity that reflects persistent household traits, such as high subjective discount rates or present bias from hyperbolic discounting or similar psychological behavior. Furthermore, having access to financial transaction data we can expand on the typical measure of liquidity – bank balances, typically the sum of checking and savings accounts – used in previous studies based on survey data and also study the role of unused credit or credit card utilization, measured as the available credit before reaching the credit card's limit, and the number of bank overdrafts, which we can identify from the description string of the transaction.

Consistent with prior literature, columns (1) and (2) show strong effects of income and all three metrics of liquidity on the MPC following the receipt of income in the cross section and when controlling for event-specific fixed effects. Post-payment MPCs are negatively correlated with bank balances and available credit on the card, while positively related to the number of overdrafts across the four quarters prior to the arrival of the payment. Similarly, consumers with higher incomes have lower post-MPCs and hence their consumption dynamics exhibit less excess sensitivity to the predictable payments as predicted by canonical macroeconomic models.

However, this finding is not robust to controlling for household fixed effects in column (3). While adding event effects does not materially affect the other coefficients, column (3) shows that when focusing on within-individual variation by adding household fixed effects, the coefficients for the role of liquidity and income either become substantially smaller (bank balances and overdrafts) or even flip sign (available credit and income).

There are relatively few studies that investigate the within-individual relationship between post-MPC and liquidity or income. The vast number of articles that investigate the relationship between post-MPCs and liquidity or income study the cross-sectional relationship. This is because financial transaction data with high-frequency observations around the payment event and with a sufficiently long panel dimension has become available only recently (Baker and Kueng 2022). Previously, studies had to rely mostly on expenditure survey data, which typically consists either of repeated cross-sections or has only a very limited panel dimension such as the British Expenditure and Food Survey (EFS, formerly called the Family Expenditure Survey, FES) or the CEX, respectively. The result that the relationship between the post-MPC and liquidity and income is weaker when isolating the within-individual variation is consistent with Gelman (2021).

Columns (4)–(6) repeat the analysis for pre-payment MPCs. The cross-sectional relationships in column (4) are weaker when compared to those of the post-payment MPC, with the income consistently positively related to pre-MPCs and smaller relationships with bank balances and overdrafts. That is, both higher-income individuals (columns 4 and 5) and especially times when individuals have high income (column 6), are associated with high pre-payment MPCs. Adding household fixed effects in column (6) shows a clearer relationship between the three liquidity measures and the pre-MPCs. When isolating within-individual variation in liquidity, we find that times when households have higher liquidity are times when they are able to pull spending forward to the pre-event period. This suggests that liquidity constraints may occasionally bind to prevent individuals from increasing consumption before income is received.

The result that the relationship between the post-MPC and liquidity and income is different in the cross section compared to within individual – and the new finding that this also applies to the pre-MPC – is consistent with the idea that persistent individual characteristics or 'types' are important in driving cross sectional MPC heterogeneity (Parker 2017). We pursue this idea further in the next section by attempting to categorize individuals into different groups based on their pre- and post-payment MPCs.

3.5 News, Salience, and Responses to 'News Shocks'

We next turn to investigate how the difference between pre- and post-payment MPCs vary with the amount of news and attention or with whether it was a repeated event. In general, we find that repeated events or events with more news coverage tend to prompt larger consumption responses surrounding the transfer itself.

As noted above, Table 5 examines how the salience or knowledge about an upcoming income transfer affects the degree of persistence of the consumption response from one event to the next within an individual. While average consumption responses within individual are strongly persistent over time, this persistence is magnified for events which we believe the individual is more aware of. In this sense, non-salience of some events induces some noise in our estimates. Moreover, given a likely jump in awareness or salience upon income arrival, low levels of salience of an upcoming event may contribute to the large discontinuities in consumption behavior at arrival, as well.

Figure 3 displays the full distribution of the difference between pre-MPCs and post-MPCs across individual-event observations for two separate sets of events. We split events by whether they are in the top or bottom half of news coverage relative to the entire sample. We find that events with low levels of news coverage – salience – tend to have both a higher mean and wider distribution of spending changes at income arrival (e.g., Post-MPC − Pre-MPC). Events with higher levels of salience tend to have more stable consumption paths in the weeks surrounding the arrival of income, suggesting that individuals are increasing consumption in anticipation of income arrival.

Table 7 reinforces this tendency in a regression format. We note that higher levels of salience, as measured by either Google Search activity or news coverage, is associated especially with increased levels of Pre-MPCs at an individual-event level. For events with higher levels of news coverage, we also observe lower levels of spending in the 1-week following income arrival. For both measures of salience, we see negative relationships between the jumps in spending around income arrival (columns 5–6), though this difference is insignificant in the case of Google Search.

4 Grouping Consumers into Types

When exploring MPC heterogeneity, it is common to split the sample based on observable characteristics like age or income and liquidity as in Section 3.4. In this section, we advance the study of MPC heterogeneity by taking advantage of the granular nature and the long panel dimension of our data combined with the analysis of multiple events, which allows us to calculate pre- and post-payment MPCs at the individual level. Our study is the first to use these novel measures to split the sample into different groups. Furthermore, instead of splitting the sample based on equally spaced percentiles, we use k-means clustering to remain as agnostic as possible in terms of the cutoff values and sizes for the different groups.

More formally, we use k-means clustering, a computationally efficient unsupervised machine learning algorithm (Forgy 1965; Bonhomme et al. 2022), to assign individuals to consumer types based on their individual-level pre- and post-payment MPCs. The algorithm chooses membership into one of k clusters by minimizing the total within-cluster variation. Figure 4 graphs the scatter plot of pre- against post-payment MPCs (i.e., the underlying distribution of the bin scatter plot in Figure 2) while also indicating the cluster each point belongs to for our preferred k of four. We arrive at our preferred value of $k = 4$ because it creates groups that map best to consumption models that are widely used in the literature.

To better see these differences in responses as well as socio-economic characteristics across types, we turn to Table 8. Here, we split individuals by both liquidity (columns 1–2) and by cluster (columns 3–6).[13]

Our main results are the first two rows of Panel A which represent the 1 week Post- and Pre- MPC for different groups. We also provide estimates of the Post- and Pre- announcement MPC. The overall patterns across the 1 week and announcement MPCs are similar with the announcement MPCs having a smaller magnitude. We believe this is the result of attenuation bias from measurement error in identifying the announcement date. The measurement error includes empirically identifying the official announcement date as well as when the announcement of each event enters into the information set of each individual.

In columns 1–2, we separately examine characteristics and average consumption responses for individuals in the top quartile of liquidity and those in the bottom quartile. Here, we see many similarities with prior literature which have extensively documented differences in MPCs along the dimension of liquidity. We note that individuals with high levels of liquidity have post-MPCs of near zero, while those with low levels of liquidity have post-MPCs approximately four times larger at both a one-week and one-month horizon and holds true across all event types.

Crucially, however, the high and low liquidity groups do not significantly differ from one another in their pre-MPC values for any event. Both have average preemptive responses of approximately zero, again consistent with most of the prior literature. In contrast, columns 3–6 sort individuals according to their types, assigned both by their average pre- and post-MPCs. We see much more significant differences along both dimensions. We have sorted the clusters by the pre-payment MPC to highlight the value added of that metric compared to the few previous papers who study MPCs heterogeneity solely based on post-MPCs. These clusters map well into the following theoretical models.

[13] Table A.5 provides estimates for individual events.

4.1 Type 1: Present Biased (∼9%)

The consumption behavior of individuals in the first cluster is largely consistent with that of highly impatient or present-biased consumers such as hyperbolic discounters. Table 8 shows that both their pre- and post-payment MPCs are large, suggesting that they prefer to consume a lot and quickly. Table A.5 confirms that these patterns of high pre- and post-MPCs appear across all events independent of whether they are one-time, repeated, or regular payment events. The pre-payment MPC is typically an order of magnitude larger than that of other consumers, including that of the canonical rational consumers in cluster 2.

Turning to auxiliary variables that were not used to form the clusters, we observe that consumers in this cluster exhibit financial distress when using different measures of financial constraints, such as a low credit ratio and low liquidity in the form of low bank balances and low available credit. Furthermore, they also exhibit high values for the APC and excess sensitivity (post-MPCs), which has been shown to be associated with present bias and hyperbolic discounting (Shea 1995; Angeletos et al. 2001; Aguiar et al. 2025). Despite this, these consumers are able to pull spending forward, indicating that they find other ways of financing their anticipatory spending.

This cluster makes up about 9% of individuals in our sample. Consumers in this cluster are attentive and forward-looking as they seem aware of upcoming events. They have a desire to smooth consumption by pulling spending forward, resulting in a positive pre-MPC. However, their pre-MPC is very large, suggesting a high subjective discount rate or hyperbolic discounting behavior. At the same time, they also respond to the arrival of the payment, possibly reflecting time-inconsistency in their consumption plans. The time-inconsistency or difficulty in following plans more generally is reflected in the very high number of overdraft fees they incur. They also score low on measures of financial sophistication.

4.2 Type 2: Canonical Rational Consumers (∼45%)

The second cluster exhibits post- and pre-payment MPCs that are both positive but small. This consumption pattern with a small one-week pre-MPC of about 0.03 on average and a small one-week post-MPC of about 0.05 is in line with that predicted by canonical macroeconomic models (Kaplan and Violante 2022).

Turning again to auxiliary characteristics that were not part of the clustering algorithm, we observe that consumers in this cluster have high levels of liquidity and low levels of financial distress. This is consistent with other studies that find that consumption behavior appears more consistent with the canonical model after conditioning on individuals with high liquidity. They also show evidence of financial sophistication, including a relatively low APC and incurring low overdraft fees.

This cluster makes up about 45% of individuals in our sample. Consumers in this cluster are attentive, forward-looking planners who successfully smooth consumption over these predictable income changes. They have substantial liquidity, although not as much as consumers in cluster 4, and are thus probably borrowing constrained at some times (either because of low total assets, as in models with just one asset such as Zeldes (1989); Deaton (1991), or because of low liquid assets as in two-asset models such as Kaplan and Violante (2014)), leading to some moderate 'excess sensitivity' of consumption when receiving the predictable payment relative to canonical models of consumption under certainty, such as the permanent income hypothesis (Friedman 1957) or the life cycle hypothesis (Ando and Modigliani 1963).

4.3 Type 3: Mental Accountants (∼24%)

The third cluster exhibits a high post-payment MPC. However, unlike the first cluster, the average pre-payment MPC is close to zero. This pattern is consistent with mental accounting (Thaler 1985; Shefrin and Thaler 1988), an explanation for consumption behavior that has recently grown in prominence .

This cluster also shows signs of low liquidity and high financial distress, albeit smaller than cluster 1. This could explain why many studies have typically categorized these individuals as liquidity constrained while more recent studies have concluded that they exhibit mental accounting (Bernard, 2023; Mijakovic, 2023). Our earlier results in Section 3.4 show that when using only within individual variation, liquidity constraints do not appear to explain consumption behavior much. These results are consistent with the recent popularity of mental accounting as an explanation of excess sensitivity compared to liquidity constraints. This cluster makes up about 24% of individuals.

We see that these individuals tend to be the least responsive to the salience of upcoming income shocks (see Appendix Table A.6). While other clusters of individuals tend to increase anticipatory spending when exposed to greater amounts of news about future income, these mental accountants have near zero response.

4.4 Type 4: Near Rational or Inattentive Consumers (∼21%)

The fourth cluster exhibits post-payment and pre-payment MPCs that are both small or negative. They have very high levels of liquidity and income, and very low levels of financial distress. In terms of observable characteristics, they look similar to the rational consumers of cluster 2.

While this cluster looks similar to cluster 2 in terms of observables, the MPC estimates suggest an important difference. Upon closer inspection, we can see that the MPC estimates for this cluster are much noisier. We can see this more clearly in the event-level responses in Table A.5. Cluster 4 generally has the most inconsistent estimates across events.

Lastly, cluster 4 has the lowest payment-to-income ratio. Consistent with Kueng (2014), this group likely has low welfare losses from not smoothing. The noisy estimates centered around zero suggest that these individuals exhibit near rational or inattentive behavior. This cluster makes up about 21% of individuals in our sample.

4.5 Discussion

We can further test whether our cluster classifications make sense by studying the behavior of MPCs with other measures across clusters.

As one example, Table 9 explores the effect of individual-level financial constraints on consumption response surrounding income payments. In Panel A, we test whether the difference between pre-payment and post-payment MPCs is significantly affected by having high liquidity or available credit. We see a greater degree of smoothing present for both the present-biased (cluster 1) and the rational (cluster 2) users. In Panel B, we narrow our focus to specifically the Pre-MPC for each cluster, finding that spending is pulled forward into the pre-period for these same users.

Appendix Table A.6 illustrates two other dimensions of heterogeneity across these clusters. Panel A displays the extent to which larger payments drive differences in Post-MPCs across individuals in the entire sample and in each cluster, individually. We find that, while larger payments relative to income tend to be associated with lower MPCs in the whole sample and in clusters 1-3, cluster 4 (the rationally inattentive cluster), responds positively to larger payments. Intuitively, this cluster is less likely to change their consumption plan for small payments, consistent with evidence in Kueng (2018).

Panel B of Table A.6 then examines differences across clusters in the response to news coverage of the various payments. Taken across the entire sample, households tend to respond preemptively in response to increases in news coverage of a given payment. However, this response differs substantially across clusters. Cluster 2 (rational users) tends to be most responsive to increases in news and salience. In contrast, cluster 3 (mental accountants) tends to have a response close to zero for increases in news, consistent with a behavioral desire to only spend following income arrival.

Our clustering results highlight the importance of the pre-payment MPC in separately identifying groups of individuals. Without using pre-payment MPCs, cluster 1 and cluster 3, as well as cluster 2 and cluster 4, look similar enough that they could be combined into one group. However, including the pre-payment MPC allows us to separate these groups. Upon separation, the characteristics of each group are consistent with theory. Cluster 1 has a higher post-payment MPC, a positive and large pre-payment MPC and the highest values of APC and excess sensitivity which have been shown to reflect present-bias. One important point to note is that these pairs of clusters have relatively similar measures of typical observables such as income, liquidity, and financial distress. Therefore, the pre-payment MPC plays an important role in identifying those that exhibit mental accounting from those that exhibit more present-biased behavior and classic rational users from more inattentive users. We are unaware of any recent studies that have highlighted which observable characteristics are correlated with mental accounting.

5 Conclusion

This paper leverages a rich set of comprehensive and high-frequency financial transaction data to examine how individuals respond to a wide range of federal and state transfer programs in the United States. In this setting, we aim to describe how spending responds both prior to and following the arrival of these income shocks. We document three main findings that highlight the importance of mapping out heterogeneity across individuals in their marginal propensities to consume (MPCs).

First, we show that consumers exhibit small but statistically significant spending increases in the days leading up to anticipated income payments. These pre-payment responses – pre-MPCs – are much smaller than the substantial post-payment MPCs that follow the arrival of income, but are robust across a wide range of income events.

Second, by estimating individual-level MPCs across multiple events per person, we find that both pre- and post-MPCs exhibit considerable heterogeneity, but are positively correlated within individuals over time. This within-person correlation is inconsistent with standard models that attribute excess sensitivity entirely to binding liquidity constraints. Moreover, after conditioning on individual-level fixed effects, we note that directly observable measures of income and liquidity no longer exhibit the 'predicted' relationship with post-MPCs. These findings suggest that persistent behavioral traits play a central role in shaping consumption dynamics, and that financial observables such as liquidity or income alone cannot fully explain observed heterogeneity in consumption responses.

Finally, we use the joint distribution of individual-level pre- and post-MPCs to classify consumers into meaningful behavioral types. These empirically derived types align closely with four theoretical archetypes: present-biased consumers, rational agents, mental accountants, and rationally inattentive consumers. The assignment of individuals to these clusters correlates with a wide range of untargeted outcomes – including average levels of liquidity, income, and financial sophistication – and also produces groups that respond distinctly to news, payment size, and liquidity. These results highlight the importance of incorporating anticipatory behavior when distinguishing between behavioral mechanisms. In particular, we show that anticipatory MPCs are crucial to separating present biasedness from mental accounting, two mechanisms that yield similarly high post-MPCs but differ sharply in their pre-payment behavior.

Together, these findings have implications for both macroeconomic theory and policy design. From a theoretical perspective, our results challenge models that assume a one-dimensional source of heterogeneity, such as liquidity constraints, and instead favor frameworks that incorporate behavioral frictions, limited attention, and present bias. From a policy perspective, our results suggest that anticipation effects, although modest in size, are pervasive and systematically related to both the salience of the policy and the behavioral traits of the targeted population. As such, failing to account for these effects may lead to biased estimates of the full consumption response and thus mischaracterize the effectiveness and distributional impact of fiscal transfer programs.

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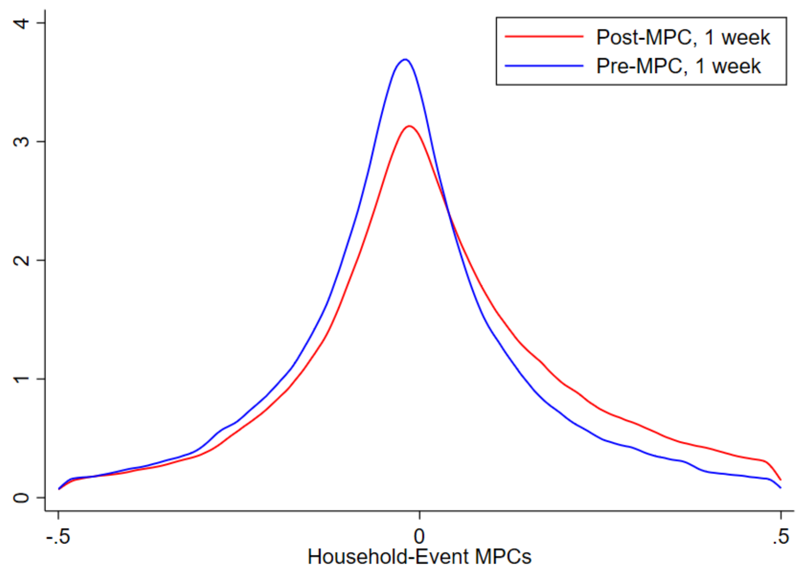
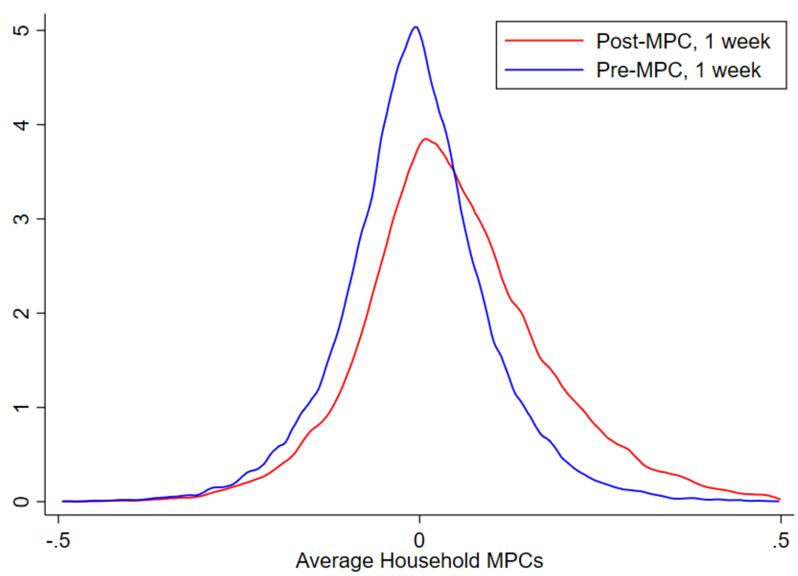
Copy of Figures and Tables from Main Text

Figure 1: Distribution of Anticipatory Pre-Payment vs. Post-Payment MPCs



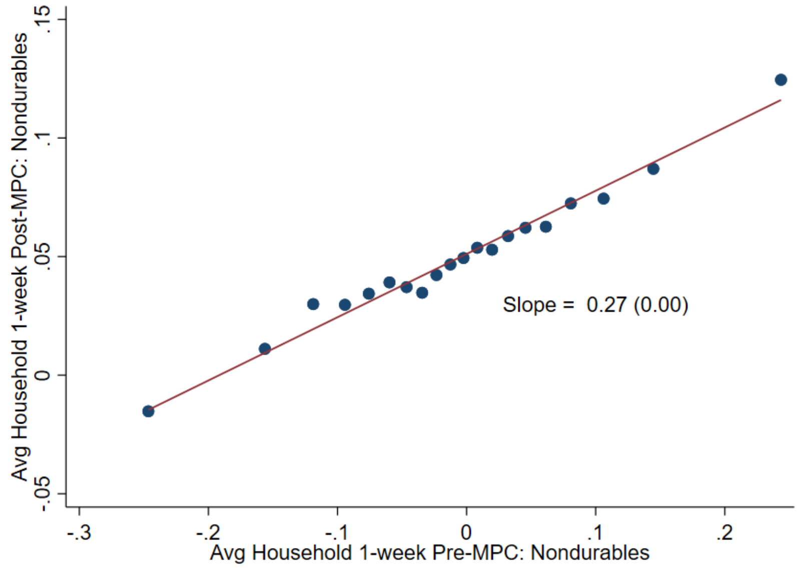
(a) Person-by-event pre-MPCs vs. post-MPCs



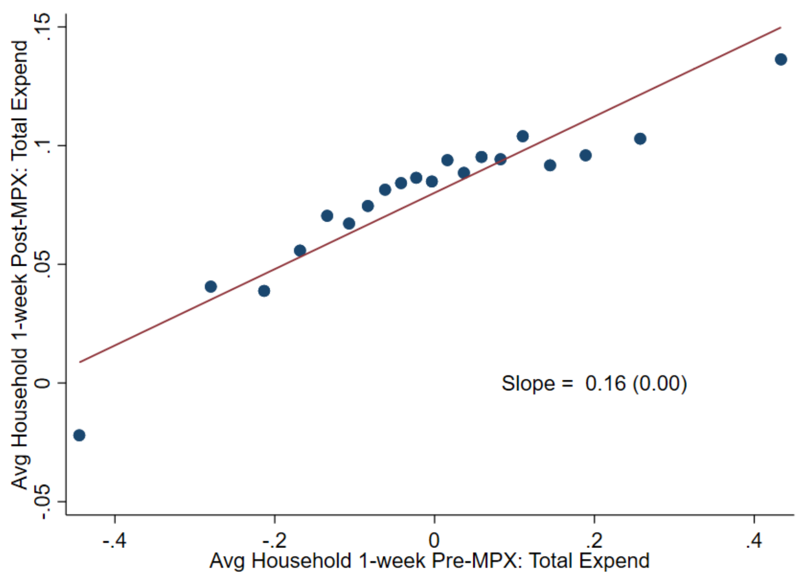
(b) Within-person average pre- and post-MPCs

Notes. This figure plots the distribution of pre- and post-payment nondurables MPCs computed over a one-week period before and after each event's payment date. Panel (a) shows kernel densities of the marginal propensity to consume out of pre-announced one-time income changes in the week before (pre-MPC) and week after (post-MPC) the arrival of income. Panel (b) shows the distribution of *average* pre- and post-MPCs across all observed events within each user. Here we restrict the sample to users with at least four events observed across all event types. Both panels utilize MPCs derived from expenditures on nondurables and services only. Each observation represents a user-event in panel (a) and a user in panel (b).

Figure 2: Relationship Between Within-Person Average Pre- and Post-MPCs



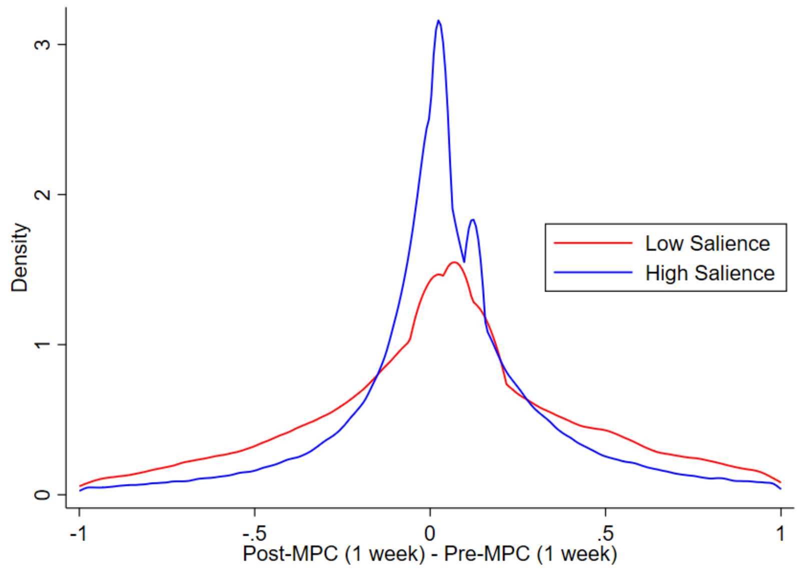
(a) Nondurables and services MPCs



(b) Total spending MPXs

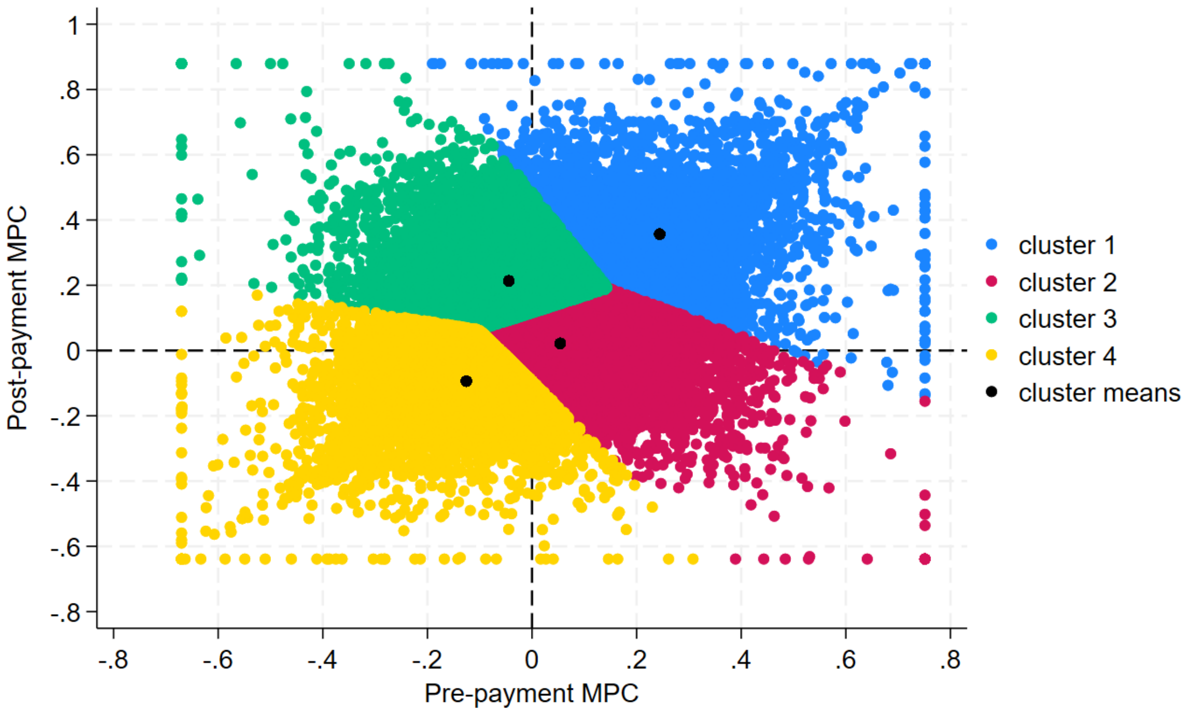
Notes. Both panels display bin-scatter plots of the one-week within-user average pre-payment MPC against the one-week average post-payment MPC across all events for each user, where each underlying observation represents a user. Panel (a) shows the relationship between pre- and post-MPCs for nondurables and services and panel (b) shows pre- vs. post-MPXs for total expenditures.

Figure 3: Difference in Pre- and Post-MPCs by Salience of Event



Notes. Displayed are two kernel densities of the 'dynamic slope', i.e., the difference (Post-MPC − Pre-MPC) at a user-event level. We measure the salience of each event based on the fraction of newspaper articles written about the event in the local media market. We then split the sample into a top and bottom half of salience and plot the two sub-samples separately.

Figure 4: Clustering of Consumer Types Based on Pre- and Post- MPCs



Notes. This figure shows a scatter plot of individual-level average one week pre-payment and post-payment MPCs. The individual-level averages are calculated by taking the average of each measure for all events observed within each individual. Each individual is assigned to a cluster based on our k means clustering algorithm and each cluster is represented by a different color. The black points represent the average pre-payment and post-payment MPC for each cluster.

Table 1: Summary Statistics

	Obs.	Mean	Std. Dev	P5	P25	P50	P75	P95
Panel A: Spending characteristics								
Total Spending: Monthly	6,801,149	5,174	4,367	92	2,116	4,165	7,115	13,486
Daily	205,747,911	171	420	0	0	20	149	809
Nondur. Spending: Monthly	6,801,149	2,881	2,443	19	1,136	2,322	4,001	7,563
Daily	205,747,911	95	210	0	0	9	97	453
Panel B: Household characteristics								
Total Monthly Income	6,801,149	6,026	5,987	0	2,127	4,499	8,051	17,604
Bank Balances	87,187	20,123	71,673	-1,093	388	1,567	5,960	100,023
Available Credit	70,202	14,509	12,215	228	5,112	12,476	20,617	37,108
Credit Ratio	70,184	0.7190	0.2985	0.0549	0.5583	0.8441	0.9533	0.9987
Overdrafts	363,348	0.5804	3.9763	0	0	0	0	2
Panel C: Payment transaction characteristics								
COVID Stimulus 1	29,684	2,222	1,018	1,200	1,200	2,400	2,900	3,900
COVID Stimulus 2	26,968	1,352	864	600	600	1,200	1,800	3,000
COVID Stimulus 3	30,091	3,275	2,115	1,400	1,400	2,800	4,200	7,000
Child Tax Credit	82,510	464	262	167	250	450	550	1,000
Alaska PF Dividend	15,467	3,538	3,077	992	1,600	2,750	4,456	9,852
Tax Refund	329,413	2,714	3,771	63	560	1,549	3,780	8,647
Paychecks	11,197,958	1,883	1,648	208	743	1,482	2,490	4,955

Notes. Panel A presents the monthly and daily income and spending amounts. Panel B presents financial characteristics of each user across the events. Note that the bank account balances and available credit amounts are not available for all individuals. Panel C presents the changes in income from fiscal events. Child Tax Credit transactions include monthly transactions for six months. Alaska PF Dividend is the annual transfer to Alaskan residents from the Alaska Permanent Fund.

Table 2: Event Dates

Event	Date of Payment	Date of Announcement	Predicted Announcement: Google Search	Predicted Announcement: Newspapers	Salience Measures: G-Search	Salience Measures: Newsp.
Panel A: One-off events						
COVID Stimulus 1	4/11/2020	3/27/2020	3/25/2020	3/27/2020	21	57
COVID Stimulus 2	12/29/2020	12/21/2020	12/21/2020	12/23/2020	33	60
COVID Stimulus 3	3/17/2021	3/11/2021	3/13/2021	3/11/2021	86	80
Panel B: One-time monthly payments for 6 months						
Child Tax Credit	7/15/2021	3/11/2021	7/13/2021	5/17/2021	43	10
	8/13/2021					
	9/15/2021					
	10/15/2021					
	11/15/2021					
	12/15/2021					
Panel C: Once every year						
Alaska PF Dividend	10/04/2012	09/18/2012	9/18/2012	9/19/2012	21	20
	10/03/2013	09/17/2013	9/18/2013	9/5/2013	20	20
	10/02/2014	09/17/2014	9/17/2014	9/18/2014	19	19
	10/01/2015	09/21/2015	9/21/2015	9/21/2015	29	29
	10/06/2016	09/23/2016	9/23/2016	9/29/2016	39	26
	10/05/2017	09/04/2017	10/3/2017	9/27/2017	49	28
	10/04/2018	09/14/2018	10/2/2018	8/15/2018	64	6
	10/03/2019	09/27/2019	9/27/2019	9/27/2019	53	25
	07/01/2020	06/12/2020	6/29/2020	5/29/2020	49	20
	10/11/2021	09/30/2021	10/8/2021	9/30/2021	25	40
	09/20/2022	09/08/2022	9/8/2022	9/8/2022	35	36
Tax Refund	Various	Filing date				

Notes. This table presents the announcement and payment dates of each income change used that is induced by fiscal policy events and measures of event salience. The date of payment reflects when the actual payment was made. The date of announcement is a subjective measure based on our reading of news media. The predicted announcement dates are based off of our two salience measure. For each one, the date reflects the highest salience measure recorded before the date of payment. For our salience measures, both of the columns G-Search (i.e., Google Search) and Newspaper reflect the average salience measure over the period that starts from the predicted announcement date and ends at the date of payment. The search measure is a relative score between 0 and 100 while the newspaper value is the number of daily articles related to the event divided by the total number of articles published in the relevant state for the relevant event, scaled by 100.

Table 3: Replication of Previous Studies' MPCs out of Fiscal Transfers

	Original study			
Event	Paper	Period	Main result	Replication
Panel A: Fiscal transfers				
COVID Stimulus 1	Baker et al. (2023)	2020.01–2020.08	0.22	0.22
Child Tax Credit	Schild et al. (2023)	2019.01–2022.03	0.41	0.37
Alaska PF Dividend	Kueng (2018)	2010–2014	0.11	0.10
Tax Refund	Graham et al. (2025)	2014–2015	0.42	0.37
Panel B: Salary receipts				
Paycheck Income	Gelman et al. (2014)	2012–2013	0.07	0.06

Notes. This table presents the replication results of existing papers. The column 'main result' reports the 1-month MPX in Baker et al. (2023), Table 3; the 3-months MPC in Schild et al. (2023), Table 10; the 1-month MPX in Graham and McDowall (2025), Figure 2; the 1-month MPC in Kueng (2018), Figure 3; and the 1-day MPX in Gelman et al. (2014), Table S3.

Table 4: Nondurable Spending Responses to Income Changes Around the Payment Date

			Post-MPC			Pre-MPC
Event	Period	Observations	1-week	1-month	3-month	1-week
Panel A: All events pooled						
Anticipated Payment	2012–2023	205,743,872	0.0357***	0.1033***	0.1853***	0.0064***
			(0.0013)	(0.0042)	(0.0084)	(0.0004)
Panel B: One-off events						
COVID Stimulus 1	2020	19,294,172	0.0478***	0.1368***	0.2446***	0.0053***
			(0.0018)	(0.0041)	(0.0095)	(0.0014)
COVID Stimulus 2	2020–2021	37,379,306	0.0815***	0.1038***	–	0.0039*
			(0.0029)	(0.0063)		(0.0023)
COVID Stimulus 3	2021	18,082,437	0.0493***	0.1351***	0.1616***	0.0081***
			(0.0014)	(0.0033)	(0.0067)	(0.0011)
Panel C: One-time monthly payments for 6 months						
Child Tax Credit	2021–2022	33,251,181	0.1193***	–	–	0.0328***
			(0.0063)			(0.0062)
Panel D: Once every year						
Alaska PF Dividend	2012–2023	205,747,911	0.0760***	0.2058***	0.3992***	0.0194***
			(0.0025)	(0.0061)	(0.0152)	(0.0015)
Tax Refund	2012–2023	205,747,911	0.0302***	0.0867***	0.1506***	0.0037***
			(0.0012)	(0.0038)	(0.0074)	(0.0003)
Panel E: Periodically						
Monthly Paycheck	2012–2023	98,787,012	0.0709***	–	–	0.0220***
			(0.0009)			(0.0007)

Notes. This table presents the responses of spending on nondurables and services to predictable income changes around the payments dates. The corresponding total spending responses (MPXs) are reported in Appendix Table A.2. The 3-month post-MPC for COVID Stimulus 2 is omitted because it overlaps with the pre-MPC of COVID Stimulus 3, which occurred 11 weeks later; see Appendix Figure A.2. Similarly, we report only the one-week post-MPC of the Child Tax Credit because of the recurring payments two to six months after the initial payment. Date and individual by day-of-month fixed effects are included in all specifications. Standard errors clustered at the individual level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Persistence of MPCs within Person

	Pre-Payment MPC		Post-Payment MPC	
	(1)	(2)	(3)	(4)
Lagged Pre-MPC	0.0249***	0.0182***		
	(0.0036)	(0.0047)		
Lagged Pre-MPC × High News		0.0104		
		(0.0281)		
Lagged Pre-MPC × Repeat Event		0.0161**		
		(0.0074)		
Lagged Post-MPC			0.116***	0.0858***
			(0.0035)	(0.0045)
Lagged Post-MPC × High News				0.0811***
				(0.0275)
Lagged Post-MPC × Repeat Event				0.0685***
				(0.0068)
Observations	313,285	313,285	313,285	313,285
R^2	0.009	0.010	0.021	0.022
Event FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Financial Controls	YES	YES	YES	YES

Notes. Dependent variables are the marginal propensity to consume out of payments in the week before (*Pre-MPC*) or the week after (*Post-MPC*) the income's arrival. *Lagged values* represent the relevant MPC value from the most recent prior event for a given user. For example, for an individual the pre- and post-MPCs out of say the April 2021 tax refund might be the lagged pre- and post-MPCs for the pre- and post-MPCs out of the Child Tax Credit in July 2021. *High News* refers to events where both the event and lagged event were in the top quartile of news coverage. *Repeat Event* refers to events in which both the event and lagged event were not the first of an event type. *Financial controls* include a moving average of logged income, bank balances, and available credit card credit. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Predictors of Anticipatory Pre-Payment MPCs and Post-Payment MPCs

	Post-Payment MPC (in %)			Pre-Payment MPC (in %)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Liquidity						
ln(Bank Balance)	-0.0031***	-0.0029***	-1.29e-05	8.89e-05	0.0003	0.0022***
	(0.0003)	(0.0003)	(0.0008)	(0.0003)	(0.0003)	(0.0007)
ln(Available Credit)	-0.0037***	-0.0038***	0.0018**	-0.0012***	-0.0011***	0.0015**
	(0.0003)	(0.0003)	(0.0007)	(0.0003)	(0.0003)	(0.0006)
Num Overdrafts	0.0030***	0.0030***	0.0012***	0.0002	0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Panel B: Lagged income						
ln(Income)	-0.0246***	-0.0258***	0.0058***	0.0029***	0.0034***	0.0244***
	(0.0009)	(0.0010)	(0.0019)	(0.0008)	(0.0008)	(0.0017)
Observations	362,579	362,579	362,579	362,579	362,579	362,579
R^2	0.007	0.010	0.194	0.000	0.002	0.158
Event FE		YES	YES		YES	YES
User FE			YES			YES

Notes. Dependent variables are the marginal propensity to consume out of income payments in the week after (*Post-Payment MPC*) in columns 1–3 or the week before (*Pre-Payment MPC*) the income's arrival in columns 4–6. Bank balances, available credit (credit card utilization), overdraft counts, and logged income are all measured as the average of the stated variable across the four quarters prior to the arrival of the payment. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: MPC and Salience

	Pre-Payment MPC		Post-Payment MPC		Difference: Post−Pre MPC	
	(1)	(2)	(3)	(4)	(5)	(6)
Google Search	0.136***		0.0412		-0.0950	
	(0.0450)		(0.0500)		(0.0626)	
State News Coverage		0.393***		-0.147**		-0.539***
		(0.0660)		(0.0724)		(0.0938)
Observations	102,346	359,209	102,346	359,209	102,346	359,209
R^2	0.287	0.147	0.329	0.184	0.320	0.162
HH FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Financial Controls	YES	YES	YES	YES	YES	YES

Notes. This table presents regressions of pre- and post-MPCs and their difference on measures of event salience. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Summary Statistics by Cluster

	Liquidity					
Sub-samples:	Low	High	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Panel A: Consumption						
Post-MPC, 1 week	0.09	0.01	0.2422***	0.0475***	0.1457***	0.0315***
			(0.0075)	(0.0014)	(0.0027)	(0.0027)
Pre-MPC, 1 week	0.00	-0.01	0.1073***	0.0327***	0.0216***	0.0033
			(0.0046)	(0.0012)	(0.0016)	(0.0022)
Post-Announcement MPC	-0.01	-0.02	0.0543***	0.0143***	0.0292***	0.0021
			(0.0042)	(0.0012)	(0.0020)	(0.0022)
Pre-Announcement MPC			0.0245***	0.0013	0.0095***	-0.0026
			(0.0040)	(0.0012)	(0.0020)	(0.0022)
Average Prop. to Cons. (APC)	0.98	0.90	1.00	0.91	0.97	0.91
Panel B: Liquidity						
Bank Balances	275	33,894	6,197	11,523	6,891	15,011
Available Credit	2,599	25,160	10,392	14,049	11,232	15,863
Credit Ratio	0.36	0.88	0.58	0.74	0.63	0.76
Number of Overdrafts	1.61	0.32	1.55	0.39	0.90	0.36
Panel C: Income						
Income	61,470	103,815	66,540	81,927	72,767	86,727
Payment-to-Income Ratio	0.05	0.04	0.04	0.05	0.05	0.03
Income Variation	0.03	0.04	0.04	0.04	0.04	0.04
Panel D: Financial Sophistication						
Investment Deposits	2,084	5,517	2,401	3,678	2,568	4,320
Finance Employee	0.03	0.10	0.05	0.07	0.04	0.09
Number of Observations	37,906	41,389	22,739	180,587	87,037	73,213
Number of Users	9,028	8,371	4,646	22,757	12,111	10,776

Notes. This table reports the means of variables for different sub-samples. The MPCs in the first three rows do not use predictable income changes from tax refunds and regular salary paychecks. MPCs from these events, which are observed much more frequently, are reported separately in the following rows. *Income Variation* is measured as the volatility of monthly income within a year divided by average income in the same year. *Finance Employee* is an indicator for an individual who received a salary from a financial institution during the sample period. *Low Liquidity* refers to the bottom quartile of both bank balances and available borrowing capacity on the credit card. *High Liquidity* refers to users in the top quartile along the same metric.

Table 9: Liquidity, Credit, and Differences in Pre- and Post-MPCs by Cluster

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Panel A. Difference (Post-MPC − pre-MPC, in %)				
ln(Bank Balance)	-0.703***	-0.190***	-0.158*	0.0110
	(0.191)	(0.0447)	(0.0835)	(0.0687)
ln(Available Credit)	-0.917***	-0.202***	-0.0913	-0.0438
	(0.173)	(0.0407)	(0.0732)	(0.0641)
R^2	0.002	0.003	0.013	0.001
Panel B. Pre-MPC (in %)				
ln(Bank Balance)	0.228*	0.0955***	-0.0962*	0.0321
	(0.122)	(0.0294)	(0.0575)	(0.0463)
ln(Available Credit)	0.519***	0.0553**	-0.256***	0.0353
	(0.110)	(0.0271)	(0.0506)	(0.0431)
R^2	0.026	0.005	0.009	0.020
Observations	22,739	180,587	87,036	73,213
Event FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes. Dependent variables are the marginal propensity to consume (MPC) out of income payments in the week before (*Pre MPC*, panel B) and the difference of this pre MPC and the post MPC the week after the income's arrival (panel A). Dependent variables multiplied by 100 for display purposes. Bank balances and available credit are measured as the average of the stated variable across the four quarters prior to the income's arrival. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix: Anticipatory Spending

Scott R. Baker, Michael Gelman, Lorenz Kueng, Seung Hyeong Lee

A Data Appendix

A.1 Choosing the number of clusters k

Choosing the number of clusters k can be challenging as there is no universally agreed upon method. We use three different measures to evaluate our choice of k.

A.1.1 Within-cluster sum of squares (WCSS)

The first method we use is WCSS. It's an intuitive metric to use because this is the object that the clustering algorithm is minimizing.

The downside is that WCSS is declining in k. Therefore choosing the smallest WCSS would in the limit choose $k = n$. In practice, practitioners use the "elbow method" which attemps to find an obvious inflection point. This "elbow" is where there is the most obvious gain from including an extra cluster.

Figure A.4 plots the WCSS by the number of clusters. The figure shows that gains from including more clusters starts to level out around 4 or 5 clusters. By this measure, our choice of 4 is not unreasonable.

A.1.2 Silhouette

Our second measure is the average Silhouette score. The silhouette score is a measure of how close any given point is to all the other points in its assigned cluster compared to the next closest cluster. Under ideal conditions, most points would be much closer to each other in its assigned cluster compared to the other clusters.

Figure A.5 shows the results. The highest score is for $k = 2$ while the rest of the clusters have comparable numbers. Although a cluster of 2 might maximize the silhouette score, we believe that there is economic value in including more clusters as they are able to identify behavior that maps to theoretic models popular in the literature.

A.1.3 R^2 measures

Our third measure is the adjusted R^2 in a regression of the slope of the MPC (post-MPC - pre-MPC) on indicator variables for each cluster k. We also analyze this measure for other alternative clustering variables post-MPC, pre-MPC, bank balance, and income. Figure A.7 plots the results. When using both the pre- and post- MPC, the adjusted R^2 levels out after a k of 5. While increasing the number of clusters can improve the fit of the model, our goal is to identify the maximum number of clusters that uniquely map to well known theoretical models. Therefore, we believe that this method also shows that our choice of k=4 is reasonable.

The results also show that using only the post-MPC to cluster explains more variation for each k relative to only using the pre-MPC. This is not surprising as the pre-MPC is likely estimated with more noise. Combining the two measures leads to sustained increases in the R^2 as k increases while the gains level out when only using each variable alone. This implies that there is some benefit to combining the two metrics that improves the fit beyond each single measure alone. This highlights the benefit of our novel pre-MPC measure.

Lastly, our analysis shows that clustering on bank balance and income explain very little of the variance of the slope of the MPC.

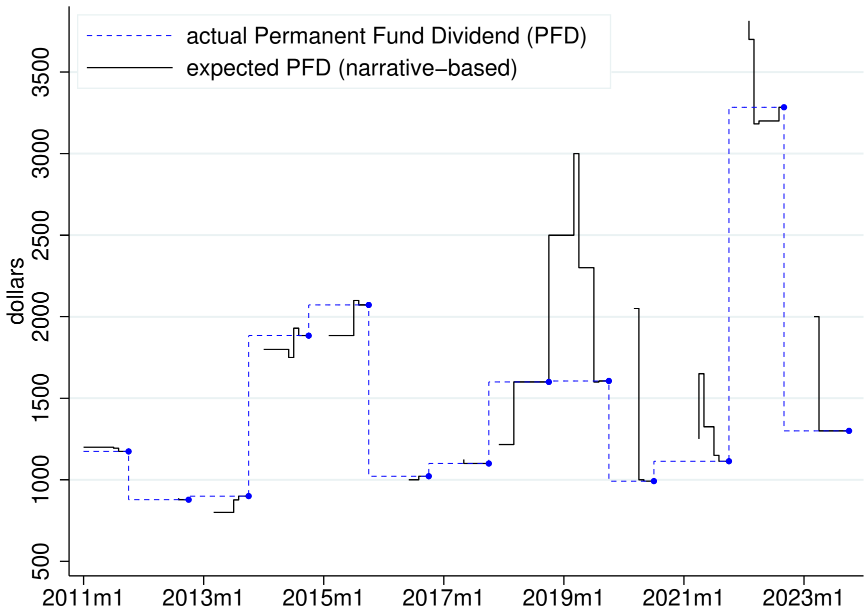
A.1.4 Summary

Figure A.6 plots the clusters classifications for k=3, 5, 6, and 7. Going to 3 to 4 allows us to split the high MPC cluster into hyperbolic discounters and mental accountants. Moving from 4 to 5 takes the low MPC cluster and splits it into two. Going from 5 to 6 splits up the low pre-MPC and high post-MPC group into two further groups where the only difference is the size of the post-MPC. This doesn't seem like a meaningful gain. While not shown here, 7 and above starts splitting qualitatively similar clusters into more extreme splits. In terms of matching the clusters to theoretical models, the biggest gains come from separating out those with both high pre- and post- MPCs from those with a low pre- MPC but high post- MPCs. After k=4, the algorithm is creating further quantitative refinements of these categories which we think aren't qualitatively important enough to warrant another split.

As discussed in the main text, we arrive at our preferred value of 4 because we believe that it creates groups that map best to consumption models that are widely used in the literature.

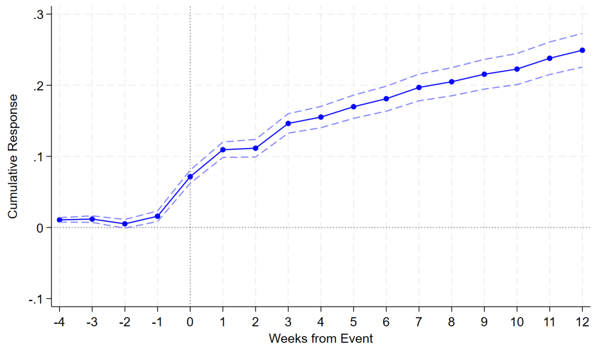
B Appendix Figures

Figure A.1: Alaska Permanent Fund Dividend News

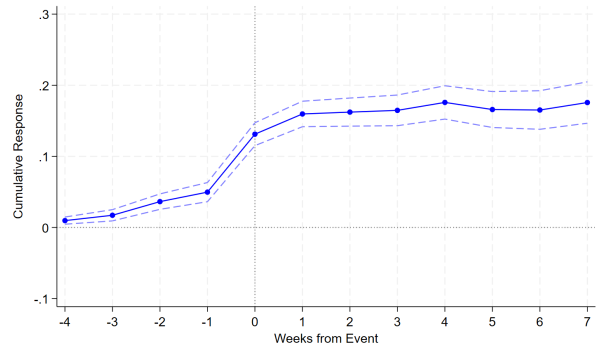


Notes. This figures shows expected amounts of the next Alaska Permanent Fund Dividend (black line) compared to the realized dividend (blue dots). The dividend expectation series is based on a narrative analysis of Alaskan newspaper and extends the series in Kueng (2018) to 2023.

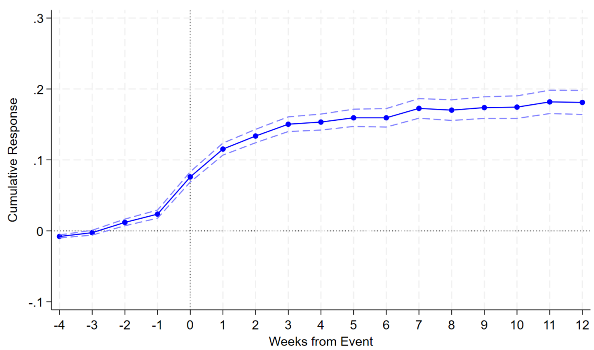
Figure A.2: Nondurable Spending Responses Relative to Payment Date



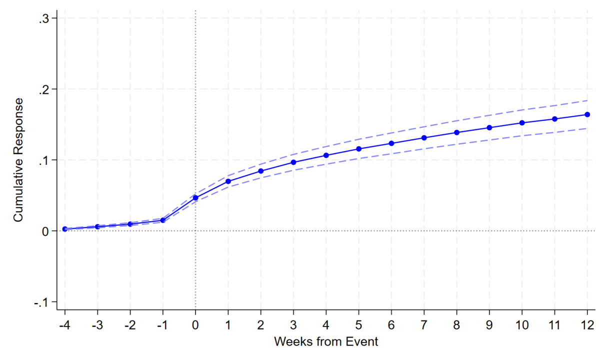
(a) COVID Stimulus 1: 4/11/2020



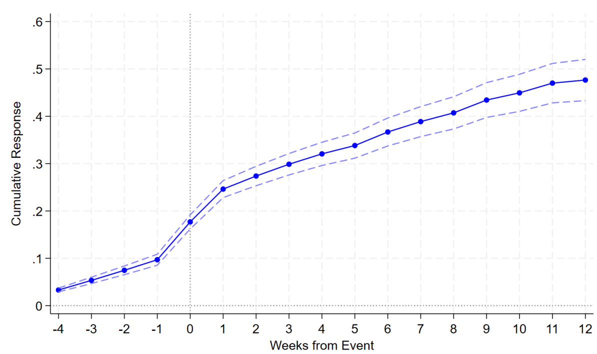
(b) COVID Stimulus 2: 12/29/2020



(c) COVID Stimulus 3: 3/17/2021



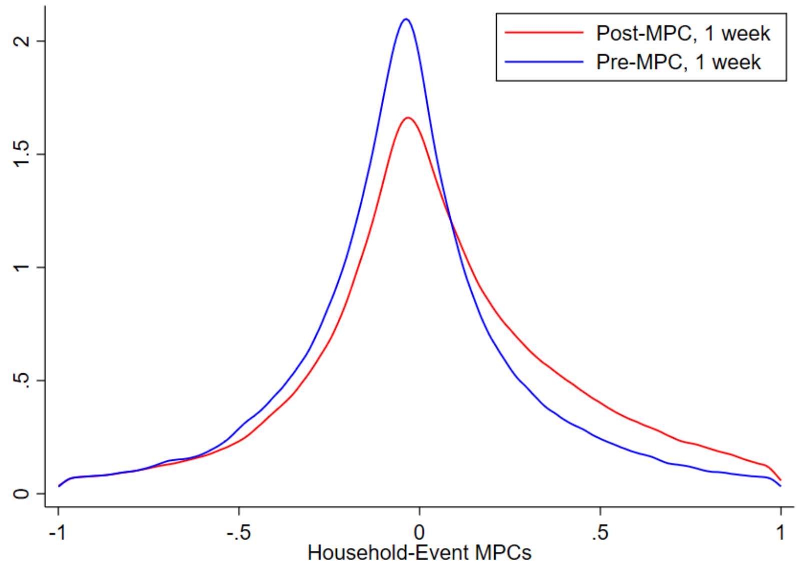
(d) Tax Refund: 2012-2023



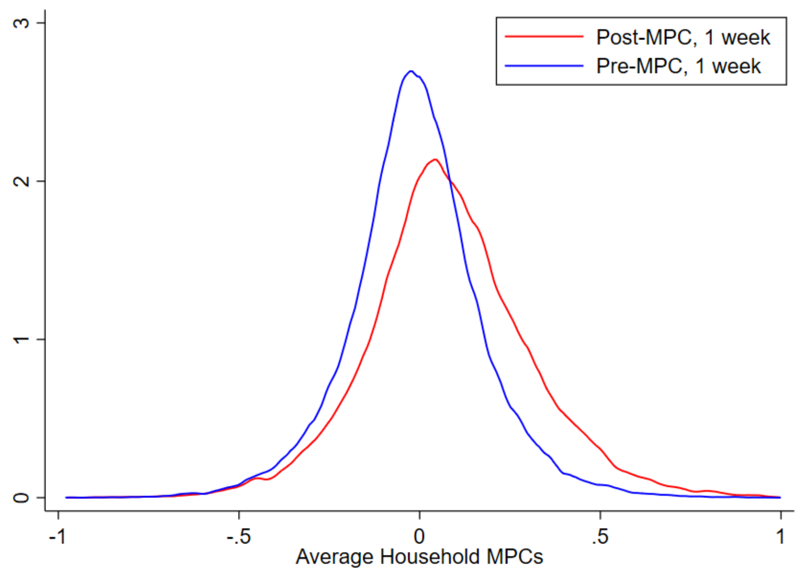
(e) Alaska Permanent Fund Dividend: 2012–2023

Notes. This figure plots the nondruable spending responses relative to payment date. We first estimate daily responses with the following distributed lead and lag specification: $c_{i,t} = \sum_{s=-28}^{90} \beta_s \; Amount_i \times \mathbf{1}[t = s]_{it} + \alpha_{i,d(t)} + \alpha_t + u_{i,t}$. We then combine the estimates into weeks relative to the payment date. The solid line shows the aggregated point estimates of β_s relative to one week prior to the payment (i.e., week -1 is normalized to zero). The vertical bars show the 95% confidence interval. Standard errors are clustered at the individual level. Date and individual-by-'day of month' fixed effects are included. Time relative to the payment date is equal to zero on the day of receiving the transfer. Since the event windows of COVID Stimulus 2 and 3 partially overlap, panel (b) is displaced by up to 7 weeks post-event.

Figure A.3: Distribution of Pre- and Post-MPXs – Total Spending



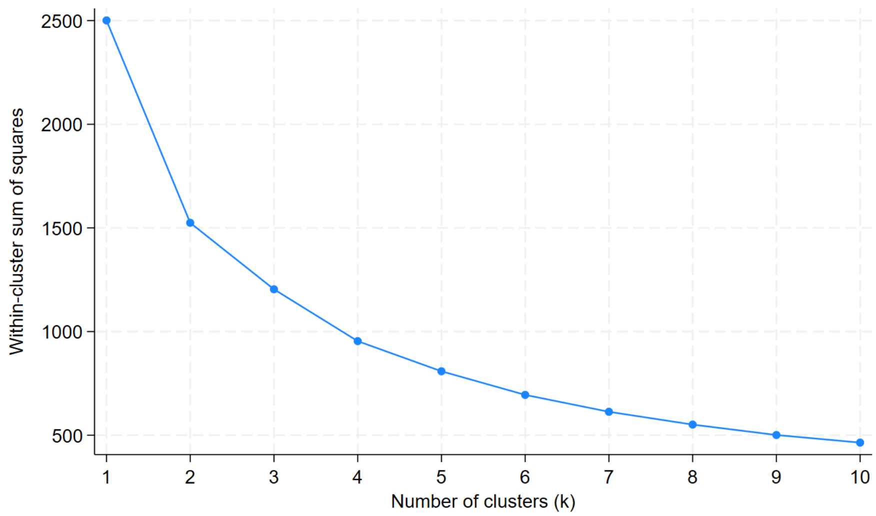
(a) One-week anticipatory (pre) MPXs and payment (post) MPXs



(b) Within-person average pre- and post-MPXs

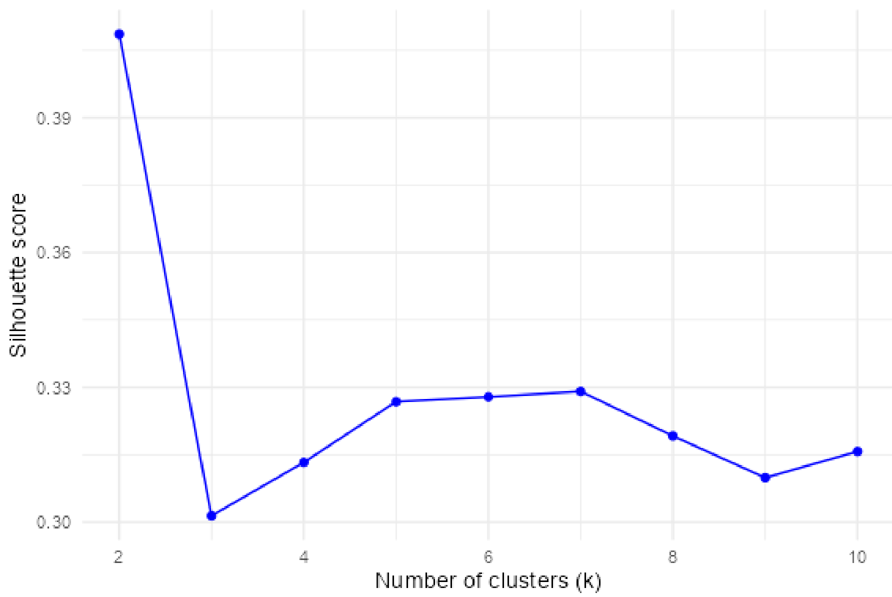
Notes. Panel (a) shows histograms of the marginal propensity to spend out of pre-announced one-time income changes in the week before (pre-MPX) and week after (post-MPX) the arrival of income. Panel (b) shows the distribution of *average* pre- and post-MPXs across all observed events within each user. Here we restrict the sample to users with at least 4 events observed across all event types. Both panels utilize MPXs derived from total expenditures. Each observation represents a user-event in panel (a) and represents a user in panel (b)

Figure A.4: Within-Cluster Sum of Squares by Number of Clusters



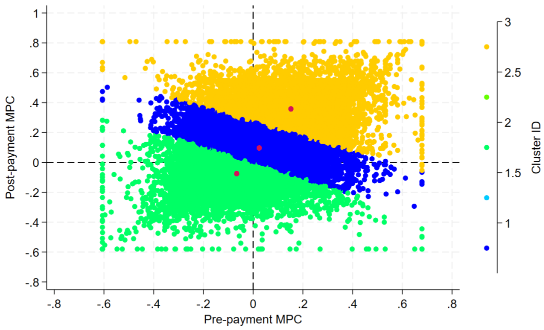
Notes. This figure plots the within-cluster sum of squares for each value of k in our k means clustering algorithm.

Figure A.5: Silhouette score by Number of Clusters

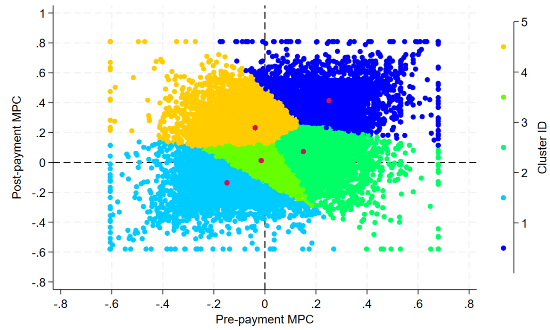


Notes. This figure plots the average silhouette score for each k (number of clusters). The silhouette score is a measure how how well each point in the cluster fits in its assigned cluster compared to the next closest cluster.

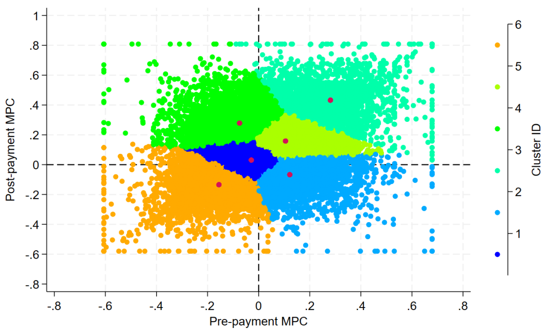
Figure A.6: Alternative Number of Clusters



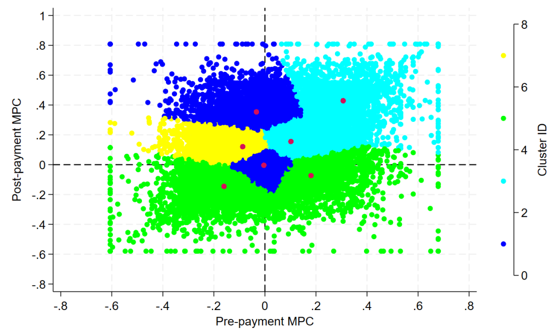
(a) k=3



(b) k=5



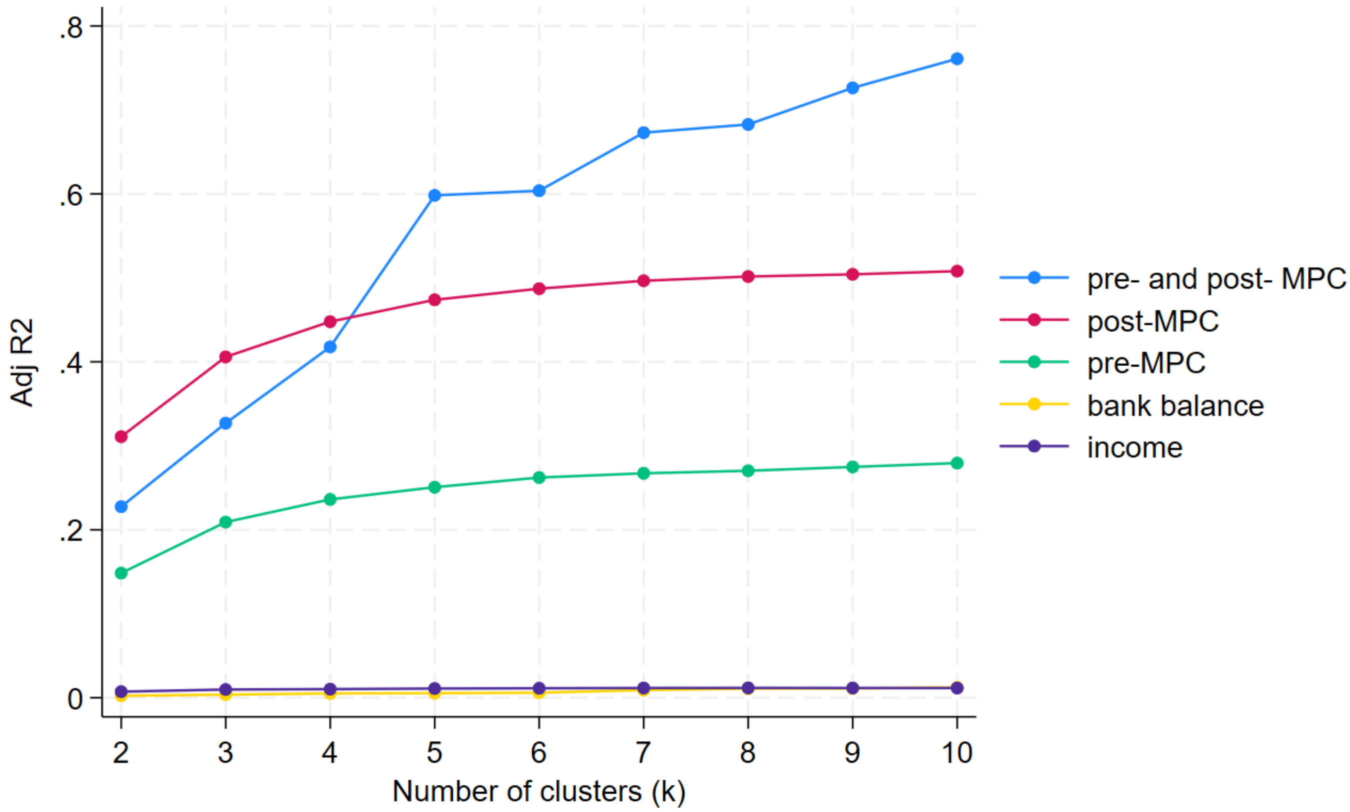
(c) k=6



(d) k=7

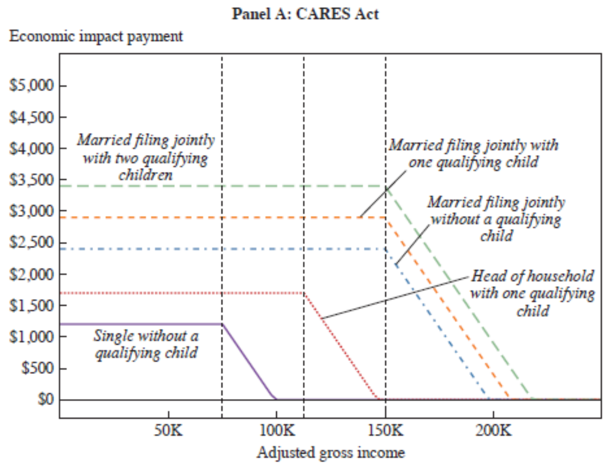
Notes. This figure shows a scatter plot of individual-level average one week pre-payment and post-payment MPCs. The individual-level averages are calculated by taking the average of each measure for all events observed within each individual. Each individual is assigned to a cluster based on our k means clustering algorithm and each cluster is represented by a different color. The red points represent the average pre-payment and post-payment MPC for each cluster.

Figure A.7: Adjusted R^2 by number of clusters (k)

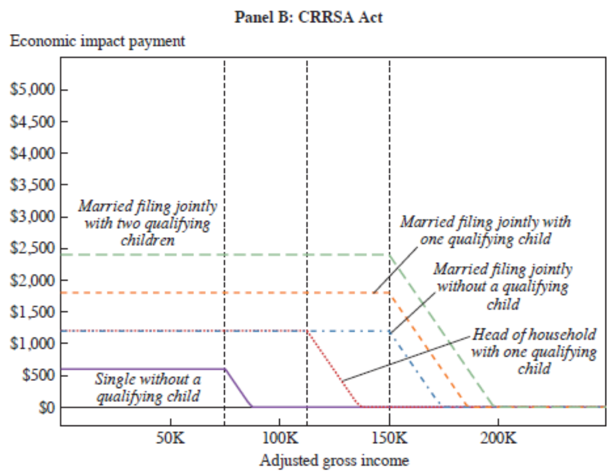


Notes. This figure shows a the R^2 of a regression of the MPC slope (post-MPC - pre-MPC) on indicator variables for each cluster k for various k.

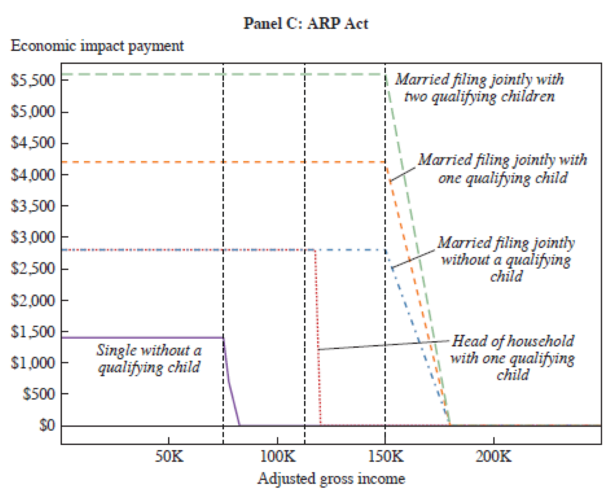
Figure A.8: Sources of Identifying Variation from the COVID Stimulus Programs



(a) COVID Stimulus 1: CARES Act of March 27, 2020



(b) COVID Stimulus 2: CRRSA Act of Dec. 29, 2020



(c) COVID Stimulus 3: ARP Act of March 11, 2021

Notes. These Figures are reproduced for convenience from Parker et al. (2022), Figure 2. CARES refers to the *Coronavirus Aid, Relief, and Economic Security* Act of 2020; CRRSA to the *Coronavirus Response and Relief Supplemental Appropriations* respectively the *Consolidated Appropriations* Act of 2021; and ARP to the *American Rescue Plan* Act of 2021.

C Appendix Tables

Table A.1: Transaction Category Classification

Transaction Category	Total Spending	Nondurable Spending	Total Income
Panel A: Spending transactions			
ATM/Cash Withdrawals	Yes	No	No
Automotive/Fuel	Yes	Yes	No
Cable/Satellite/Telecom	Yes	Yes	No
Charitable Giving	Yes	No	No
Check Payment	Yes	No	No
Education	Yes	Yes	No
Electronics/General Merchandise	Yes	Yes	No
Entertainment/Recreation	Yes	Yes	No
Gifts	Yes	No	No
Groceries	Yes	Yes	No
Healthcare/Medical	Yes	Yes	No
Home Improvement	Yes	No	No
Insurance	Yes	Yes	No
Loans	Yes	No	No
Mortgage	Yes	No	No
Office Expenses	Yes	Yes	No
Other Expenses	Yes	No	No
Personal/Family	Yes	Yes	No
Pets/Pet Care	Yes	Yes	No
Postage/Shipping	Yes	Yes	No
Rent	Yes	No	No
Restaurants	Yes	Yes	No
Service Charges/Fees	Yes	No	No
Services/Supplies	Yes	Yes	No
Subscriptions/Renewals	Yes	Yes	No
Travel	Yes	Yes	No
Utilities	Yes	Yes	No
Panel B: Other transactions			
Credit Card Payments	No	No	No
Deposits	No	No	Yes
Expense Reimbursement	No	No	No
Interest Income	No	No	Yes
Investment/Retirement Income	No	No	Yes
Other Income	No	No	Yes
Refunds/Adjustments	No	No	No
Retirement Contributions	No	No	No
Rewards	No	No	No
Salary/Regular Income	No	No	Yes
Sales/Services Income	No	No	Yes
Savings	No	No	No
Securities Trades	No	No	No
Taxes	No	No	No
Financial Account Transfers	No	No	No

Notes. This table presents the transaction category classification.

Table A.2: Responses to Income Changes Around the Payment Date: Total Spending

			Post-MPX			Pre-MPX
Event	Period	Observations	1-week	1-month	3-month	1-week
Panel A: All events pooled						
Anticipated Payment	2012–2023	205,743,872	0.0761***	0.2066***	0.3586***	0.0142***
			(0.0028)	(0.0079)	(0.0153)	(0.0008)
Panel B: One-off events						
COVID Stimulus 1	2020	19,294,172	0.1023***	0.2639***	0.4485***	0.0120***
			(0.0033)	(0.0073)	(0.0167)	(0.0028)
COVID Stimulus 2	2020–2021	37,379,306	0.1398***	0.1708***	–	0.0135***
			(0.0053)	(0.0111)		(0.0042)
COVID Stimulus 3	2021	18,082,437	0.0984***	0.2311***	0.2746***	0.0141***
			(0.0025)	(0.0055)	(0.0113)	(0.0021)
Panel C: One-time monthly payments for 6 months						
Child Tax Credit	2021–2022	33,251,181	0.1761***	–	–	0.0264**
			(0.0107)			(0.0112)
Panel D: Once every year						
Alaska PF Dividend	2012–2023	205,747,911	0.1293***	0.3108***	0.5243***	0.0217***
			(0.0042)	(0.0098)	(0.0241)	(0.0025)
Tax Refund	2012–2023	205,747,911	0.0682***	0.1844***	0.3085***	0.0110***
			(0.0029)	(0.0076)	(0.0140)	(0.0008)
Panel E: Periodically						
Monthly Paycheck	2012–2023	98,787,012	0.1573***	–	–	0.0432***
			(0.0019)			(0.0013)

Notes. This table reports the same statistics as Table 4 but for total expenditures (MPXs) instead of spending on nondurables and services (MPCs). See Table 4 for details.

Table A.3: One Week Spending Responses Around the Announcement Date

			Announcement Date	
Event	Period	Observations	Pre-MPC	Post-MPC
Panel A: Nondurable spending (MPCs)				
COVID Stimulus 1	2020	19,294,172	-0.0069***	-0.0055***
			(0.0016)	(0.0017)
COVID Stimulus 2	2020–2021	37,379,306	0.0004	0.0241***
			(0.0028)	(0.0029)
COVID Stimulus 3	2021	18,082,437	0.0049***	0.0252***
			(0.0012)	(0.0013)
Alaska PF Dividend	2012–2023	205,747,911	0.0151***	0.0236***
			(0.0014)	(0.0016)
Panel B: Total spending (MPXs)				
COVID Stimulus 1	2020	19,294,172	-0.0025	0.0027
			(0.0030)	(0.0034)
COVID Stimulus 2	2020–2021	37,379,306	-0.0030	0.0289***
			(0.0048)	(0.0049)
COVID Stimulus 3	2021	18,082,437	0.0049**	0.0500***
			(0.0023)	(0.0024)
Alaska PF Dividend	2012–2023	205,747,911	0.0278***	0.0378***
			(0.0026)	(0.0027)

Notes. This table presents the one-week spending responses to future fiscal income transfers around the time of announcement. For the COVID Stimulus 3, the post-announcement-MPC may contain the payment dates for several individuals due to the close time gap between the announcement and payment. Date and Individual-by-day of month fixed effects are applied. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Relationship between Pre- and Post-Payment MPCs

	Dependent variable: Pre-Payment MPC, one-week					
	(1)	(2)	(3)	(4)	(5)	(6)
Post-MPC, one-week	0.0633***	0.0563***	0.0581***			
	(0.0015)	(0.0017)	(0.0019)			
Post-MPC, one-month				0.0423***	0.0410***	0.0424***
				(0.0006)	(0.0007)	(0.0008)
Observations	348,785	348,785	272,514	348,785	348,785	272,514
R^2	0.007	0.169	0.173	0.015	0.176	0.181
Event FE	YES	YES	YES	YES	YES	YES
User FE		YES	YES		YES	YES
Financial Controls			YES			YES

Notes. This table presents regressions of Pre-MPCs on Post-MPCs of varying horizons. Financial controls include bank balances, available credit card credit, income, and the count of incurred overdrafts as well as a user's average MPC out of paychecks and a user's average propensity to consume (APC) across the sample period. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: One-Week Nondurable Spending Responses by Cluster

Event	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Panel A: One-off events				
COVID Stimulus 1: Post-MPC	0.1966***	0.0153***	0.1095***	-0.0016
	(0.0090)	(0.0021)	(0.0039)	(0.0036)
Pre-MPC	0.0614***	0.0146***	-0.0110***	-0.0219***
	(0.0064)	(0.0020)	(0.0028)	(0.0032)
COVID Stimulus 2: Post-MPC	0.3251***	0.0229***	0.2067***	-0.0227***
	(0.0135)	(0.0034)	(0.0059)	(0.0065)
Pre-MPC	0.1039***	0.0316***	-0.0599***	-0.0454***
	(0.0125)	(0.0032)	(0.0044)	(0.0057)
COVID Stimulus 3: Post-MPC	0.1532***	0.0233***	0.0986***	0.0151***
	(0.0067)	(0.0016)	(0.0031)	(0.0029)
Pre-MPC	0.0403***	0.0096***	0.0073***	-0.0102***
	(0.0051)	(0.0015)	(0.0024)	(0.0026)
Panel B: One-time monthly payments for 6 months				
Child Tax Credit: Post-MPC	0.6621***	0.0546***	0.3224***	-0.2527***
	(0.0281)	(0.0079)	(0.0122)	(0.0164)
Pre-MPC	0.4693***	0.1238***	-0.0883***	-0.3263***
	(0.0300)	(0.0081)	(0.0124)	(0.0157)
Panel C: Once every year				
Alaska PF Dividend: Post-MPC	0.2038***	0.0481***	0.1349***	0.0517***
	(0.0235)	(0.0026)	(0.0049)	(0.0058)
Pre-MPC	0.0599***	0.0214***	0.0119***	0.0175***
	(0.0094)	(0.0020)	(0.0027)	(0.0044)
Tax Refund: Post-MPC	0.1129***	0.0179***	0.0831***	0.0076***
	(0.0170)	(0.0010)	(0.0026)	(0.0012)
Pre-MPC	0.0314***	0.0063***	-0.0038***	-0.0038***
	(0.0045)	(0.0005)	(0.0006)	(0.0011)
Panel D: Periodically				
Monthly Paycheck: Post-MPC	0.1844***	0.055***	0.1103***	0.0322***
	(0.0046)	(0.0011)	(0.0022)	(0.0017)
Pre-MPC	0.0872***	0.0275***	0.0168***	0.0041***
	(0.0032)	(0.0008)	(0.0014)	(0.0014)

Notes. This table presents the one-week nondurable spending responses around the payment date by cluster. Date and individual-by-day of month fixed effects are applied. Standard errors clustered at the individual level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Payment Size, Salience and MPCs, by Cluster

	All Clusters	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Panel A. Post-MPC					
Payment-to-Income Ratio	-0.545***	-4.223***	-0.161***	-2.108***	2.459***
	(0.0435)	(0.184)	(0.0546)	(0.0884)	(0.115)
R^2	0.193	0.235	0.143	0.161	0.168
Panel B. Pre-MPC					
State News Coverage	0.248***	0.269	0.422***	-0.0277	0.230
	(0.0910)	(0.421)	(0.122)	(0.180)	(0.207)
R^2	0.147	0.143	0.088	0.105	0.111
Observations	345,325	21,050	172,043	82,448	69,784
HH FE	YES	YES	YES	YES	YES
Event FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Financial Controls	YES	YES	YES	YES	YES

Notes. Panel A presents results of regressions of Post-MPCs on the ratio between the payment amount and an individual's annual income. Panel B displays results of regressions of Pre-MPCs on the amount of news coverage for a particular event in the state of residence for an individual. Financial controls include bank balances, available credit card credit, income, and the count of incurred overdrafts as well as a user's average MPC out of paychecks and a user's average propensity to consume (APC) across the sample period. Standard errors clustered at the individual level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.