Anticipation and Consumption

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Abstract

This paper introduces a model of how the timing of information affects consumption decisions and tests its predictions in both developed and developing contexts. In our model, consumers form intertemporal plans and experience utility from anticipating future consumption. The model predicts excess sensitivity of spending to receiving a windfall, with smaller spending responses when there is more time to anticipate receiving the payment. The prediction that waiting leads to more patient decisions does not depend on whether consumers are liquidity constrained. Using Nielsen Consumer Panel data, we find higher marginal propensities to spend for households scheduled to receive the 2008 Economic Stimulus Payments sooner. Using data from randomized experiments in Kenya and Malawi, we find higher savings and assets among households scheduled to wait longer before receiving lump-sum unconditional cash transfers. Finally, we discuss existing evidence on how consumption responds to gains, losses, and news in light of our model.

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1 Introduction

Households with higher propensities to plan have higher savings (Lusardi, 1999, 2001; Ameriks *et al.*, 2003). Despite the importance of financial planning and the pervasiveness of thinking about money, economic models offer little guidance as to how time spent anticipating future consumption affects decision making.

Models of intertemporal choice typically assume, as Berns, Laibson and Loewenstein (2007) note in their neuroeconomics survey article, "that choices have no utility consequences other than the consumption events that result from those choices [...]. In practice, however, when a plan is made in advance [...] there is a waiting period during which the future outcome is anticipated."[1] As a particular example, they report that anticipatory activity in neural systems "has been associated with the prospect of receiving a financial windfall."

In this paper, we present a model in which consumers experience utility from anticipation. Section 2 derives implications for how the timing of information affects intertemporal consumption decisions. Specifically, the model makes predictions about how consumers react to consumption opportunities depending on how much they can anticipate those opportunities. Our main result shows that more time to anticipate leads decision makers to put more weight on future consumption, thereby making more patient choices. The model captures the intuition that decision makers overreact to surprises, as they overconsume in response to windfalls (Stone, 2005; Kőszegi and Rabin, 2009), but surprises wear out over time (Thakral and Tô, forthcoming), so that waiting longer before receiving a windfall induces consumers to save more. Our model predicts similar patterns for liquidity-constrained and unconstrained consumers as well as higher marginal propensities to consume out of smaller windfalls.

The prediction that receiving information earlier orients consumers toward the future is in stark contrast with discounted-utility models of intertemporal choice (Samuelson, 1937; Ainslie, 1975; Mazur, 1984; Loewenstein and Prelec, 1992; Harvey, 1994; Laibson, 1997). Under such models, the timing of news does not affect choices because decision makers who receive information at different times face identical intertemporal tradeoffs once the consumption opportunity arises. Anticipatory utility,

[1] They also point out that while "this period of anticipation might have its own affective consequences [...] [t]he period between decision and outcome has received relatively little consideration from economic researchers because economic models typically do not treat purely mental events as intrinsic sources of utility."

by contrast, predicts a complementarity between waiting times and saving. Longer waiting times enable consumers to experience more anticipatory utility, and a greater stock of anticipatory utility increases the marginal utility of saving.

Testing the model's predictions requires exogenous variation in when households learn about a windfall payment relative to when they receive it. We examine two distinct domains that have this feature. The first consists of a natural experiment provided by the randomized disbursement dates of a U.S. fiscal stimulus payment (Parker *et al.*, 2013). The second involves variation induced by randomized controlled trials (RCTs) on unconditional cash transfers in Kenya (Haushofer and Shapiro, 2016) and Malawi (Brune *et al.*, 2017). Although these settings have been explored in previous work, our empirical findings in each case—greater consumption responses among households that receive payments sooner after announcement—are new.

In Section 3, we use Nielsen Consumer Panel data to study consumption expenditure responses to the tax rebates sent to low- and middle-income American households as part of the Economic Stimulus Act of 2008 (Broda and Parker, 2014; Parker, 2017). Our identification strategy, as in prior research, relies on the fact that the last two digits of the recipient's Social Security number (SSN) determined the timing of payment over a three-month period. While previous papers estimate an impulse response function of consumption to the receipt of payment by comparing households a given number of weeks since receiving a stimulus payment with households that will receive payments later, our work additionally exploits variation in waiting times across households as motivated by our model of anticipatory utility. We find that faster disbursement of stimulus payments leads to a substantial change in spending behavior, with households receiving payments at the earliest date spending twice as much as the average household.

Our empirical results in the domain of tax rebates contribute to an extensive literature in household finance, public economics, and macroeconomics on tests of intertemporal consumption models, notably the life-cycle/permanent-income hypothesis (Modigliani and Brumberg, 1954; Friedman, 1957; Hall, 1978). The review article by Jappelli and Pistaferri (2010) emphasizes "two distinct questions" that the literature considers, namely how consumption responds to anticipated income changes and how consumption responds to unexpected shocks. Our work goes beyond this distinction by positing the importance of the duration over which an income shock is anticipated. The most closely related papers in this literature to ours are those that use household-

level data to estimate the consumption impacts of stimulus payments (Johnson *et al.*, 2006; Parker *et al.*, 2013) and examine the role of liquidity constraints. We build on the existing work methodologically by using a two-step estimation approach.[2] Our findings point toward a novel role for the timing of information in designing effective stabilization policies.

In Sections 4 and 5, we present new analyses of raw data from two published RCTs. The first is an impact evaluation of unconditional cash transfers by a non-governmental organization (GiveDirectly) using a sample of households in Rarieda, Kenya (Haushofer and Shapiro, 2016). The second is a windfall experiment in partnership with a commercial bank (NBS Bank) to understand how households manage cash without formal financial products using a sample of households in villages near Mulanje, Malawi (Brune *et al.*, 2017).

The Kenya study contains a set of treatments to compare lump-sum payments with a series of nine monthly installments. To facilitate that comparison, the lump-sum transfers take place at randomly selected but pre-announced times within nine months of enrollment in the program. This previously unexploited random variation in the timing of lump-sum transfers thus provides an ideal experiment for testing our predictions. Among households that wait longer to receive their transfer payments, we find increases in savings and investments.

The Malawi study contains payment-delay treatments to understand whether time-inconsistent behavior provides scope for financial products such as savings defaults to improve welfare. While the authors find no evidence that delaying payments affects the amount or composition of spending, our analysis of the data focuses on different forms of savings, which overlap to some extent with their expenditure measures, thus leading to new conclusions. In particular, we find significant increases in savings in response to receiving a delayed windfall payment.

Our analyses of these experimental data relate to a large body of work in development economics on cash transfers as a tool for alleviating poverty (Hanlon *et al.*, 2012). In a systematic review of the design of cash transfers, Bastagli *et al.* (2016) note the following core features: complementary interventions, conditionality, duration, frequency, main recipient, predictability and reliability, size, and timing of transfer payments. Our work relates most closely to, but is distinct from, the issues of timing

[2]See Borusyak and Jaravel (2017) for a discussion of possible biases in previous approaches and a related proposal for improvement.

and predictability. While timing there refers to making funds available to households at specific instances when needs arise, such as the time to pay school fees or to acquire agricultural inputs (Duflo *et al.*, 2011), our results pertain to the timing of payments relative to when households learn about them. Predictability refers to reducing uncertainty associated with failing to deliver expected transfers on time; for instance, Bazzi *et al.* (2015) document reduced consumption expenditures in response to an unanticipated delay in disbursement of an unconditional cash transfer program in Indonesia, consistent with liquidity constraints. Our evidence complements this by focusing on how anticipated delays or waiting periods affect household decision making. Utility from anticipation thus suggests the potential for a new design feature—waiting times—to prompt agents to "slow down and spend more time thinking," leading to less impulsive behavior (Heller *et al.*, 2017).

Section 6 discusses additional predictions of our model as well as the relationship of the model with existing empirical evidence. Our model provides an explanation for the widely documented phenomena of excess sensitivity and excess smoothness of consumption (Campbell and Deaton, 1989): Households in our model adjust consumption when they receive additional income rather than new information to avoid a loss from deviating from their consumption plan, consistent with ideas of mental accounting from Shefrin and Thaler (1988).[3] Our model reconciles seemingly conflicting findings in the literature that consumption responds to anticipated payments in some settings (Kueng, 2018) but not others (Browning and Collado, 2001) by emphasizing the timing of information and the time horizon over which households anticipate changes in income. We also discuss how the model can explain asymmetric patterns of consumption smoothing, i.e., smoothing in response to losses but not gains (Baugh *et al.*, forthcoming), and we show that the model predicts a decreasing relationship between the size of a windfall and the marginal propensity to consume, as recent work by Fagereng *et al.* (forthcoming) documents empirically. Furthermore, we discuss how our model captures the intuition behind a broader range of phenomena related to waiting times and patience beyond spending-saving decisions. Several lab and field experiments document a relationship between waiting time and impatience in decisions about specific consumption goods or effort allocation. The evidence

[3]This contrasts with the predictions of a dynamic model of expectations-based reference dependence (Kőszegi and Rabin, 2009), which predicts that consumption increases in response to news about future gains.

from these experimental settings supports the view that waiting times lead to more patient decision making for reasons that do not rely on particular features of spending decisions.[4] We conclude in Section 7.

2 Model of anticipatory utility and waiting periods

This section presents a model in which consumers form intertemporal plans and experience utility from anticipating future consumption. We adapt the general framework of anticipatory utility in intertemporal choice problems from Thakral (2020b) to a simple consumption-savings problem.[5] Our analysis focuses on how the timing of information about a windfall affects expenditures. The main results show how waiting times lead to more weight on future consumption and hence more patient decision making. The main text describes the results in the context of a simple example, while Appendix A provides more general and formal statements of the propositions.

2.1 Basic setup

We introduce the components of the model in a special case with three periods: Information exogenously arrives in period 0, and consumption takes place in periods 1 and 2. In the information period, an agent learns about a windfall $W \geq 0$. In each consumption period $t \in \{1, 2\}$, the agent chooses period-t consumption c_t subject to the budget constraint $c_1 + c_2 \leq W$.

We use the non-terminal consumption period to represent short-term spending and the terminal period to represent long-term savings. Accordingly, we assume that period-1 consumption exhibits diminishing marginal utility, and we refer to the marginal utility of terminal-period consumption as the marginal utility of lifetime income, which is constant. We denote consumption utility in period $t \in \{1, 2\}$ by

[4] Potential explanations that only pertain to spending decisions include having more time to remember high-value investments, having more time for long-term needs to arise, or having more time to formulate and commit to a savings plan; however, these explanations would neither account for the experimental results on consumption goods and effort decisions, nor would they account for our finding of similar spending patterns for consumers who are not liquidity constrained.

[5] Thakral (2020b) introduces a model of anticipatory utility motivated by neural evidence and analyzes its implications for intertemporal choice. While that paper primarily considers choices over exogenous consumption streams, we apply the model to a consumption-savings problem. Loewenstein (1987) also presents a model of anticipatory utility and intertemporal choice, which Thakral (2020b) discusses in detail.

$m_t(c)$, where $m_t'(c) > 0$, $m_1''(c) < 0$, and $m_2''(c) = 0$. We normalize the marginal utility of lifetime income to 1 by setting $m_2(c) = c$, and we assume $m_1'(0) = 1$ so that a consumption-utility-maximizing agent saves the entire windfall until the terminal period.

2.2 Anticipatory utility

In addition to experiencing utility from current consumption, the agent derives utility from two additional sources. The first is from looking forward to consumption in future periods, which we model through optimally chosen levels of anticipation of future consumption.[6] The second is from differences between realized outcomes and levels of anticipation, which we model through gain-loss utility as in models of reference-dependent preferences (Kőszegi and Rabin, 2006, 2009). Given a level of anticipation α_τ of period-τ consumption utility, we denote the utility from revising the level of anticipation to α_τ' by $n(\alpha_\tau' \,|\, \alpha_\tau)$. We refer to $\alpha_\tau' - \alpha_\tau$ as the degree of experienced anticipation and often abuse notation by simply writing $n(\alpha_\tau' - \alpha_\tau)$. We assume that gain-loss utility takes the same form, i.e., that $n(\alpha_\tau' \,|\, \alpha_\tau)$ also describes the utility from realizing consumption utility α_τ' relative to a reference point given by the level of anticipation α_τ. We also assume time separability and additivity.

The anticipatory utility function n satisfies the properties of a value function from prospect theory (Kahneman and Tversky, 1979).[7] First, when experienced anticipation is positive (resp., negative), we have $n'' < 0$ (resp., $n'' > 0$). In other words, n exhibits diminishing sensitivity to the magnitude of experienced anticipation. Second, for $\alpha > 0$, we have $n(\alpha) < -n(-\alpha)$ and $n'(\alpha) < n'(-\alpha)$. This implies that negative experienced anticipation has larger utility consequences than positive experienced anticipation of equal magnitude. Third, we normalize $n(0)$ to zero.

The agent chooses levels of anticipation and consumption in each period to maximize an undiscounted sum of future utility. Let α_τ^t denote the period-t level of anticipation of period-τ consumption utility, where $t < \tau$. In period 0, the agent chooses levels α_1^0 and α_2^0 of anticipation of period-1 and period-2 consumption utilities, respectively. In period 1, the agent chooses consumption c_1 and a level α_2^1 of anticipation of period-2

[6] This captures an effect that the literature on anticipatory utility refers to as "savoring" (Loewenstein, 1987).

[7] The applications of this model of anticipatory utility span the domains of intertemporal choice (Thakral, 2020b), choice under risk (Thakral, 2020a), and preferences for information (Thakral, 2020c).

consumption utility. In period 2, the agent chooses consumption c_2 (determined by the choice of c_1 since the budget constraint will bind). We summarize the sources of utility in each period as follows:

$$
\begin{aligned}
u_0 &= n\Big(\alpha_1^0 \,\Big|\, 0\Big) + n\Big(\alpha_2^0 \,\Big|\, 0\Big) \\
u_1 &= m_1(c_1) + n\Big(m_1(c_1) \,\Big|\, \alpha_1^0\Big) + n\Big(\alpha_2^1 \,\Big|\, \alpha_2^0\Big) \\
u_2 &= m_2(c_2) + n\Big(m_2(c_2) \,\Big|\, \alpha_2^1\Big).
\end{aligned}
$$

In period 0, the agent derives flow utility only from anticipation of future consumption, with $n(\alpha_1^0 \,|\, 0)$ representing the utility (in period 0) from anticipating a level α_1^0 of period-1 consumption utility, and with $n(\alpha_2^0 \,|\, 0)$ representing the utility (in period 0) from anticipating a level α_2^0 of period-2 consumption utility. Period-1 flow utility has components from all three sources: utility $m_1(c_1)$ from consuming c_1, utility $n(m_1(c_1) \,|\, \alpha_1^0)$ from the gain of consuming c_1 relative to the previously anticipated level of period-1 consumption utility α_1^0, and utility $n(\alpha_2^1 \,|\, \alpha_2^0)$ from increasing anticipation of period-2 consumption from α_2^0 to α_2^1. Period-2 flow utility consists of consumption utility $m_2(c_2)$ and gain utility $n(m_2(c_2) \,|\, \alpha_2^1)$ from consuming c_2 relative to the previously anticipated level of period-2 consumption utility α_2^1. In each period t, the agent maximizes $U_t = \sum_{t' \geq t} u_{t'}$.

2.3 Optimal anticipation and consumption

We solve for the optimal anticipation and consumption choices using backward induction. In period 2, the agent takes period-1 consumption c_1 (and the level of anticipation α_2^1) as given and chooses c_2 to maximize $U_2 = u_2$. In period 1, the agent takes the period-0 levels of anticipation α_1^0 and α_2^0 and the optimal period-2 consumption $c_2(c_1)$ as given and chooses consumption c_1 and a revised level of anticipation of period-2 consumption α_2^1 to maximize $U_1 = u_1 + U_2$. In period 0, the agent chooses anticipation α_1^0 and α_2^0 of period-1 and period-2 consumption to maximize $U_0 = u_0 + U_1$, taking as given the optimal consumption profile (c_1, c_2) and optimal period-1 anticipation of period-2 consumption (α_2^1).

Before proceeding, we note that the solution must satisfy $\alpha_1^0 \leq m_1(c_1)$ and $\alpha_2^0 \leq \alpha_2^1 \leq m_2(c_2)$. This follows from the property that negative experienced anticipation has larger utility consequences than positive experienced anticipation of equal magnitude

(see Lemma 1 in Appendix A for details). This enables us to consider the anticipatory utility function over the positive domain.

Period 2

The agent maximizes $U_2 = u_2$ by setting $c_2(c_1) = W - c_1$ since the budget constraint binds.

Period 1

The agent maximizes $U_1 = u_1 + u_2$ by choosing α_2^1 and c_1 that satisfy the following first-order conditions:

$$n'\Big(\alpha_2^1 - \alpha_2^0\Big) = n'\Big(W - c_1 - \alpha_2^1\Big) \tag{1}$$

$$m_1'(c_1)\Big(1 + n'\Big(m_1(c_1) - \alpha_1^0\Big)\Big) = 1 + n'\Big(W - c_1 - \alpha_2^1\Big). \tag{2}$$

Unlike in the case without anticipatory utility, Equation (2) implies that optimal period-1 consumption must be positive since the marginal utility of period-1 consumption (left-hand side) exceeds the marginal utility of period-1 consumption (right-hand side) at $c_1 = 0$.

The first-order condition with respect to α_2^1, given by Equation (1), implies that $\alpha_2^1 - \alpha_2^0 = W - c_1 - \alpha_2^1$, or equivalently,

$$\alpha_2^1 = \frac{c_2(c_1) + \alpha_2^0}{2}. \tag{3}$$

In other words, given the level of anticipation of period-2 consumption that the agent has already experienced, the agent maximizes utility by revising the level of anticipation halfway to the optimal level of consumption utility (and leaving the other half to be experienced as gain utility). This follows from concavity of the anticipatory utility function when the degree of anticipation experienced is positive. Given the result in Equation (3), the first-order condition with respect to c_1 from Equation (2) defines an expression for the optimal choice of period-1 consumption c_1 as a function of period-0 anticipation (α_1^0 and α_2^0).

Period 0

The agent maximizes $U_0 = u_0 + u_1 + u_2$ by choosing α_1^0 and α_2^0 that satisfy the following first-order conditions:

$$n'\left(\alpha_1^0\right) = n'\left(m_1(c_1) - \alpha_1^0\right) \tag{4}$$

$$n'\left(\alpha_2^0\right) = n'\left(\alpha_2^1 - \alpha_2^0\right). \tag{5}$$

The first-order condition with respect to α_1^0, given by Equation (4), implies that $\alpha_1^0 = m_1(c_1) - \alpha_1^0$, or equivalently

$$\alpha_1^0 = \frac{m_1(c_1)}{2}. \tag{6}$$

As in the period-1 decision to anticipate period-2 consumption, the agent maximizes by equating the utility from anticipating period-1 consumption in period 0 with the gain utility in period 1 due to concavity of the anticipatory utility function in the positive domain.

The first-order condition with respect to α_2^0, given by Equation (5), implies that $\alpha_2^0 = \alpha_2^1 - \alpha_2^0$, or equivalently

$$\alpha_2^0 = \frac{\alpha_2^1}{2}. \tag{7}$$

Similar to before, the agent maximizes utility by revising the level of anticipation halfway to the optimal level of anticipation that will serve as a reference point for period-2 consumption (and leaving the other half to be experienced as utility from anticipation in period 1). By combining Equation (7) with Equation (3), we obtain

$$\alpha_2^0 = \frac{c_2(c_1)}{3} \tag{8}$$

$$\alpha_2^1 = \frac{2c_2(c_1)}{3}. \tag{9}$$

This illustrates a general feature of the model: When looking forward to future consumption, the agent optimally chooses to revise the level of anticipation by equal amounts in each period.

Proposition (Optimal anticipation)**.** *The agent optimally equates the level of experienced anticipation across all periods.*

Proposition 1 in Appendix A formalizes this result, which captures a "savoring" effect (Loewenstein, 1987). Given our symmetric treatment of utility from anticipation and utility from realized gains (relative to the anticipated level of consumption utility), the agent also equates the optimal the degree of anticipation experienced in each period with the gain utility in the consumption period. With this characterization of optimal anticipation choices, optimal consumption results from solving Equation (2), or equivalently

$$m_1'(c_1)\left(1 + n'\left(\frac{m_1(c_1)}{2}\right)\right) = 1 + n'\left(\frac{W - c_1}{3}\right). \tag{10}$$

2.4 Waiting times

Having shown how anticipatory utility enters the model in a simple case with three periods (information, short-term consumption, and long-term consumption), we now proceed to introduce a waiting period between the information and consumption periods. As before, the agent exogenously learns in period 0 about a windfall $W > 0$. In period 1, no actions take place. Short-term and long-term consumption decisions then occur in periods 2 and 3, respectively. The notation and assumptions from the previous setup apply with the periods re-indexed accordingly.

We interpret period 1 as a *waiting period*: The agent does not take any actions but still experiences utility from anticipating future consumption. In each period t, the agent chooses α_τ^t (for $\tau \in \{2, 3\}$ and $t < \tau$) and c_t (for $t \in \{2, 3\}$) to maximize $U_t = \sum_{t' \geq t} u_{t'}$ where

$$\begin{aligned}
u_0 &= n\left(\alpha_2^0 \,\middle|\, 0\right) + n\left(\alpha_3^0 \,\middle|\, 0\right) \\
u_1 &= n\left(\alpha_2^1 \,\middle|\, \alpha_2^0\right) + n\left(\alpha_3^1 \,\middle|\, \alpha_3^0\right) \\
u_2 &= m_2(c_2) + n\left(m_2(c_2) \,\middle|\, \alpha_2^1\right) + n\left(\alpha_3^2 \,\middle|\, \alpha_3^1\right) \\
u_3 &= c_3 + n\left(c_3 \,\middle|\, \alpha_3^2\right).
\end{aligned}$$

Using backward induction, we find that optimal anticipation takes the form

$$\begin{aligned}
\alpha_2^0 &= \frac{m_2(c_2)}{3} \\
\alpha_2^1 &= \frac{2m_2(c_2)}{3} \\
\alpha_3^0 &= \frac{W - c_2}{4} \\
\alpha_3^1 &= \frac{W - c_2}{2} \\
\alpha_3^2 &= \frac{3(W - c_2)}{4},
\end{aligned}$$

and period-2 consumption solves

$$m_2'(c_2)\left(1 + n'\left(\frac{m_2(c_2)}{3}\right)\right) = 1 + n'\left(\frac{W - c_2}{4}\right). \tag{11}$$

Our main result, formalized as Proposition 2 in Appendix A, states that adding a waiting period induces lower short-term consumption.

Proposition (Optimal consumption with waiting periods)**.** *Longer waiting times lead to lower spending out of windfalls.*

The comparison between Equation (10) and Equation (11) illustrates this result in the context of this example. In each case, the agent faces a tradeoff between the enjoyment of greater short-term consumption and that of looking forward to greater long-term consumption. With more waiting periods, the agent experiences greater anticipation before making a consumption decision, and this increases the marginal utility of long-term consumption.[8] In other words, a longer time waiting time enables the consumer to enjoy savoring future consumption, which leads to more patient decision making.

Our model's prediction holds even if consumers do not face binding liquidity constraints. Although our description of the model implicitly assumes that consumption does not take place during waiting periods (i.e., after learning about but before

[8]This intuition relates to dynamic models of habit formation (Ryder and Heal, 1973) and reference-dependent utility (Kőszegi and Rabin, 2009). In the former, increasing current consumption leads to a greater habit stock and therefore increases the marginal utility of future consumption. In the latter, increasing current consumption reduces expectations (the reference point) of future consumption and therefore decreases the marginal utility of future consumption.

receiving the windfall), our model can accommodate similar patterns of behavior for both constrained and unconstrained consumers.

Proposition (Liquidity constraints)**.** *Optimal consumption only increases upon receiving a windfall payment, even if consumers can spend in advance.*

Proposition 3 in Appendix A derives this result under the assumption that households do not treat the future windfall as fungible with their existing liquid wealth (Thaler, 1999). If households spend out of funds that were planned for use in the future, they experience a loss with respect to future consumption that is later offset by an equal-sized gain when the windfall arrives, which can lead to a decrease in utility overall due to loss aversion. Thus, the model can also explain how consumption changes only in response to the *arrival* of the windfall and not to *news* about the windfall.

Sections 3 to 5 provide empirical tests of our main prediction. We discuss additional theoretical predictions of the model and the associated empirical evidence in Section 6.

3 Tax rebates in the US

This section analyzes our first empirical setting: the natural experiment provided by the randomized disbursement dates of the 2008 Economic Stimulus Payments (Parker *et al.*, 2013; Broda and Parker, 2014; Parker, 2017).

3.1 Setting

In response to the start of the recession in December 2007, the U.S. federal government approved an economic stimulus package in February 2008. All households with positive net income tax liability or at least $3,000 of qualifying income (Social Security, Veterans Affairs, or Railroad Retirement benefits) in 2007 were eligible for the Economic Stimulus Payments (ESPs).

In total, about 130 million U.S. tax filers received approximately $100 billion in tax rebates. Eligible taxpayers received a base payment of $600 ($1,200 for couples filing jointly) if their 2007 federal income tax liability exceeded that amount. Those with tax liabilities between $300 and $600 ($600 and $1,200 for couples) received a base payment equal to their tax liability, and those with tax liabilities of less than $300

($600 for couples filing jointly) received a base payment of $300 ($600 for couples). Households received an additional $300 for each child that qualified for the child tax credit in 2007. Payments were reduced by 5 percent of the amount by which adjusted gross income exceeded $75,000 ($150,000 for couples).

Payment dates followed a pre-announced timeline. The Internal Revenue Service (IRS) announced a disbursement schedule on March 17, with the earliest payments scheduled for the first week of May. Appendix Table 1 shows the ESP disbursement schedule.[9] Although the payment schedule and amounts were known in advance, households received notification letters from the IRS several days prior to their payment date. Payment dates were staggered because of the infeasibility of mailing all notification letters at the same time. The last two digits of a taxpayer's Social Security Number (SSN), which are effectively randomly assigned, determined their scheduled payment date.[10] On April 25, President Bush stated that the Treasury would start distributing stimulus payments several days earlier than expected.

The 2008 ESPs were the first large tax rebate to use electronic funds transfers (EFTs). About 80 million individual income tax returns were filed electronically in 2007, and tax filers who had provided the IRS with a personal bank account number for their income tax refunds received ESPs through direct deposit into their bank accounts. For tax returns that either provided no bank information or a tax preparer's bank information (e.g., due to a refund anticipation loan, or due to using the refund amount to pay tax preparation fees), the IRS sent paper checks in the mail.

3.2 Data

A multi-wave survey designed by Broda and Parker (2014) provides information about stimulus payments linked with detailed consumer expenditure data from the Nielsen Consumer Panel (NCP, formerly Homescan Consumer Panel).

The NCP data contain information on household demographics (e.g., household size and composition, income, and race) as well as daily spending of about 60,000 active households collected electronically from handheld barcode scanners. NCP households track spending on household items that primarily fall in the grocery, drugstore, and

[9] Some households received ESPs later than scheduled due to filing their income tax return late.

[10] SSNs assigned prior to June 25, 2011 consist of an area number (first three digits), a group number (middle two digits), and a sequentially assigned serial number (last four digits). The serial number is assigned sequentially within each group.

mass-merchandise sectors (see Broda and Weinstein 2010 for additional information). The spending data are aggregated to a weekly level to line up with the frequency of ESP disbursement.

The survey asks households whether they received a tax rebate via direct deposit or check, the dollar amount, the month and day they received their payment, and several questions related to general household financial planning. About 48,000 households provided responses to the survey, of which about 39,000 report receiving a stimulus payment. Among these, Broda and Parker (2014) note that some households do not report a payment date, report a payment date outside the randomized disbursement period, or provide inconsistent responses across multiple waves of the survey. Removing such observations, the remaining sample consists of about 29,000 households. We obtain the same analysis sample thanks to the replication files provided by Parker (2017). We further restrict the sample to households that report receiving a stimulus payment of at least $300. We interpret our results as internally valid estimates for the subsample of NCP panelists or the population that they represent (Bronnenberg *et al.*, 2015).

Nonrandom selection of households into the treatment sample would create difficulties for estimating causal impacts. As Broda and Parker (2014) argue, insofar as invalid survey responses are uncorrelated with payment dates, the selection criteria do not create bias in estimating average treatment effects among the remaining sample (though treatment effect heterogeneity can lead to bias in estimating population parameters). To examine the consistency of payment dates in our sample with the randomization, we test whether households receiving ESPs at different times have similar characteristics in Supplementary Appendix A.1. The sample of households receiving ESPs by direct deposit appears to be randomly distributed across the scheduled payment dates (Appendix Table 2). However, among the sample of households receiving ESPs by paper check, our balance tests reveal systematic differences by payment date across a wide range of characteristics (Appendix Table 3). These patterns could arise due to a systematic relationship between household characteristics and reporting payment dates inaccurately among respondents receiving paper checks. Even if households report payment dates accurately, another possibility stems from the longer disbursement period for paper checks: Since households that did not file their tax returns on time could receive stimulus payments later than dictated by the disbursement schedule, households who receive paper checks late (but still within the

randomized disbursement period) would be misclassified as being randomly assigned to a late payment date. Our analysis therefore focuses on the sample of households receiving payments by direct deposit.

3.3 Estimation methodology

The goal of this section is to develop an econometric framework for testing the predictions from Section 2 about the relationship between waiting times and expenditures induced by the tax rebate.

To facilitate the exposition, we begin by describing our empirical strategy as applied to the standard question in this literature: estimating the impulse response function of consumption to the receipt of payment. In analyzing a class of problems that encompasses this application, Borusyak and Jaravel (2017) elucidate an extrapolation performed by ordinary least squares (OLS) methods under heterogeneous treatment timing. Their work underscores the difficulty of identifying long-term effects in this context. Credible identification hinges on the presence of not-yet-treated units for constructing counterfactuals: Under random assignment of treatment timing, causal estimates obtain from comparing households a given number of weeks since receiving a stimulus payment with households that will receive payments later. Our analysis therefore focuses primarily on shorter-term impacts.

We use a two-step estimation approach. First we estimate time and household fixed effects independently of the causal effect of treatment by using only pre-treatment data. Then we estimate dynamic treatment effects—i.e., the impact on spending k periods after receiving an ESP for $k \geq 0$—after partialling out the estimated time and household fixed effects.

Formally, denote by E_i the time period of the event that i becomes treated, let $D_{it} = \mathbf{1}_{\{t \geq E_i\}}$ be an indicator for being treated, and define $K_{it} = t - E_i$ to be time relative to treatment. Let Θ be a set of time-invariant household characteristics, and let Y_{it} denote an outcome at time t for household i with time-invariant characteristics $\Theta_i \subset \Theta$.

The first step consists of a regression of the outcome Y_{it} on group-specific time effects $\beta_{\theta t}$ using pre-treatment data:

$$Y_{it} = \alpha_i + \sum_{\theta \in \Theta_i} \beta_{\theta t} + \nu_{it}, \quad \{i, t : K_{it} < -\underline{k}\} \tag{12}$$

where α_i are household fixed effects and $\beta_{\theta t}$ are characteristic-specific time trends. Note that we also exclude data within $\underline{k}$ periods from the treatment date to avoid estimating possible changes in outcomes resulting from the upcoming treatment.

In the second step, we model

$$Y_{it} = \widehat{\alpha_i} + \sum_{\theta \in \Theta_i} \widehat{\beta_{\theta t}} + \sum_{k=-\tilde{k}}^{\overline{k}} \gamma_k \mathbf{1}_{\{K_{it}=k\}} + \varepsilon_{it}, \tag{13}$$

where $\widehat{\alpha_i}$ and $\widehat{\beta_{\theta t}}$ are the estimated parameters from Equation (12), γ_k is the effect of treatment k periods after being treated, $\tilde{k}$ is the number of periods of pre-rebate treatment effects to estimate, and $\overline{k}$ is the number of periods of post-treatment effects. We define the cumulative spending impact over a t-week period as $\Gamma_t := \sum_{k=0}^{t-1} \gamma_k$. Note that $\max_i E_i - \min_i E_i - \underline{k} - 1$ is the maximum number of post-treatment effects that can be causally identified (i.e., for which $\widehat{\beta_{\theta t}}$ exists to construct a counterfactual). We use a block-bootstrap procedure to compute standard errors adjusted for clustering at the household level.

We proceed to adapt this framework to test our main prediction. The model in Section 2 posits that spending responses vary based on when households receive payments relative to when they are informed. Since households in our data receive payments according to a pre-announced disbursement schedule, variation in waiting time reduces to variation in treatment time. We therefore modify the second step in our estimation to incorporate heterogeneous treatment effects as follows:

$$Y_{it} = \widehat{\alpha_i} + \sum_{\theta \in \Theta_i} \widehat{\beta_{\theta t}} + \sum_{k=0}^{\overline{k}} \gamma_k^{E_i} \mathbf{1}_{\{K_{it}=k\}} + \varepsilon_{it}. \tag{14}$$

The parameter γ_k^τ represents the causal impact of receiving a rebate k periods ago among households treated in period τ. Analogous to before, we define $\Gamma_t^\tau := \sum_{k=0}^{t-1} \gamma_k^\tau$. We test whether the spending impacts satisfy $\Gamma_k^\tau > \Gamma_k^{\tau'}$ for $\tau < \tau'$, i.e., that households receiving rebate payments sooner after the announcement exhibit higher spending responses.

3.4 Impact of stimulus payments on spending

3.4.1 Assumptions

Operationalizing the two-step econometric procedure from Section 3.3 requires making assumptions such as how spending would have evolved over time for treated households in the absence of the stimulus payment. For our main results, the treatment group consists of households that report receiving a stimulus payment by direct deposit within two days of the scheduled payment date, and the comparison group consists of all households that report receiving a stimulus payment within the disbursement period associated with their reported payment method (direct deposit or paper check) as in Broda and Parker (2014); Parker (2017). We make the following assumptions in estimating Equation (12). First, to determine the counterfactual time trend for spending, the set of characteristics Θ consists of income groups (less than \$15,000; \$15,000–\$30,000; \$30,000–\$50,000; \$50,000–\$70,000; \$70,000–\$100,000; over \$100,000) and deciles of average expenditure by household size in the first quarter of 2008. Second, receiving a rebate check does not affect household spending two weeks in advance ($\underline{k} = 1$). Section 3.4.4 shows that our results are not sensitive to any of the above assumptions.

3.4.2 Average spending impacts

Before presenting our main results on the timing of stimulus payments, we discuss the average impact of receiving a stimulus payment on spending as a benchmark. This corresponds to estimating the Γ_t parameters derived from Equation (13). To put the cumulative spending impacts into perspective, note that the Nielsen data account for approximately 15 percent to 30 percent of household expenditure (Borusyak and Jaravel, 2017; Coibion *et al.*, forthcoming), and the average ESP for direct deposit households is approximately \$1,000.

We find broadly similar magnitudes to those in Broda and Parker (2014) when estimating Equation (13) for three subsamples of EFT households: our main estimation sample consisting of households receiving EFTs near the scheduled payment date, the subset of households receiving EFTs exactly on the scheduled payment date, and all other households that report receiving EFTs. Across these subsamples, our point estimates for Γ_1 range from \$6.67 to \$11.24, and our point estimates for Γ_4 range from \$24.98 to \$44.04, as shown in Figure 1 and Supplementary Appendix Table 1; we also

find insignificant spending responses after the month of payment receipt, with point estimates for $\Gamma_8 - \Gamma_4$ ranging from −\$12.06 to \$11.59.[11] Consistent with their results, we find no spending response in weeks prior to receiving payment.

3.4.3 Impact of timing of stimulus payments

We proceed to test whether households exhibit greater spending responses to payments that arrive earlier. Thus we estimate Equation (14) and test whether the cumulative 4-week spending impacts Γ_4^w vary across groups. Households received EFTs during the 18th, 19th, and 20th weeks of the year, which we denote as periods $w = 1$, $w = 2$, and $w = 3$, respectively (Appendix Table 1). These dates correspond to 6, 7, and 8 weeks after the original IRS announcement, but using the IRS announcement as a point of reference likely understates the extent to which the payments come as a surprise to the first group, especially in light of President Bush's April 25 announcement that the payments would begin sooner than originally stated.[12]

The data show a clear pattern of lower spending impacts for households that wait longer to receive their payments. Figure 2 summarizes our main results for various samples of households.[13] The left panel displays estimates of Γ_4^w for households receiving payments in different weeks, as well as p-values from testing the null hypotheses that $\Gamma_4^1 = \Gamma_4^2 = \Gamma_4^3$, while the right panel displays the confidence interval for the difference in spending between the first and last groups.

We begin by discussing the full sample of households receiving EFTs near the scheduled payment date. Among households randomly assigned to receive payments in the first week, we estimate a \$65.25 increase in spending during the four weeks after receiving the ESP, about twice as large as the increase in spending for the average household. The monthly spending impact for a household receiving payment in the first week is similar in magnitude to combining the impact on a household

[11] In estimating the impact of ESPs on spending in the week of receiving payment (Γ_1), Broda and Parker (2014) report point estimates ranging from \$12.8 to \$13.8. They obtain point estimates of the four-week or one-month cumulative increase in spending (Γ_4) ranging from \$27.9 to \$47.6. See Tables 3 and 4 in Broda and Parker (2014) and the discussion therein regarding the differences in magnitudes between their weekly and monthly analyses. They also report an insignificant average increase in spending of \$9.3 one month later ($\Gamma_8 - \Gamma_4$) in their preferred specification.

[12] Kaplan and Violante (2014) argue in favor of the informational assumption that all households learn about rebate payments upon disbursement of the first set of payments (i.e., households in the first group treat the payments as a surprise).

[13] Appendix Figure 1 displays cumulative spending effects during the four weeks following ESP receipt. Also see Supplementary Appendix Table 2 for the main results in the form of a table.

receiving payment one week later ($45.24) with the impact on a household receiving payment two weeks later ($18.73). This suggests an important role for the timing of payments in designing effective fiscal stimulus. The remaining rows of Figure 2 examine subsamples based on survey responses to questions pertaining to liquid assets and behaviors related to financial planning and spending as explored by Parker (2017).

To investigate the importance of liquidity, we divide the sample into two groups based on whether the household reports having at least two months of income available in cash, bank accounts, or easily accessible funds in case of an unexpected decline in income or increase in expenses, and we reestimate Equation (12) and Equation (14). Parker (2017) reports point estimates of the marginal propensity to consume NCP goods in the four weeks following ESP receipt ranging from 2.04 to 2.08 percent for households with sufficient liquid wealth and 4.87 to 6.57 percent for households without sufficient liquid wealth. Consistent with these findings as well as other prior literature (Zeldes, 1989; Johnson *et al.*, 2006; Agarwal *et al.*, 2007), the results in the second and third rows of Figure 2 show higher spending responses among households without liquidity. In addition, we find significant heterogeneity based on the timing of payment for both constrained and unconstrained households. Among households receiving payments in the third week, we find a spending response of close to zero for those with sufficient liquidity. Randomly assigning more liquid households to receive payments at the beginning of the disbursement period leads to substantial increases in spending of about $50 over the four weeks after receiving their ESP. We find a similar effect size for the subset of liquidity-constrained households that have to wait until the third week of the disbursement period to receive their payments. Our estimates thus imply an effect of waiting times large enough to close the gap in spending responses between households with and without sufficient liquid wealth.

We next examine heterogeneity in ESP spending responses by financial planning tendencies. We divide households into two groups based on whether they report reviewing their household's financial information in the last few years and formulating a financial plan for their long-term future. Intuitively, we might expect households that formulate consumption plans to exhibit lower propensities to spend out of windfalls (Reis, 2006). Indeed Parker (2017) finds a negative relationship between financial planning and ESP spending responses, and we find a similar relationship on average. In a possible exception to this general pattern, households that make financial plans and receive ESPs in the first week exhibit the largest spending responses ($74.58

for planners compared to $58.06 for non-planners). The finding that the largest spending responses come from households that engage in financial planning does not seem consistent with the view that planning generically induces higher savings. Our model suggests a more nuanced perspective. Consumers who engage in financial planning, thereby looking forward to future consumption, more strongly exhibit the consequences of anticipatory utility. As Section 2 highlights, this entails both overreactions to windfalls as well as sharp reductions in spending in response to waiting times.

The last pair of rows in Figure 2 separately consider households that characterize themselves as spending types and saving types, a measure of impatience.[14] We find, consistent with the results in Parker (2017), that more patient households spend less in response to the ESPs. Moreover, both self-reported spending types and saving types exhibit stronger responses to payments that arrive earlier. The consistency across these groups corroborates the notion that more time to anticipate future consumption impacts intertemporal decision making through channels distinct from impatience.

In addition to analyzing spending responses across households with different self-reported financial circumstances, we estimate heterogeneity in spending impacts by objective household characteristics. The relationship between waiting times and spending responses persists for households receiving different rebate amounts (Appendix Figure 2).[15] The results replicate for single individuals, couples, households with and without children (Appendix Figure 3), suggesting that the effects do not rely on individual decision making in isolation. The same pattern also emerges for high- and low-expenditure households as well as high- and low-income households (Appendix Figure 4), consistent with our theoretical predictions.

3.4.4 Robustness

This section explores the sensitivity of our results to the assumptions for determining the counterfactual spending trend in Equation (12), the comparison group of not-yet-treated households, and the treatment groups in Equation (14).

[14] The survey question asks, "In general, are you or other household members the sort of people who would rather spend your money and enjoy it today or save more for the future?" As Parker (2017) notes, the phrasing attempts to elicit a stable household characteristic rather than their response to the stimulus payments.

[15] To obtain marginal propensities to consume, we extend Equation (12) and Equation (14) by interacting the treatment indicator with the rebate amount. Also see Supplementary Appendix A.2 and Supplementary Appendix Table 3.

We begin by considering alternative sets of characteristics in the first step of the estimation (Panel A of Figure 3 and Supplementary Appendix Table 5). In our baseline specification, these characteristics include deciles of pre-rebate average expenditure and six income categories. Removing the income categories from the set Θ does not change the magnitudes of the estimated ESP spending impacts. Instead removing the expenditure deciles leads to slightly smaller estimates, though the differences across households receiving ESPs in different weeks remains equally substantial. The same holds if we remove both sets of characteristics and include only household fixed effects and period fixed effects. Allowing for differential spending trends based on the rebate amount leads to similar magnitudes as our main specification, as does replacing contemporaneous income with lagged values of income (for which the data contain much fewer missing values). Omitting household fixed effects leads to somewhat larger estimates.

We next consider alternative sets of comparison households (Panel B of Figure 3 and Supplementary Appendix Table 5). The baseline specification uses all households that receive ESPs within the disbursement period associated with their reported payment method to estimate counterfactual spending, using only data from at least two weeks before their reported payment weeks. Excluding one, two, or three additional weeks of data preceding ESP receipt slightly increases our estimates of the spending impacts. We also examine the sensitivity of our estimates to alternative specifications of the set of comparison households. Restricting the set of households to only those receiving paper checks, or further restricting to those that receive paper checks near the scheduled payment dates, leads to similar estimates of the ESP spending impacts. We obtain slightly larger point estimates if we use households receiving paper checks in July to ensure that the composition of households used to estimate each of the week fixed effects in Equation (12) remains stable. In our main specification as well as each of these alternative specifications, we find no significant spending responses in the weeks prior to receiving the ESP, providing evidence to support the validity of the estimated counterfactual spending trend (Appendix Table 4).

Lastly, we examine how our estimates change under different specifications of the treatment groups (Panel C of Figure 3 and Supplementary Appendix Table 5). Excluding households that report no spending for a consecutive four-week period does not change the magnitudes of our estimates. Restricting the sample of direct deposit households to those that report receiving their ESP on the exact day specified by the

disbursement schedule also leads to similar point estimates.

3.5 Alternative explanations

Our model of anticipatory utility provides a simple intuition for the empirical results: Households spend more in response to more surprising windfalls. The fact that liquidity constrained and unconstrained households exhibit similar patterns suggests an important role for this channel. Taking the two extreme cases, our explanation nests the standard notion that consumers should respond to anticipated income changes but not unexpected income shocks. Moreover, the model makes additional predictions which we discuss in Section 6. In the rest of this section, we assess the plausibility of various alternative explanations.

3.5.1 Borrowing, debt, and non-Nielsen spending

Since our consumption data only consist of spending on household items (Broda and Weinstein, 2010), changes in other forms of spending could potentially occur. Smaller spending responses among households that wait longer before receiving payments may arise if more time allows households to spend more of their ESPs in advance. Although our data show no evidence of additional spending in advance, households might either increase debt payments or increase non-NCP consumption (e.g., by borrowing, assuming that liquidity-constrained households have access to credit or are more likely to have access to credit if they have more time). The former possibility appears inconsistent with previous work on the 2001 and 2008 tax rebates (Agarwal *et al.*, 2007; Bertrand and Morse, 2009) documenting increases in debt payments upon *receiving* ESPs as opposed to in advance, while evidence on responses to state tax rebates from the Consumer Expenditure Survey (Heim, 2007) rejects the latter.

Alternatively, we might also observe a relationship between waiting times and spending responses if longer wait times simply lead to a compositional shift toward non-NCP expenditures. The question on self-reported ESP spending from the (Broda and Parker, 2014) survey provides evidence against this concern. The survey asks households to think about the "extra amount" they are spending because of the tax rebate and report how much of the additional spending falls in the following categories: household products, entertainment, durable goods, clothing, and other. Interpreting these data presents some difficulties because they reflect a combination of spending

responses and households' awareness of their spending responses. With this caveat in mind, we find that households in later payment groups do not report spending more of the ESPs on average than households in earlier payment groups.[16]

3.5.2 Planning and commitment

One could view our model as formalizing a channel through which planning or thinking about future consumption leads to more patient decision making. To facilitate this interpretation, we distinguish between forms of planning that pertain specifically to spending decisions and more general notions of planning. As we discuss in Section 6, related findings on intertemporal effort allocations and decisions regarding specific consumption goods in lab and field experiments suggest that the underlying mechanisms do not rely on particular features of spending decisions. Nonetheless, we discuss spending-related forms of planning in more detail below.

The ability to seek commitment or formulate spending plans provides a possible channel through which waiting times can lead to more forward-looking behavior. Consumers waiting longer may have more time to remember high-value investments, more time for long-term needs to arise, or more time to seek commitments to save or better savings opportunities. These channels hold less relevance in the case of unconstrained households, for which we observe the same pattern of higher spending after shorter waiting times. Moreover, waiting longer also means more time to plan to *spend* when the money arrives, so the direction of the expected effect would be ambiguous without a theory of planning. A model in which restricting consumption depletes willpower (Ozdenoren *et al.*, 2012) provides one such theory, which predicts greater spending upon receiving a long-awaited windfall (for consumers that have access to liquidity or credit), the opposite of what we observe.

A model of planning costs with rational inattention (Reis, 2006) provides another possible theory. Since consumers update their plans infrequently, a greater time distance between the announcement and the payment increases the probability that the plan they hold upon receiving the ESP accounts for the news about the windfall.[17]

[16] This holds for all categories of spending. Compared to households receiving ESPs in the first week of May, those receiving ESPs in the second week report spending \$5 to \$45 less and those receiving ESPs in the third week report spending \$35 to \$64 less.

[17] Longer waiting times would not matter for consumers with high planning costs since they rationally choose not to form consumption plans and therefore live "hand-to-mouth" by absorbing all income shocks through consumption.

Those who have not yet updated their consumption plans by the time they receive payment—which disproportionately consists of consumers in the earliest payment group—would not account for the windfall and therefore save whatever remains after consuming their previously planned amount. Our data show the opposite pattern.[18] Alternatively, if we view the financial crisis and stimulus payments as an "extraordinary event" (Reis, 2006), then consumers in all payment groups would revise their plans, in which case the waiting time would not affect spending.

3.5.3 Time effects

Testing our model's main prediction requires exogenous variation in when households learn about a windfall payment relative to when they receive it. In the setting of the 2008 stimulus payments, since households receive information about payments at the same time, the duration of anticipation does not vary independently of calendar time. If the marginal propensity to consume varies over the course of a month with fluctuations in cash on hand, we might expect to find larger spending responses in weeks when households must make rent payments or pay other bills, which tends to occur at the beginning of the month. On the other hand, we might expect to find smaller spending responses in weeks when households receive paychecks, which tends to push in the opposite direction. For a household making rent payments at the beginning of the month and receiving weekly paychecks, this would plausibly lead to larger spending responses to payments received in the first week of May and similar (smaller) responses to payments received in later weeks.[19] We do not find any evidence of large consumption responses to payments received at the beginning of the month for households receiving ESPs in June and July, though this test does not use the ideal source of random variation in payment dates (Appendix Table 3). The finding that households with different levels of income and liquidity exhibit similar patterns further

[18] Another possibility might be that consumers receiving payments later update their consumption plans downward, e.g., because of new information on the severity of the crisis, which might lead to larger absolute spending responses for households in the earliest payment group. Our difference-in-differences estimation approach addresses this concern because the households that we use to construct the counterfactual spending trend would also be just as likely to have adjusted their spending plan and face the same macroeconomic conditions.

[19] Similarly, for households receiving biweekly paychecks, we would expect a non-monotonic pattern, with the largest response to receiving payments in the second week, and the smallest response to receiving payments in the third week. For households receiving monthly paychecks, we would expect to find larger responses to ESPs received in later weeks of the month.

limits the plausibility of explanations relying on calendar-time effects or interactions with the paycheck cycle.

4 Cash transfers in Kenya

This section analyzes our second empirical setting: an impact evaluation of unconditional cash transfers from the non-profit organization GiveDirectly, which delivers tens of millions of dollars in donations each year via the mobile-phone-based payment service M-Pesa to households in extreme poverty.

4.1 Setting and data

Haushofer and Shapiro (2016) conduct an RCT to evaluate the impacts of unconditional cash transfers by GiveDirectly in rural Kenya from June 2011 to January 2013 on a wide range of outcomes including assets and consumption. The participants consist of 1,008 households from 120 villages in the Rarieda province of Western Kenya who meet the simple means-test criterion of living in a home with a thatched roof.[20]

The researchers randomized 503 households into treatment arms that vary by whether households receive KES 24,000 (USD 384 PPP) or KES 94,000 (USD 1,505 PPP).[21] Among the 366 households receiving the smaller transfer amount, 193 households received one-time lump-sum transfers.[22] The magnitude of these one-time payments equates to about six months of revenue for the average household.

Households learned of the transfers during a visit from a GiveDirectly representative. During these visits, the representative announced the amount and timing of the payments. Households receiving one-time lump-sum transfers would receive their payment on the first day of a randomly selected month among the nine months following the date of the visit.[23] The outcome measures come from an endline survey

[20]The villages chosen for the study were those that had the highest proportion of thatched roofs in Rarieda. The average village in the sample consists of 100 households.

[21]As in Haushofer and Shapiro (2016), we report all USD values at purchasing power parity using the World Bank PPP conversion factor of 62.44 KES/USD for private consumption in 2012. The transfer amounts roughly correspond to USD 300 nominal and USD 1,000 nominal.

[22]The remaining 173 households received monthly transfers over a nine month period. The 137 treated households receiving the larger transfer amount received the bulk of their payments at a monthly frequency as well, as Supplementary Appendix B.1 explains.

[23]Households also received an initial transfer of KES 1,200 immediately following the announcement visit.

which takes place about 14 months after the baseline survey. Eliminating 7 households for which transfer dates do not appear in the data, 8 attriting households for which the data do not contain endline survey outcomes, and 6 households that receive transfers after the endline survey (primarily due to registration issues with M-Pesa), our remaining sample consists of 172 households.[24]

We use random variation in payment dates among households in the lump-sum treatment to estimate the impact of longer waiting times. Since previous research using the GiveDirectly data does not utilize this source of variation in waiting times, we conduct balance tests before proceeding. Consistent with random assignment, household characteristics and baseline measures do not significantly differ across households experiencing different waiting times (Appendix Table 5). We define a longer waiting time as more than $k \in \{2, \ldots, 8\}$ weeks from the announcement visit. While the Haushofer and Shapiro (2016) experimental design involves randomizing the timing of the lump-sum transfers to facilitate comparability with their monthly-transfer treatment, our paper uses a distinct, previously unexploited source of variation—experimentally induced random variation in the extent to which households anticipated their transfer payments—to examine how waiting periods affect decision making.

4.2 Estimation and results

To estimate the impact of longer waiting times, we follow the econometric strategy in Haushofer and Shapiro (2016) by conditioning on baseline levels of the outcome variables to improve statistical power. Letting T_{vh}^k indicate a waiting time of more than $k \in \{2, \ldots, 8\}$ weeks since the announcement, we estimate

$$y_{vh}^E = \alpha_v + \beta_k T_{vh}^k + \gamma y_{vh}^B + \varepsilon_{vh}^B, \tag{15}$$

where y_{vh}^t represents the baseline ($t = B$) or endline ($t = E$) outcome of interest for household h in village v, α_v captures village-level fixed effects, T_{vh}^k indicates treatment with a longer waiting time, and ε_{vh}^B is an idiosyncratic error term.[25] The parameter β_k represents the causal impact of a longer waiting time relative to a shorter waiting

[24]The attrition and non-compliance rates in our sample are similar to but slightly lower than in the complete sample of 1,008 households. See Supplementary Appendix B.1 for additional details on the samples.

[25]For the small set of outcomes with a few missing baseline measures, we encode missing values and control for an indicator δM_{vh}^B for missing values: $y_{vh}^E = \alpha_v + \beta T_{vh} + \gamma y_{vh}^B + \delta M_{vh}^B + \varepsilon_{vh}^B$.

time.

We consider four broad outcome measures: savings, assets, durables, and investments. The measure of savings consists of the total value of savings in all savings accounts, including M-Pesa. Assets consist of various types of livestock (cattle; small livestock such as pigs, sheep, and goats; birds such as chicken, turkeys, doves, and quails) and durables. Durables include furniture, agricultural tools, appliances, and other movable assets such as bicycles and cell phones. Investments consist of durable investment (durable assets and non-agricultural business investment in durables) and non-durable investment (agricultural inputs, enterprise expenses, educational expenses, and savings). We present all values in 2012 USD PPP. These measures from Haushofer and Shapiro (2016) capture outcomes at the time of the endline survey, unlike the results in Section 3.4 which constitute an impulse response of spending to windfalls.

We present results under a variety of specifications, varying the definitions of the treatment group (shorter waiting times) and comparison group (longer waiting times). Figure 4 displays the main results, which support the hypothesis that shorter waiting times lead to significant reductions in future-oriented decision making. Each dot in the figure corresponds to an estimate of the treatment effect from Equation (15) and the associated 95 percent confidence interval for a given definition of shorter and longer waiting times. We vary the definition of a shorter waiting times between 2 weeks and 8 weeks, and we vary the regression sample to include waiting times between 90 days and 270 days. For example, the first specification compares households receiving transfers within 14 days of the announcement date with households receiving transfers up to 90 days after the announcement date. We find substantial decreases in the probability of having nonzero savings among households randomly assigned to receive cash transfers sooner after the announcement visit. The decrease in savings does not arise due to substitution into other stores of value such as durables or other assets and investments. Households facing the shortest waiting times—those receiving transfers in the first month after the announcement—exhibit the strongest reductions in endline savings, assets, durables, and investments.

Varying the range of waiting times in the comparison group does not affect our results, suggesting that the estimates reflect the impact of differences in waiting times rather than differences in endline survey timing. Figure 5 corroborates this by plotting outcomes across the distribution of waiting times. If shorter waiting times lead to lower savings solely because households can experience a longer period of elevated

consumption before the endline survey takes place, we would expect to see a linear relationship between waiting times and the various outcomes. The binned scatterplots instead confirm that households facing the shortest waiting times exhibit especially strong reductions in endline savings, assets, durables, and investments, consistent with a substantive shift in decision-making.[26]

We obtain similar results under various alternative estimation approaches. Equation (15) uses an analysis of covariance (ANCOVA) approach (Frison and Pocock, 1992; McKenzie, 2012). As an alternative, we analyze differences-in-differences, and we find similar differences between the treatment and comparison groups when defining the outcome variable as the difference between the endline and baseline measure (Appendix Figure 5). We also obtain similar estimates when altering the ANCOVA approach by adding quadratic controls for baseline outcomes (Supplementary Appendix Figure 7) or removing village fixed effects (Supplementary Appendix Figure 8). We also document similar patterns for other outcomes variables: value of savings, durable investment, non-durable investment, and total assets including non-thatched roofs (Supplementary Appendix Figure 9).

5 Cash transfers in Malawi

This section analyzes our final empirical setting: a field experiment in Malawi among several (orthogonal) interventions in partnership with the commercial bank NBS to encourage savings.

5.1 Setting and data

Brune *et al.* (2017) conduct an experiment to examine how formal financial products influence consumption decisions by making windfall payments to a sample of 474 randomly selected households living in villages within six kilometers of the NBS bank branch in Mulanje, Malawi. The researchers randomly vary whether households receive transfer payments of MK 25,000 (USD 176.50 PPP) via cash or direct deposit in

[26] All specifications contain controls for baseline outcomes and village fixed effects. Plotting the difference between endline and baseline outcomes gives the same pattern (Supplementary Appendix Figure 4). Plotting only baseline outcomes provides evidence of balance (Supplementary Appendix Figure 5). Supplementary Appendix Figure 6 presents a formal test which rejects the null hypothesis of a linear relationship between waiting times and outcomes.

March–April 2014.[27] The magnitude of the transfers equates to about four times the existing formal savings among households in the sample. Households receive information about whether and when they will receive transfers during an in-person visit to the bank branch. Prior to the visit, households have some awareness of the scope of the transfers, as the research team informs them during baseline surveying of their eligibility for a cash prize of up to MK 25,000 if they visit the branch exactly two days later.

Participants either receive payments immediately or with a delay, randomized independently of the main treatment arm (i.e., whether the household receives the transfer via cash or direct deposit). A total of 318 households receive non-immediate payments, with 158 receiving payments after a one-day delay and 160 receiving payments after an eight-day delay. The remaining 156 households in our sample receive payments immediately. In our main specifications, we pool together households treated with payment delays because Brune *et al.* (2017) note that specifications that separately estimate the impacts of different payment delays tend not to have enough power to detect small effect sizes.[28]

We use the experimentally induced variation in payment delays to examine effects on expenditures and savings. All outcomes measures derive from a survey containing questions based on Malawi's Third Integrated Household Survey (IHS-3), which each household completes one week after their transfer payment date. The survey includes an expenditure module and a savings module. Consistent with random assignment, baseline characteristics do not significantly differ among households receiving payments immediately or with a delay (Appendix Table 6); Brune *et al.* (2017, Table 3) also show that baseline characteristics across the treatment arms appear balanced. The original study by Brune *et al.* (2017) contains some analysis of the effects of payment delays to understand the mechanisms through which formal bank accounts affect spending, including time inconsistency. They focus on broad categories of expenditures—food, non-food, planned, and unplanned—and find no substantial differences across treatment arms.[29] Our analysis of the data focuses on various forms of savings.

[27] We report USD values at purchasing power parity using the conversion factor 141.64 MK/USD as in Brune *et al.* (2017). The transfer amounts correspond to about USD 60 nominal.

[28] Appendix Table 7 presents results that disaggregate the delayed-windfall treatment groups.

[29] Brune *et al.* (2017, Table A3) report some evidence that the longest payment delay leads to a significant reduction in unplanned food expenditures, consistent with what our model would predict.

5.2 Estimation and results

To obtain the causal impact of non-immediate payments, we estimate an analog of Equation (15) as in Brune *et al.* (2017):

$$y^E_{vwh} = \alpha_v + \beta T_{vwh} + \gamma y^B_{vwh} + \delta_w + \varepsilon^B_{vwh}, \tag{16}$$

where y^t_{vwh} represents the baseline ($t = B$) or endline ($t = E$) outcome of interest for household h in village v surveyed in week w, α_v and δ_w capture village and week-of-first-survey fixed effects, T_{vwh} indicates treatment with a payment delay, and ε^B_{vwh} is an idiosyncratic error term. The parameter β represents the causal impact of a delayed relative to an immediate windfall.

The outcomes consists of various forms of savings. Total savings, as Table 1 Column (1) shows, increases significantly as a consequence of anticipated payment delays. While the estimates tend to have low precision, the large magnitudes appear to arise due to increases in *in-kind savings* (Column 2). In-kind savings consist of advance purchases of farm inputs, business inventory, and bags of maize (see the questionnaire in Supplementary Appendix Figure 1). The analysis in Brune *et al.* (2017) focuses on expenditure rather than savings and finds little influence of payment delays. As a possible explanation for the discrepancy between the large impact on savings that we observe and the previous results on spending, note that the expenditure survey asks how much households *paid in total* for various consumption goods over the past seven days (Supplementary Appendix Figure 2); these consumption goods include maize, which households also purchase as a form of in-kind savings.[30]

We also find a large positive point estimate for financial assets (Column 3), which consist of both formal savings (accounts at NBS or other banks) and informal savings (village savings groups, ROSCAs, cash not for daily living expenses kept at home or in a secret hiding place). Disaggregating these components of financial assets, we find slightly higher increases in informal savings (Appendix Table 7). Furthermore, increases in savings stem primarily from the behavior of households in the eight-day-delay treatment rather than in the one-day-delay treatment (also see Appendix Table 7).

[30]See Browning *et al.* (2014) for a discussion of the well-known challenges of measuring household consumption using survey data. The Malawi IHS-3 questionnaire, which serves as a basis for the expenditure survey in this field experiment, asks specifically about how much households *consume* ("food both eaten communally in the household and that eaten separately by individual household members") over the past seven days (Supplementary Appendix Figure 3).

Overall the results support the hypothesis that waiting periods cause substantial shifts in household decision making.

6 Discussion

This section discusses additional evidence in psychology and economics on how waiting time and deliberation affect choice as well as the broader implications of our framework for consumption decisions.

6.1 Waiting times

Our model relates to an emerging set of experimental results regarding the relationship between waiting times and impatience. Dai and Fishbach (2013) document in lab experiments that waiting times can increase patience not only when choosing among monetary amounts but also when choosing among consumption goods (e.g., different models of electronics, or different sizes of chocolate truffles). More recent work in economics documents similar patterns for intertemporal effort allocations and consumption decisions in developing countries (Imas *et al.*, 2018) as well as healthy food choices (Brownback *et al.*, 2019; DeJarnette, 2020). The evidence across different choice problems provide support for the underlying psychological mechanisms in our model.

To rationalize more patient decision making after longer waiting times, existing work invokes uncertainty about future utility coupled with more precise mental simulations over shorter time horizons following Gabaix and Laibson (2017), though these elements may be less pertinent for our applications; moreover, the Gabaix and Laibson (2017) model can also accommodate effects in the opposite direction, as DeJarnette (2020) notes. Anticipatory utility, by contrast, makes a clear testable prediction.

Laajaj (2017) provides further support for the channels through which anticipatory utility operates. Using data from Mozambique, Laajaj (2017) shows that providing incentives to save and subsidies for agricultural inputs results in households reporting longer planning horizons. Thus, interventions that lead to greater savings and asset accumulation cause households to choose to think more about the future. Our model can also shed light on the relationship between impatience and income, as Thakral and

Tô (2020) establish in a model of anticipatory utility that incorporates temptation goods.

6.2 Consumption smoothing

An extensive body of empirical evidence documents that consumption responds to the implementation (excess sensitivity), rather than the announcement (excess smoothness), of tax policy changes (Poterba, 1988; Heim, 2007; Mertens and Ravn, 2012; Broda and Parker, 2014). Our model provides an explanation for these patterns (Appendix A.4), which follows from our discussion of how the theoretical predictions hold even if consumers have liquid assets or can borrow against their future earnings (Proposition 3). Consistent with the predictions of the model, we document empirically that households reporting different levels of liquidity exhibit similar relationships between waiting times and spending responses (Figure 2).

Synthesizing evidence across different settings also provides a validation of the channel our model posits. Despite the considerable empirical evidence related to consumption smoothing, the literature does not provide a consensus on when deviations from the standard model occur (Jappelli and Pistaferri, 2010). For example, Spanish workers who receive extra paychecks as fully predictable non-performance-related bonus payments appear to smooth consumption (Browning and Collado, 2001), but consumption increases in response to receiving large predetermined payments from the Alaska Permanent Fund Dividend (PFD), even for high-income consumers (Kueng, 2018). Previous research investigates a "magnitude effect" whereby consumers smooth only when facing large income changes but finds mixed evidence (Kreinin, 1961; Souleles, 1999; Stephens and Unayama, 2011; Scholnick, 2013). In the case of the PFD, payments average $1,650 to each Alaskan citizen or about $4,600 per household (Kueng, 2018), which is comparable in scale to the bonus payments in Spain that provide households with one-fourteenth of their annual income in the form of an extra paycheck in June and December (Browning and Collado, 2001), yet the data show excess sensitivity in the former but not the latter setting. Viewing both of these as "anticipated" income changes would overlook a significant difference in timing: Spanish workers face virtually no uncertainty regarding the bonus payments due to the highly institutionalized system; Alaskan households, by contrast, learn about the size of their PFD payments through an official announcement from the governor in

September, and they receive payments in October.[31] Analyzing two different types of "anticipated" income changes in a consistent setting, Hori and Shimizutani (2009) find much higher marginal propensities to consume from end-of-year tax refunds than from extra paychecks using Japanese household-level data. Our model clarifies that the dichotomy between anticipated and unanticipated income changes may be misleading if consumption responses depend on the duration between when a household learns about an income change and when the income change occurs.

The model also offers an explanation for the phenomenon of "asymmetric consumption smoothing" (Baugh *et al.*, forthcoming; Ganong *et al.*, 2020). Proposition 4 in Appendix A characterizes how the agent responds to losses and shows that consumers facing losses smooth consumption by reducing future savings to maintain their current levels of short-term consumption. Our model matches stylized facts regarding spending responses to gains, losses, news about gains and losses, and loans. In particular, the model predicts consumption responses to gains but not news about future gains or interest-free loans, and the model predicts the same response to losses as to news about future losses (Fuster *et al.*, forthcoming). We discuss these relationships in more detail in Appendix A.6.

Finally, our model predicts a decreasing relationship between the marginal propensity to consume and the size of the windfall (Proposition 5 in Appendix A).[32] Using the GiveDirectly data, Haushofer and Shapiro (2016) document smaller marginal propensities to consume for households randomly assigned to receive large transfer amounts. Using the Nielsen data, although stimulus payment amounts are not independent of household characteristics, Appendix Figure 2 and Supplementary Appendix Table 3 show that households receiving small rebates amounts have the highest marginal propensities to spend. Recent work by Fagereng *et al.* (forthcoming) establishes this relationship empirically by exploiting exogenous variation in the size of lottery prizes and imputing expenditure from Norwegian administrative data.[33] This result also

[31] Despite the high predictability of the PFD payments at the end of the fiscal year in June, Alaskan households may rationally face uncertainty about the payments until the official announcement in September; for example, a gubernatorial veto in 2016 cut the dividend payments in half (a reduction of about $2,300 per household) relative to their predicted value.

[32] The same prediction also arises in a model with illiquidity (Kaplan and Violante, 2014; Huntley and Michelangeli, 2014).

[33] As they point out, previous work uses survey evidence on hypothetical income shocks and reaches mixed conclusions: Fuster *et al.* (forthcoming) find an increasing relationship, whereas Christelis *et al.* (2019) find a decreasing relationship.

formalizes an intuition by Shefrin and Thaler (1988) that larger windfalls are more likely to enter mental accounts with smaller propensities to consume.

7 Conclusion

We use existing observational and experimental data to document a consistent set of new results across multiple settings. In the context of both developed and developing countries, additional time spent anticipating a windfall payment leads to lower consumption responses. This robust pattern holds across consumers differing by levels of income, liquidity, access to formal financial products, demographic characteristics, and the magnitude of windfall payments. We show theoretically that these results follow from a model of anticipatory utility. The model and empirical results suggest a novel role for the timing of information in the design of tax and transfer programs. When policymakers intend to stimulate spending, as in the case of tax rebates, our results highlight the importance of rapid disbursement of payments. To encourage longer-term investments, as policymakers may desire when delivering cash transfers to impoverished households, announcing payments in advance may lead to more future-oriented decision making.

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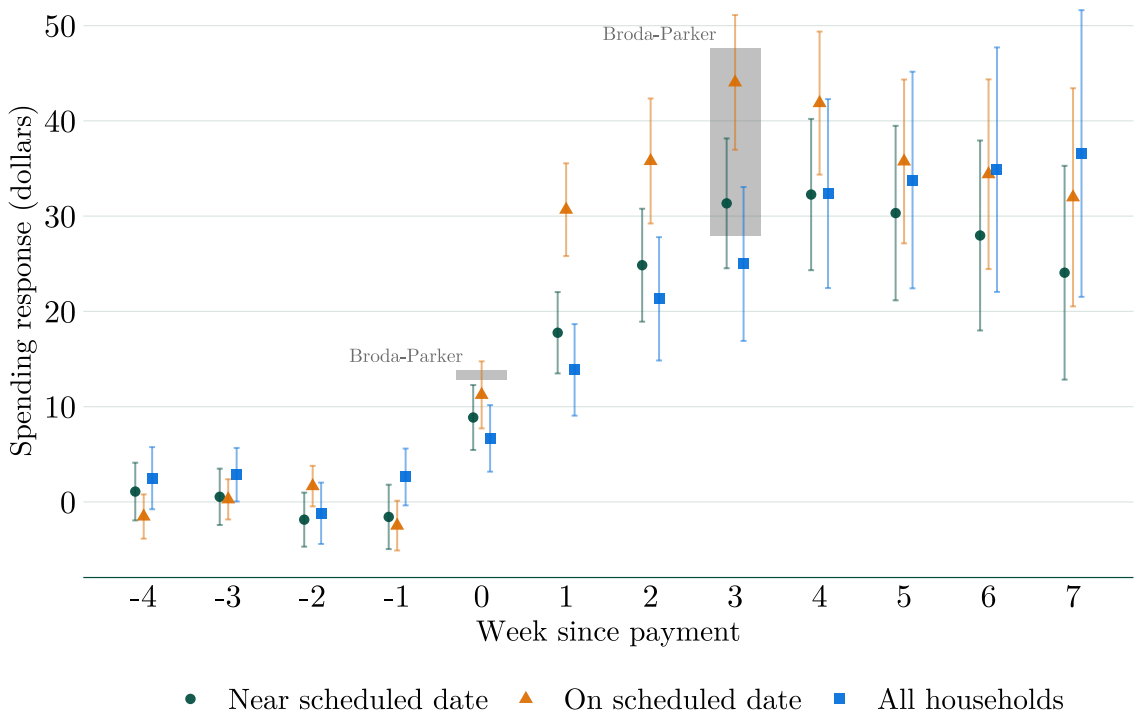
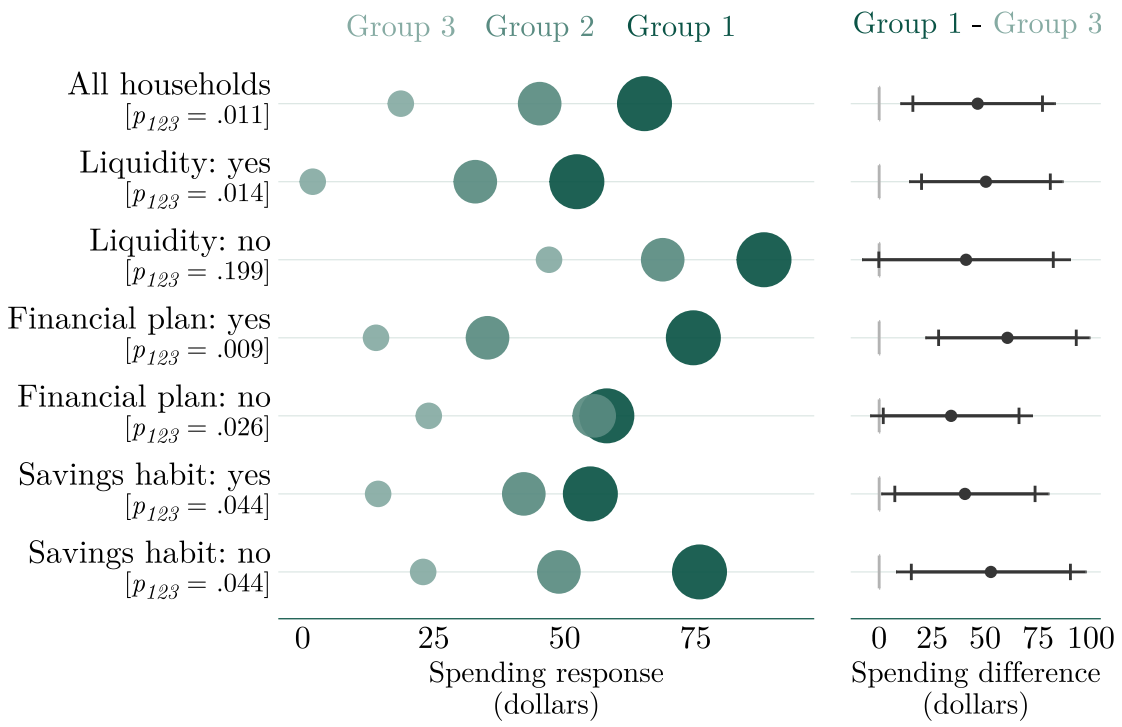
Figure 1: ESP Spending Responses—Average Impacts



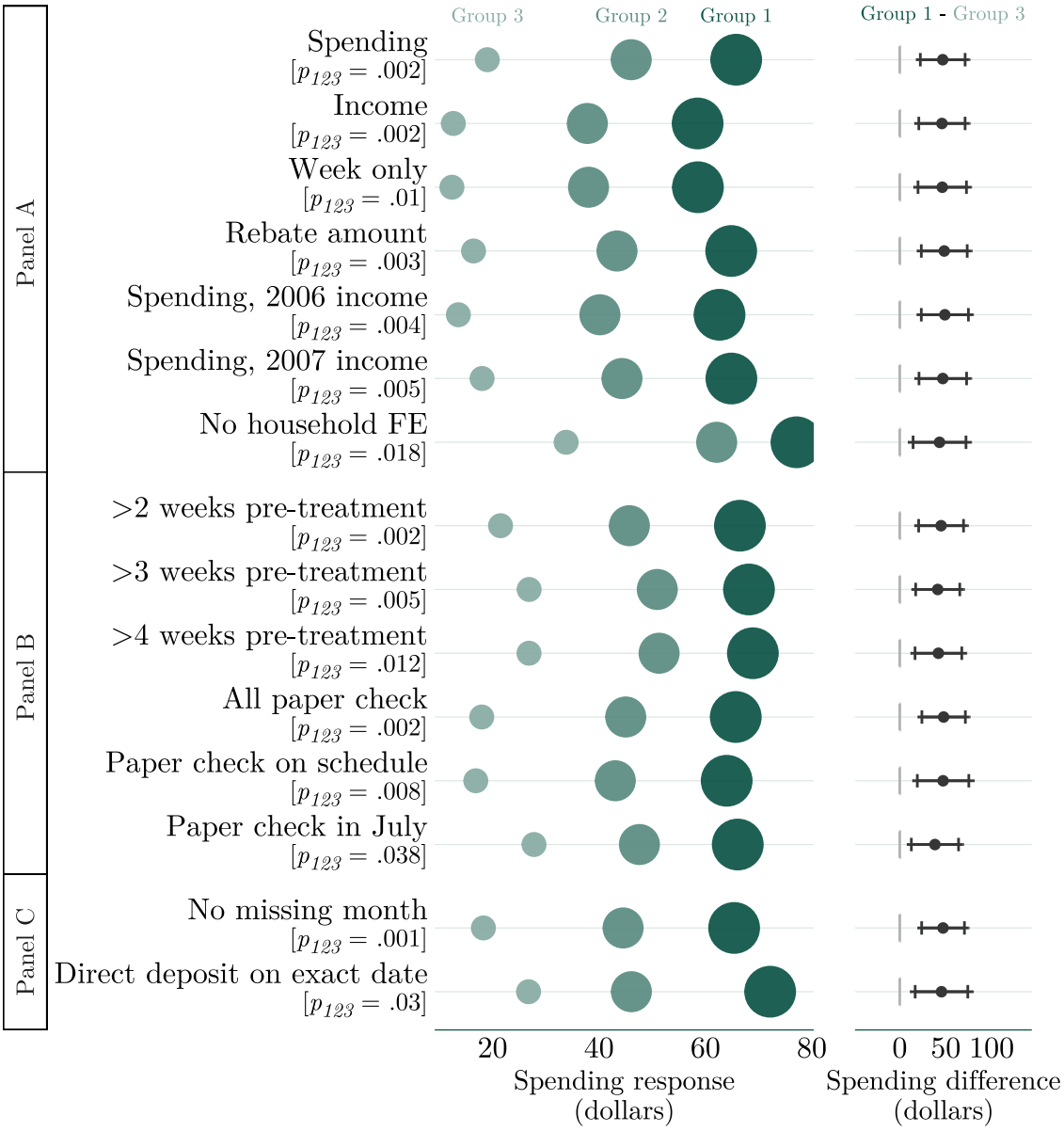
Note: This figure presents estimates of the weekly spending response γ_k (weeks -4 to -1) and the cumulative spending response Γ_k (weeks 0 to 7) from Equation (13) for various samples. For comparison, the shaded box denotes the range of point estimates reported by Broda and Parker (2014). The "Near scheduled date" sample consists of households receiving direct deposits three days leading up to the scheduled payment date or the weekend after. The "On scheduled date" sample consists of households receiving direct deposits on the date specified in Appendix Table 1. The "All households" sample consists of all households receiving direct deposits. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Figure 2: ESP Spending Responses by Timing of Payment



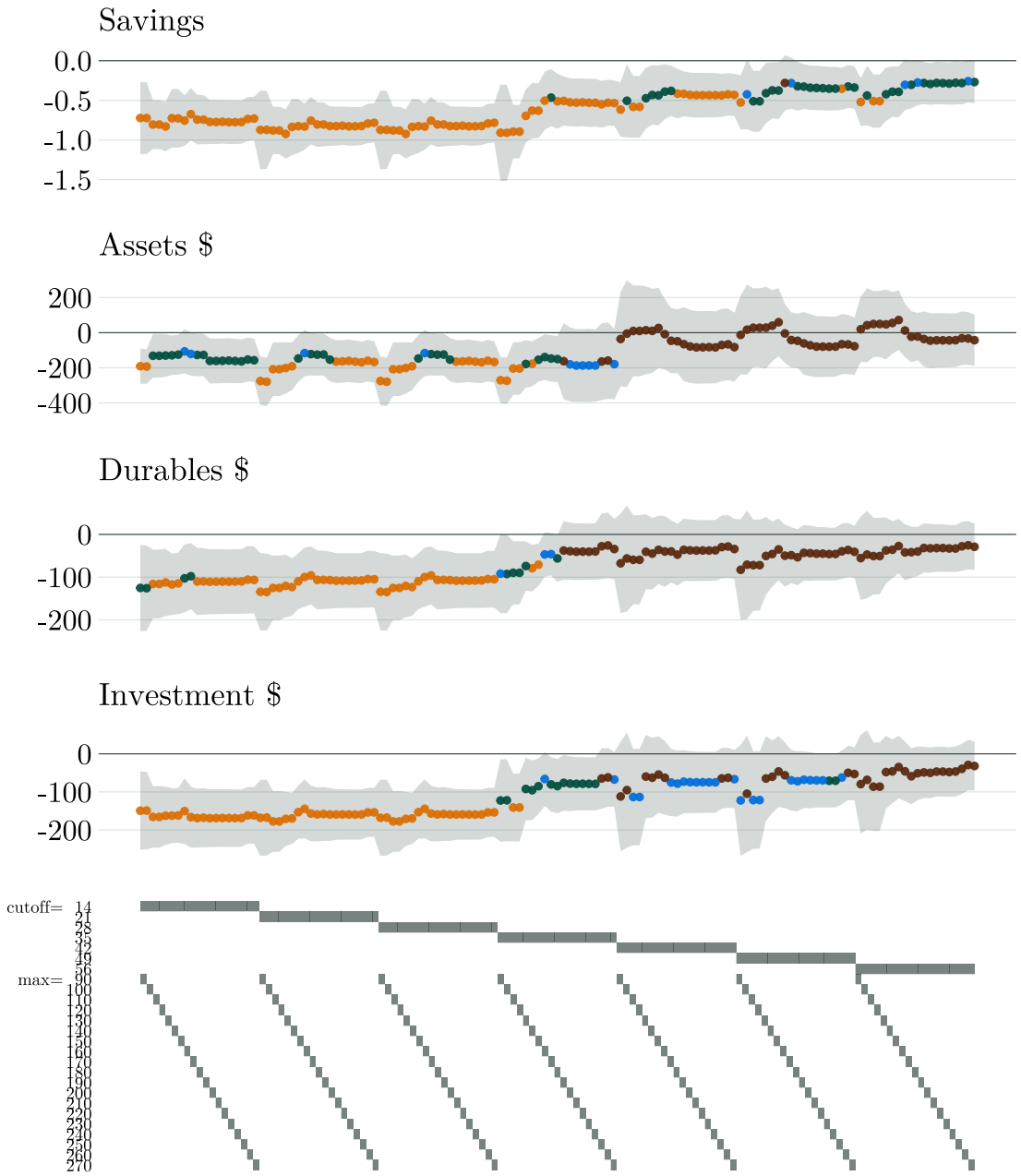
Note: The panel on the left presents estimates from Equation (14) of the four-week cumulative ESP spending response Γ_4^w for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively, and the p-value labeled p_{123} corresponds to the null hypothesis of equality across groups. The panel on the right displays the difference in spending between Group 1 and Group 3, along with a 95 percent confidence interval (black line) and 90 percent confidence interval (vertical endpoints). Liquidity is an indicator for reporting that the household has at least two months of income available in easily accessible funds. Financial plan is an indicator for reporting that the household has gathered together its financial information, reviewed it in detail, and formulated a financial plan for the long-term future. Savings habit is an indicator for reporting that household members would rather save more for the future than spend their money and enjoy it today. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Figure 3: ESP Spending Responses by Timing of Payment—Alternative Specifications



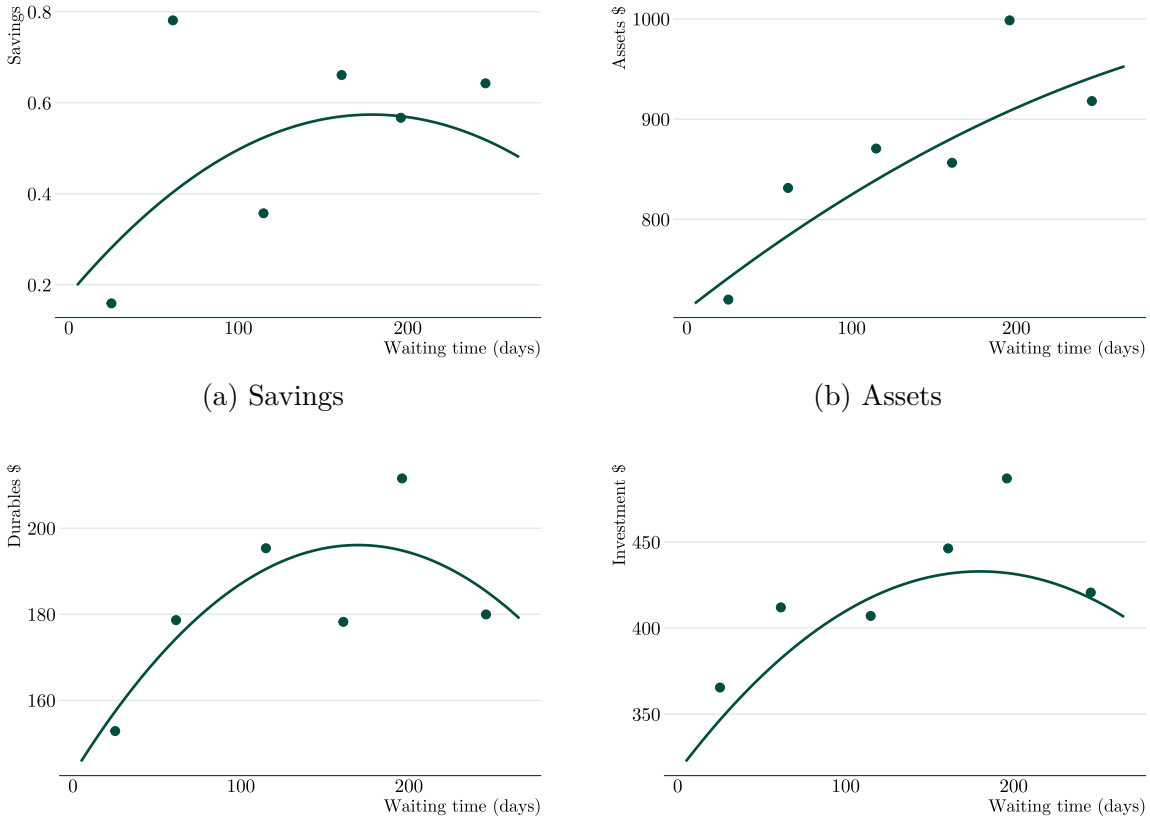
Note: The panel on the left presents estimates from alternative specifications of Equation (14) of the four-week cumulative ESP spending response Γ_4^w for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively. Panel A considers alternative sets of characteristics in the first step of the estimation, Panel B considers alternative sets of comparison households, and Panel C considers different specifications of the treatment group. The p-value labeled p_{123} corresponds to the null hypothesis of equality across groups. The panel on the right displays the difference in spending between Group 1 and Group 3, along with a 95 percent confidence interval (black line) and 90 percent confidence interval (vertical endpoints). Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Figure 4: Impact of Shorter Wait for Cash Transfers (Kenya)



Note: Each dot corresponds to an estimate of the treatment effect, β_k, from Equation (15) and the associated 95 percent confidence interval. Each specification corresponds to a different definition of the treatment group (short waiting times) and the comparison group (long waiting times), with "cutoff" denoting the threshold for defining a short waiting time and "max" denoting the maximum number of days of waiting time in the comparison group. Savings is an indicator for reporting nonzero savings, and the remaining magnitudes are reported in 2012 USD PPP. Colors denote statistical significance at the 1 percent (orange), 5 percent (green), and 10 percent (blue) levels.

Figure 5: Relationship between Waiting Times and Outcomes (Kenya)



(a) Savings

(b) Assets

(c) Durables

(d) Investment

Note: Each figure depicts the relationship between waiting times and outcomes in the form of a binned scatterplot. The line shows the fit of a global second-order polynomial. See Section 4.2 for details on the outcomes.

Table 1: Impact of Non-Immediate Windfall on Savings (Malawi)

	(1) Total	(2) In-kind	(3) Financial
Delay treatment	77.95	68.49	20.66
	(34.89)	(25.59)	(17.05)

Note: Each columns presents estimates of β, the casual impact of a delayed relative to an immediate windfall, from Equation (16). The sample consists of 474 households receiving MK 25,000 (USD 176.50 PPP) windfalls from the field experiment by Brune *et al.* (2017). The outcome in the first column, total savings, combines in-kind savings and total financial assets. In-kind savings (Column 2) consist of advance purchases of farm inputs, business inventory, and bags of maize. Total financial assets (Column 3) consist of formal savings (e.g., balances at bank, microfinance institution, and employee savings accounts) and informal savings (e.g., savings clubs, safely kept cash). All values are reported in USD PPP adjusted using the 2014 exchange rate 141.64 MK/USD. Standard errors are reported in parentheses.

Online Appendix

A Theoretical results

A.1 Setup

Let $T \geq 1$. Consider an agent who experiences utility from anticipating future consumption and faces the following *consumption-savings problem with $T-1$ waiting periods*. In period 0, the agent exogenously learns about a windfall $W > 0$. Consumption takes place only in periods T (short term) and $T+1$ (long term). If $T \geq 2$, then in periods 1 through $T-1$, the agent does not take any actions but still experiences utility from anticipating future consumption. The consumer chooses spending in period T; in other words, the consumer cannot commit to a consumption decision in advance.

Denote short-term consumption utility by $m(\cdot)$, and assume $m(0) = 0$, $m' > 0$, $m'(0) = 1$, $m'' < 0$, and $m''' > 0$. Assume that long-term consumption utility is simply given by total savings. For $\tau \in \{T, T+1\}$ and $t < \tau$, let α_τ^t denote the period-t level of anticipation of period-τ consumption utility. Anticipatory utility satisfies $n(0) = 0$, $n' > 0$, $n''(\alpha) < 0$ if $\alpha > 0$, $n''(\alpha) > 0$ if $\alpha < 0$, $n''' > 0$, $n'''' < 0$, $n(\alpha) < -n(-\alpha)$ and $n'(\alpha) < -n'(-\alpha)$ for $\alpha > 0$, and $|m''(0)| \geq |n''(0)|$. Letting c denote (period-T)

spending, flow utility is given by

$$
\begin{aligned}
u_0 &= n\Big(\alpha_T^0 \,\Big|\, 0\Big) + n\Big(\alpha_{T+1}^0 \,\Big|\, 0\Big) \\
u_t &= n\Big(\alpha_T^t \,\Big|\, \alpha_T^{t-1}\Big) + n\Big(\alpha_{T+1}^t \,\Big|\, \alpha_{T+1}^{t-1}\Big), \quad 0 < t < T \\
u_T &= m(c) + n\Big(m(c) \,\Big|\, \alpha_T^{T-1}\Big) + n\Big(\alpha_{T+1}^T \,\Big|\, \alpha_{T+1}^{T-1}\Big) \\
u_{T+1} &= W - c + n\Big(W - c \,\Big|\, \alpha_{T+1}^T\Big)
\end{aligned}
$$

The agent chooses levels of anticipation in each period $t \leq T+1$ and consumption c in period T to maximize an undiscounted sum of future utility $U_t = u_t + U_{t+1}$ (where $U_{T+2} \coloneqq 0$).

A.2 Optimal anticipation

We begin by noting that optimal anticipation in response to information about a windfall gain is non-decreasing, which enables us to consider the anticipatory utility function over the positive domain.

Lemma 1. *Optimal anticipation in the consumption-savings problem with $T-1$ waiting periods is non-decreasing: $\alpha_\tau^{t_1} \leq \alpha_\tau^{t_2} \leq m_\tau(c_\tau)$ for all t_1, t_2, τ satisfying $t_1 < t_2 < \tau$ and $\tau \in \{T, T+1\}$.*

Proof. Suppose on the contrary that optimal anticipation strictly decreases, i.e., $\alpha_\tau^{t_1} = \alpha_\tau^{t_2} + \delta$ for some $\delta > 0$, with $t_1 < t_2 < \tau$ and $\tau \in \{T, T+1\}$. By the concavity of n in the positive domain and the property that negative experienced anticipation has larger utility consequences than positive experienced anticipation of equal magnitude, we have

$$n\Big(\alpha_\tau^{t_2} + \delta\Big) < n\Big(\alpha_\tau^{t_2}\Big) + n(\delta) < n\Big(\alpha_\tau^{t_2}\Big) - n(-\delta)$$

This implies

$$n\Big(\alpha_\tau^{t_1}\Big) + n\Big(\alpha_\tau^{t_2} - \alpha_\tau^{t_1}\Big) < n\Big(\alpha_\tau^{t_2}\Big) + n(0),$$

so the decision maker would have preferred to set $\alpha_\tau^{t_1} = \alpha_\tau^{t_2}$. An analogous argument rules out the possibility that optimal anticipation exceeds optimal consumption utility. □

We use this lemma to establish the following characterization of optimal anticipation:

Proposition 1. *Let c_T be the optimal short-term consumption in the consumption-savings problem with $T-1$ waiting periods. Optimal anticipation satisfies*

$$\alpha_\tau^t = \frac{(t+1)m_\tau}{\tau+1},$$

where $\tau \in \{T, T+1\}$, $m_T = m(c_T)$, $m_{T+1} = W - c_T$, and $t < \tau$.

Proof. Let $m_T(c) = m(c)$ and $m_{T+1}(c) = W - c$. For $\tau \in \{T, T+1\}$, in period $\tau - 1$ the agent chooses $\alpha_\tau^{\tau-1}$ to maximize $U_{\tau-1} = u_{\tau-1} + U_\tau$. Note that

$$\begin{aligned}\frac{\partial U_\tau}{\partial \alpha_\tau^{\tau-1}} &= \frac{\partial u_\tau}{\partial \alpha_\tau^{\tau-1}} \\ &= \frac{\partial n(m_\tau(c) \,|\, \alpha_\tau^{\tau-1})}{\partial \alpha_\tau^{\tau-1}} \\ &= -n'\Big(m_\tau(c) - \alpha_\tau^{\tau-1}\Big)\end{aligned}$$

and

$$\begin{aligned}\frac{\partial u_{\tau-1}}{\partial \alpha_\tau^{\tau-1}} &= \frac{\partial n(\alpha_\tau^{\tau-1} \,|\, \alpha_\tau^{\tau-2})}{\partial \alpha_\tau^{\tau-1}} \\ &= n'\Big(\alpha_\tau^{\tau-1} - \alpha_\tau^{\tau-2}\Big).\end{aligned}$$

Thus the first-order condition with respect to $\alpha_\tau^{\tau-1}$ is given by

$$n'\Big(\alpha_\tau^{\tau-1} - \alpha_\tau^{\tau-2}\Big) - n'\Big(m_\tau(c) - \alpha_\tau^{\tau-1}\Big) = 0,$$

which implies

$$\alpha_T^{T-1} - \alpha_T^{T-2} = m(c) - \alpha_T^{T-1} \tag{17}$$

$$\alpha_{T+1}^{T} - \alpha_{T+1}^{T-1} = W - c - \alpha_{T+1}^{T} \tag{18}$$

For $\tau \in \{T, T+1\}$, in period $t < \tau$ with $(t, \tau) \neq (T-1, T)$ the agent chooses α_T^t and α_{T+1}^t to maximize $U_t = u_t + U_{t+1}$. Note that

$$\begin{aligned}\frac{\partial u_t}{\partial \alpha_\tau^t} &= \frac{\partial n(\alpha_\tau^t \,|\, \alpha_\tau^{t-1})}{\partial \alpha_\tau^t} \\ &= n'\Big(\alpha_\tau^t - \alpha_\tau^{t-1}\Big).\end{aligned}$$

and

$$\begin{aligned}\frac{\partial U_{t+1}}{\partial \alpha_\tau^t} &= \frac{\partial u_{t+1}}{\partial \alpha_\tau^t} \\ &= \frac{\partial n(\alpha_\tau^{t+1} \,|\, \alpha_\tau^t)}{\partial \alpha_\tau^t} \\ &= -n'\Big(\alpha_\tau^{t+1} - \alpha_\tau^t\Big).\end{aligned}$$

Thus the first-order condition with respect to α_τ^t is given by

$$n'\Big(\alpha_\tau^t - \alpha_\tau^{t-1}\Big) - n'\Big(\alpha_\tau^{t+1} - \alpha_\tau^t\Big) = 0,$$

which implies

$$\alpha_\tau^t - \alpha_\tau^{t-1} = \alpha_\tau^{t+1} - \alpha_\tau^t. \tag{19}$$

In period 0, the agent chooses α_T^0 and α_{T+1}^0 to maximize $U_0 = u_0 + U_1$. Note that for $\tau \in \{T, T+1\}$ we have

$$\begin{aligned}\frac{\partial U_0}{\partial \alpha_\tau^0} &= \frac{\partial u_0}{\partial \alpha_\tau^0} \\ &= \frac{\partial n(\alpha_\tau^1 \,|\, \alpha_\tau^0)}{\partial \alpha_\tau^0} \\ &= -n'\Big(\alpha_\tau^1 - \alpha_\tau^0\Big),\end{aligned}$$

and

$$\begin{aligned}\frac{\partial u_t}{\partial \alpha_\tau^0} &= \frac{\partial n(\alpha_\tau^0 \,|\, 0)}{\partial \alpha_\tau^0} \\ &= n'\Big(\alpha_\tau^0 - \alpha_\tau^{t-1}\Big).\end{aligned}$$

Thus the first-order condition with respect to α_τ^0 is given by

$$n'\Big(\alpha_\tau^0\Big) - n'\Big(\alpha_\tau^1 - \alpha_\tau^0\Big) = 0$$

which implies

$$2\alpha_\tau^0 = \alpha_\tau^1. \tag{20}$$

By combining Equation (20) with Equation (19), we see that the agent optimally

chooses to revise the level of anticipation by equal amounts in each period:

$$\alpha_\tau^{t+1} - \alpha_\tau^t = \alpha_\tau^0, \tag{21}$$

for $\tau \in \{T, T+1\}$, $t < \tau$, and $(t, \tau) \neq (T-1, T)$, or equivalently

$$\alpha_\tau^t = (t+1)\alpha_\tau^0 \tag{22}$$

for $t < \tau$. Then combining Equation (22) with Equation (17) and Equation (18) gives the following relationship between optimal consumption utility and initial levels of anticipation:

$$\begin{aligned} m(c) &= (T+1)\alpha_T^0 \\ W - c &= (T+2)\alpha_{T+1}^0. \end{aligned}$$

Solving for α_τ^0 and substituting back into Equation (22) gives the desired characterization. □

A.3 Optimal consumption

Let x_T denote the optimal short-term consumption in the consumption-savings problem with $T-1$ waiting periods. Given that the agent chooses optimal anticipation characterized in Proposition 1, the marginal utility of short-term spending is given by

$$S_T(c) = m'(c)\left(1 + n'\left(\frac{m(c)}{T+1}\right)\right)$$

and the marginal utility of long-term saving is given by

$$L_T(c) = 1 + n'\left(\frac{c}{T+2}\right).$$

The optimal short-term consumption x_T satisfies $S_T(x_T) = L_T(W - x_T)$. Thus we obtain a sequence $(x_T)_{t\geq 1}$ defined by

$$m'(x_T)\left(1 + n'\left(\frac{m(x_T)}{T+1}\right)\right) = 1 + n'\left(\frac{W - x_T}{T+2}\right). \tag{23}$$

Proposition 2. *Optimal short-term consumption x_T in the consumption-savings problem with $T-1$ waiting periods exceeds optimal short-term consumption x_{T+1} in the consumption-savings problem with T waiting periods. In other words, longer waiting time leads to lower spending out of windfalls.*

Proof. Define the functions

$$\begin{aligned}
M(x,t) &= 1 - m'(x) \\
N(x,t) &= m'(x)n'\left(\frac{m(x)}{T+1}\right) - n'\left(\frac{W-x}{T+2}\right) \\
\Delta(x,t) &= M(x,t) - N(x,t)
\end{aligned}$$

on $x \in [0, W]$ for $T \geq 1$. The first partial derivatives of M and N with respect to x are given by

$$\begin{aligned}
\frac{\partial M(x,t)}{\partial x} &= -m''(x) > 0 \\
\frac{\partial N(x,t)}{\partial x} &= m'(x)n''\left(\frac{m(x)}{T+1}\right)\frac{m'(x)}{T+1} + m''(x)n'\left(\frac{m(x)}{T+1}\right) + \frac{1}{T+2}n''\left(\frac{W-x}{T+2}\right) < 0
\end{aligned}$$

and the second partial derivatives of M and N with respect to x are given by

$$\begin{aligned}
\frac{\partial^2 M(x,t)}{\partial x^2} &= -m'''(x) \\
&< 0 \\
\frac{\partial^2 N(x,t)}{\partial x^2} &= \frac{1}{(T+1)^2}(m'(x))^3 n'''\left(\frac{m(x)}{T+1}\right) + \frac{2}{T+1}m'(x)m''(x)n''\left(\frac{m(x)}{T+1}\right) \\
&\quad + m''(x)n''\left(\frac{m(x)}{T+1}\right)\frac{m'(x)}{T+1} + m'''(x)n'\left(\frac{m(x)}{T+1}\right) - \frac{1}{(T+2)^2}n'''\left(\frac{W-x}{T+2}\right) \\
&> 0
\end{aligned}$$

Note that x_T satisfies $\Delta(x_T, t) = 0$, and x_{T+1} satisfies $\Delta(x_{T+1}, T+1) = 0$. Since $\Delta(x,t)$ is increasing in x and $\Delta(0,T) < 0$ and $\Delta(W,T) > 0$, we have $x_T \in (0, W)$ for all T.

We need to show that $x_T > x_{T+1}$ for all T. Combining $N(x_{T+1}, T+1) = M(x_{T+1}, T+1)$ with the fact that N is decreasing in x and M is increasing in x, we have $x_T > x_{T+1}$ if and only if $N(x_T, T+1) < M(x_T, T+1)$ (or, equivalently,

$\Delta(x_T, T+1) > 0)$. Therefore, it suffices to show

$$\left.\frac{\partial \Delta(x,T)}{\partial T}\right|_{x=x_T} > 0. \tag{24}$$

To determine the sign of $\frac{\partial \Delta}{\partial t}$ at $x = x_T$, we proceed in three steps. First, we establish a condition that would be sufficient for showing that Equation (24) holds. Second, we establish an upper bound on x_T by making use of the fact that N is decreasing and convex in x and M is increasing and concave in x. Third, we use the bound from the second step to show that condition from the first step holds, thus completing the proof.

Step 1. Since

$$\begin{aligned}\frac{\partial \Delta(x_T,T)}{\partial T} &= \frac{\partial M(x_T,T)}{\partial T} - \frac{\partial N(x_T,T)}{\partial T} \\ &= -\frac{W-x_T}{(T+2)^2} n''\left(\frac{W-x_T}{T+2}\right) + m'(x_T)\frac{m(x_T)}{(T+1)^2} n''\left(\frac{m(x_T)}{T+1}\right),\end{aligned}$$

Equation (24) is equivalent to

$$m'(x_T)\frac{m(x_T)}{(T+1)^2} n''\left(\frac{m(x_T)}{T+1}\right) > \frac{W-x_T}{(T+2)^2} n''\left(\frac{W-x_T}{T+2}\right),$$

or

$$\frac{n''\left(\frac{m(x_T)}{T+1}\right)}{n''\left(\frac{W-x_T}{T+2}\right)} < \frac{(T+1)^2}{(T+2)^2}\frac{W-x_T}{m'(x_T)m(x_T)}. \tag{25}$$

We start by making two observations which will yield a condition from which Equation (25) follows. First, since $n'' < 0$ is increasing, we have

$$\frac{n''\left(\frac{m(x_T)}{T+1}\right)}{n''\left(\frac{W-x_T}{T+2}\right)} < \frac{n''(0)}{n''\left(\frac{W}{T+2}\right)}. \tag{26}$$

Second, since $m'(x_T)m(x_T) < x_T$, we have

$$\frac{(T+1)^2}{(T+2)^2}\frac{W-x_T}{x_T} < \frac{(T+1)^2}{(T+2)^2}\frac{W-x_T}{m'(x_T)m(x_T)}. \tag{27}$$

By combining Equations (26) and (27), we see that Equation (25) would follow from

$$\frac{n''(0)}{n''\left(\frac{W}{T+2}\right)} < \frac{(T+1)^2}{(T+2)^2}\frac{W-x_T}{x_T}$$

or equivalently

$$\frac{x_T}{W} < \frac{1}{\frac{n''(0)}{n''\left(\frac{W}{T+2}\right)}\frac{(T+2)^2}{(T+1)^2}+1} = \frac{(T+1)^2 n''\left(\frac{W}{T+2}\right)}{(T+1)^2 n''\left(\frac{W}{T+2}\right)+(T+2)^2 n''(0)}. \tag{28}$$

Therefore it suffices to prove that Equation (28) holds.

Step 2. We next derive an upper bound for x_T based on our assumptions about the curvature of N and M.

Letting $m_T(x)$ be the convex envelope of $M(x,T)$, since M is increasing and concave in x, we have

$$\begin{aligned} m_T(x) &= \frac{M(W,T)-M(0,T)}{W}x + M(0,T) \\ &= \frac{n'(0)-n'\left(\frac{W}{T+2}\right)}{W}x + 1 + n'\left(\frac{W}{T+2}\right) \\ &< M(x,T) \end{aligned}$$

for $x \in (0,W)$. Letting $n_T(x)$ be the concave envelope of $N(x,T+1)$, since N is decreasing and convex in x, we have

$$\begin{aligned} n_T(x) &= \frac{N(W,T+1)-N(0,T+1)}{W}x + N(0,T+1) \\ &= \frac{\left(m'(W)\left(1+n'\left(\frac{m(W)}{T+2}\right)\right)\right)-(1+n'(0))}{W}x + 1 + n'(0) \\ &> N(x,T+1) \end{aligned}$$

for $x \in (0,W)$. In particular, at x_T, we have $m_T(x_T) < M(x_T,T) = N(x_T,T) < n_T(x_T)$. For $\bar{x}_T$ satisfying $m_T(\bar{x}_T) = n_T(\bar{x}_T)$, we must have $x_T < \bar{x}_T$ since m_T is increasing and n_T is decreasing. Thus we obtain an upper bound on x_T given by the

intersection between m_T and n_T:

$$\frac{n'(0) - n'\left(\frac{W}{T+2}\right)}{W}\bar{x}_T + 1 + n'\left(\frac{W}{T+2}\right) = \frac{\left(m'(W)\left(1 + n'\left(\frac{m(W)}{T+2}\right)\right)\right) - (1 + n'(0))}{W}\bar{x}_T + 1 + n'(0)$$

which implies

$$\frac{\bar{x}_T}{W} = \frac{n'(0) - n'\left(\frac{W}{T+2}\right)}{2n'(0) - n'\left(\frac{W}{T+2}\right) - m'(W)n'\left(\frac{m(W)}{T+2}\right) + 1 - m'(W)}.$$

Since $n'(0) > n'\left(\frac{m(W)}{T+2}\right) > m'(W)n'\left(\frac{m(W)}{T+2}\right)$, we have

$$\frac{\bar{x}_T}{W} < \frac{n'(0) - n'\left(\frac{W}{T+2}\right)}{n'(0) - n'\left(\frac{W}{T+2}\right) + 1 - m'(W)},$$

and thus we conclude

$$\frac{x_T}{W} < \frac{n'(0) - n'\left(\frac{W}{T+2}\right)}{n'(0) - n'\left(\frac{W}{T+2}\right) + 1 - m'(W)}. \tag{29}$$

Step 3. We complete the proof by showing that

$$\frac{n'(0) - n'\left(\frac{W}{T+2}\right)}{n'(0) - n'\left(\frac{W}{T+2}\right) + 1 - m'(W)} < \frac{(T+1)^2 n''\left(\frac{W}{T+2}\right)}{(T+1)^2 n''\left(\frac{W}{T+2}\right) + (T+2)^2 n''(0)}, \tag{30}$$

as this would imply that the sufficient condition given by Equation (28) from step 1 follows from the bound established by Equation (29) from step 2.

Note that Equation (30) is equivalent to

$$\left(n'(0) - n'\left(\frac{W}{T+2}\right)\right)(T+2)^2 n''(0) > (T+1)^2 n''\left(\frac{W}{T+2}\right)(1 - m'(W))$$

or

$$\frac{(T+2)}{(T+1)^2}\frac{n''(0)}{n''\left(\frac{W}{T+2}\right)}\frac{n'\left(\frac{W}{T+2}\right) - n'(0)}{\frac{W}{T+2}} > \frac{m'(W) - 1}{W}. \tag{31}$$

We conclude by describing two different sets of sufficient conditions for this result.

For small windfalls $W \to 0$, the condition in Equation (31) becomes $\frac{T+2}{(T+1)^2}n''(0) > m''(0)$, so having $|m''(0)| \geq |n''(0)|$ would be sufficient.

Otherwise, we can establish the result under the assumption that $|n''(0)|$ and $n'''(0)$ are sufficiently small and $n''' > 0, n'''' < 0$ as follows. If $n''(0) + \frac{W}{T+2}n'''(0) < 0$ and n'' is concave, then we have $n'''(0) > \frac{n''\left(\frac{W}{T+2}\right) - n''(0)}{\frac{W}{T+2}}$ and hence

$$\frac{n''(0)}{n''(0) + \frac{W}{T+2}n'''(0)} > \frac{n''(0)}{n''\left(\frac{W}{T+2}\right)}. \tag{32}$$

Since n' is decreasing and convex, we have

$$\frac{n'\left(\frac{W}{T+2}\right) - n'(0)}{\frac{W}{T+2}} > n''(0). \tag{33}$$

Equations (32) and (33) imply

$$\frac{(T+2)}{(T+1)^2}\frac{n''(0)}{n''\left(\frac{W}{T+2}\right)}\frac{n'\left(\frac{W}{T+2}\right) - n'(0)}{\frac{W}{T+2}} > \frac{(T+2)}{(T+1)^2}\frac{n''(0)}{n''\left(\frac{W}{T+2}\right)}n''(0) > \frac{(T+2)}{(T+1)^2}\frac{n''(0)}{n''(0) + \frac{W}{T+2}n'''(0)}n''(0).$$

Therefore, along with $n''' > 0, n'''' < 0$, having $|n''(0)|$ and $n'''(0)$ sufficiently small that $n''(0) + \frac{W}{T+2}n'''(0) < 0$ and

$$\frac{(T+2)}{(T+1)^2}\frac{(n''(0))^2}{n''(0) + \frac{W}{T+2}n'''(0)} > \frac{m'(W) - 1}{W}$$

would also be sufficient for Equation (31) to hold. □

A.4 Credit constraints

This section relaxes the assumption, implicit in our description of the model, that consumption does not take place during waiting periods (i.e., after learning about but before receiving the windfall). We demonstrate that the characterization of optimal anticipation and optimal consumption remains the same if households do not face credit constraints. Specifically, if households spend out of funds that were planned for use in the future (and benefit from the associated anticipatory utility), they experience a loss with respect to future consumption that is later offset by an equal-sized gain when the windfall arrives. If the household is sufficiently loss averse, this would lead to a decrease in utility overall. Our model thus builds on the intuition that

"households act as if they used a system of mental accounts which violate the principle of fungibility" (Shefrin and Thaler, 1988).

Consider a consumption-savings problem with $T-1$ waiting periods. Prior to learning about the windfall, the consumer plans to consume 0 in each period $\{0, 1, \ldots, T\}$ and to consume the entire budget B in period $T+1$. In response to the windfall W, a consumer who does not experience anticipatory utility would optimally choose to consume 0 in each period $\{0, 1, \ldots, T\}$ and to consume $B+W$ in period $T+1$, given our assumption that the marginal utility of short-term consumption does not exceed the marginal utility of savings (normalized to 1).

Now we consider the implications of anticipatory utility. We will show the following result.

Proposition 3. *For all $t < T$, the consumer does not deviate from setting $c_t = 0$.*

Proof. It suffices to show this result for period $t = T-1$, since consuming in the latest possible waiting period maximizes the anticipatory utility that the consumer would experience under a deviation.

If the consumer chooses $c_{T-1} \neq 0$, then flow utility would be

$$
\begin{aligned}
u_0 &= n\Big(\alpha^0_{T-1} - 0\Big) + n\Big(\alpha^0_T - 0\Big) + n\Big(\alpha^0_{T+1} - B\Big) \\
u_t &= n\Big(\alpha^t_{T-1} - \alpha^{t-1}_{T-1}\Big) + n\Big(\alpha^t_T - \alpha^{t-1}_T\Big) + n\Big(\alpha^t_{T+1} - \alpha^{t-1}_{T+1}\Big), \quad 0 < t < T-1 \\
u_{T-1} &= m(c_{T-1}) + n(-m(c_{T-1})) + n\Big(m(c_{T-1}) - \alpha^{T-2}_{T-1}\Big) + n\Big(\alpha^{T-1}_T - \alpha^{T-2}_T\Big) + n\Big(\alpha^{T-1}_{T+1} - \alpha^{T-2}_{T+1}\Big) \\
u_T &= m(c_T) + n(m(c_{T-1})) + n\Big(m(c) - \alpha^{T-1}_T\Big) + n\Big(\alpha^T_{T+1} - \alpha^{T-1}_{T+1}\Big) \\
u_{T+1} &= W - c_T - c_{T-1} + n\Big(W - c_T - c_{T-1} - \alpha^T_{T+1}\Big)
\end{aligned}
$$

Following the logic in Proposition 1, optimal anticipation of period $T-1$ consumption increases by $\frac{m(c_{T-1})}{T}$ each period. Utility from anticipating consumption in period $T-1$ is bounded above by $Tn'(0)c_{T-1}$. The increase in consumption utility is bounded above by $m'(0)c_{T-1}$. Therefore, a sufficient condition for any such deviation to be unprofitable is that the consumer is sufficiently loss averse that $n(-m(c_{T-1})) + n(m(c_{T-1})) < -(Tn'(0) + m'(0))c_{T-1}$ as $c_{T-1} \to 0$, or equivalently, $(n^+)'(0) + (n^-)'(0) < -(Tn'(0) + m'(0))$.

The same argument applies to any combination of nonzero consumption levels in periods before the windfall arrives. □

Therefore, even if consumers have liquid assets or can borrow against their future earnings, our model can explain how consumption changes only in response to the *arrival* of the windfall and not to *news* about the windfall.

A.5 Asymmetric consumption smoothing

Proposition 2 demonstrates how agents in our model do not perfectly smooth consumption in response to gains. Rather than allocating the entirety of a windfall gain to savings (modeled as the long-term consumption period which does not exhibit diminishing marginal utility), the agent chooses to spend in the short-term. This section proceeds to analyze whether agents smooth consumption in response to losses. In the baseline model for examining responses to gains, we normalize optimal short-term consumption to zero. To examine changes in consumption in response to losses, since consumption cannot be negative, we modify the model by normalizing optimal short-term consumption to 1. Specifically, the consumption utility function satisfies $m' > 0$ with $m'(1) = 1$, and we assume that the budget is sufficiently large for the first-order condition to hold at the optimum: $B > T$. Note that this does not alter our characterization of responses to gains.

Proposition 4. *A consumer facing a loss smooths consumption by reducing future savings to maintain their current level of short-term consumption.*

Proof. To illustrate how the agent reacts to losses, we will consider a consumption-savings problem without waiting periods. Adding waiting periods (i.e,. moving the loss to the future) does not affect any of the tradeoffs discussed here. The consumer initially plans to consume 1 in period 1 and to consume the remaining budget $B - 1$ in period 2. Suppose that in period 0, the consumer learns that the budget will decrease to $B' \in (1, B)$, a loss of $\ell = B - B'$. This reduction in the budget leads to loss in anticipatory utility of $-n(-\ell)$, regardless of whether the agent reduces consumption in period 1 or in period 2. This follows from the fact that the anticipatory utility function is convex in the negative domain, so the agent prefers to integrate losses together. The timing of realized losses, however, does not affect their anticipatory utility. Thus, any preference over when to reduce consumption depends only on consumption utility. Due to diminishing marginal utility of short-term consumption utility, the agent faces greater negative consequences of realizing a loss in period 1. Optimal consumption therefore leads the agent to exhibit consumption-smoothing behavior when facing a

loss. The agent prefers to reduce savings to maintain the current level of short-term consumption. □

A.6 Gains, losses, news about gains and losses, and loans

In this section, we summarize some of the key predictions of our model regarding how consumption responds to gains, losses, and news about future gains and losses. Fuster *et al.* (forthcoming) document several important patterns using reported preferences from a survey featuring hypothetical scenarios: consumption responses to gains, no response to news about future gains, and similar responses to losses as to news about future losses.

Regarding gains, Appendix A.3 illustrates how the model predicts consumption responses to gains, while Appendix A.4 shows how the model predicts no response to news about future gains. Appendix A.4 also explains why households would not respond to the offer of a one-year interest-free loan.

Regarding losses, Appendix A.5 shows how the model predicts the same response to losses as to news about future losses. Note that Appendix A.5 assumes utility from short-term consumption is concave while utility from long-term consumption (i.e,. savings) is linear, which leads to consumption-smoothing behavior of the form documented empirically by Baugh *et al.* (forthcoming). However, even in a more general framework which incorporates many consumption periods (rather than capturing the value of savings through a terminal long-term consumption period), the prediction of the same consumption responses to losses as well as to news about future losses would still hold. In such a model, the consumer can react to losses (or to news about losses) by decreasing current consumption, and the response to losses would be larger than the response to gains, as Fuster *et al.* (forthcoming) document in their survey about hypothetical spending scenarios.

For comparison, the Kőszegi and Rabin (2009) model of news utility also makes predictions about responses to gains, losses, and news about gains and losses. In their model, consumption changes only in response to new information—as opposed to in response to anticipated changes in income. Specifically, their model predicts increases in consumption in response to gains or news about future gains, but delays in decreasing consumption in response to losses or news about future losses. Therefore, their model makes similar predictions regarding asymmetric consumption smoothing

(i.e., increased spending in response to gains but not decreased spending in response to losses), and their model makes similar predictions regarding the similarity in responses to losses and responses to news about future losses (as Fuster *et al.* forthcoming document). However, their model does not accommodate the empirical observation that contemporaneous consumption responds to gains but not news about future gains (Fuster *et al.*, forthcoming), whereas our model provides an explanation for this pattern as well (Appendix A.4).

A.7 MPC heterogeneity by size of windfall

Proposition 5. *The fraction of a windfall spent on short-term consumption is a decreasing function of the size of the windfall:* $\frac{\partial \frac{c}{W}}{\partial W} < 0$.

Proof. It suffices to show that $\frac{\partial^2 c}{\partial W^2} < 0$.

Recall that optimal consumption satisfies $\frac{\partial S_T}{\partial c} = \frac{\partial L_T}{\partial c}$ from Equation (23). Differentiating this allows us to examine how the propensity to spend out of a windfall varies with the size of the windfall:

$$\begin{aligned} S_T(c) &= L_T(W-c) \\ \frac{dS_T(c)}{dW} &= \frac{dL_T(W-c)}{dW} \\ S_T'(c)\frac{\partial c}{\partial W} &= L_T'(W-c)\left(1-\frac{\partial c}{\partial W}\right) \end{aligned}$$

Rearranging gives

$$\frac{\partial c}{\partial W} = \frac{L_T'(W-c)}{S_T'(c)+L_T'(W-c)},$$

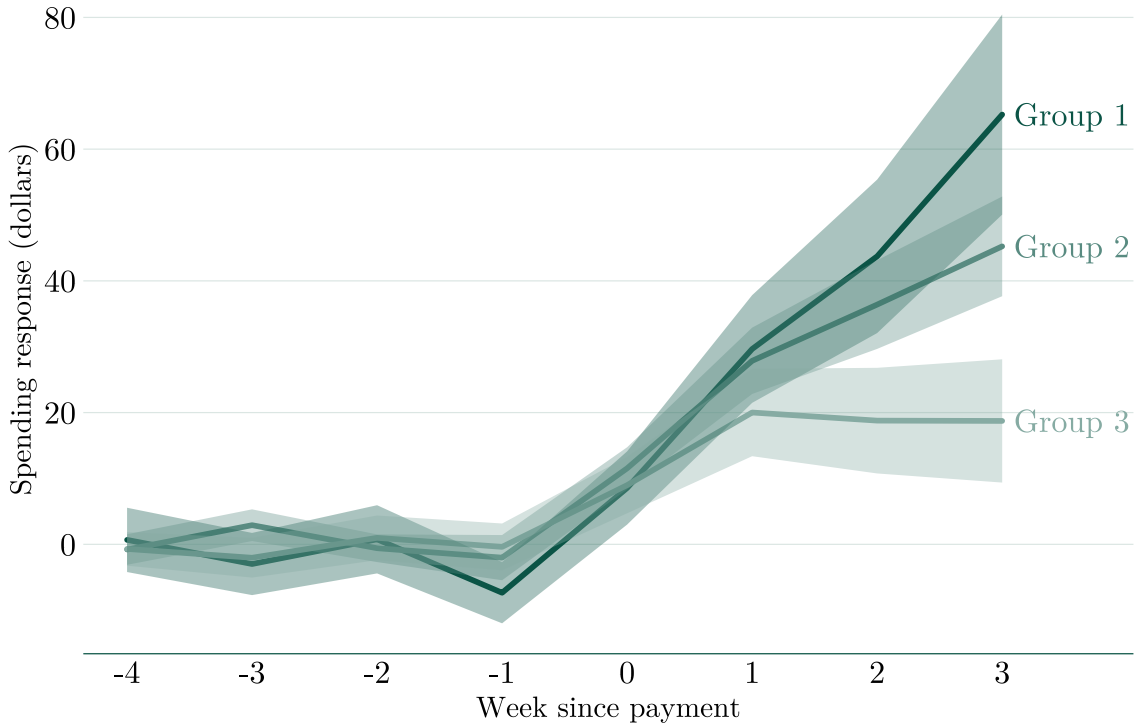
which is positive since $L_T'(W-c) = \frac{1}{T+2}n''\left(\frac{W-c}{T+2}\right) < 0$ and $S_T'(c) = m''(c) + \frac{(m'(c))^2}{T+1}n''\left(\frac{m(c)}{T+1}\right) < 0$.

Differentiating again gives

$$\frac{\partial^2 c}{\partial W^2} = \frac{(S_T'(c)+L_T'(W-c))L_T''(W-c)\left(1-\frac{\partial c}{\partial W}\right) - L_T'(W-c)\left[S_T''(c)\frac{\partial c}{\partial W} + L_T''(W-c)\left(1-\frac{\partial c}{\partial W}\right)\right]}{\left(S_T'(c)+L_T'(W-c)\right)^2},$$

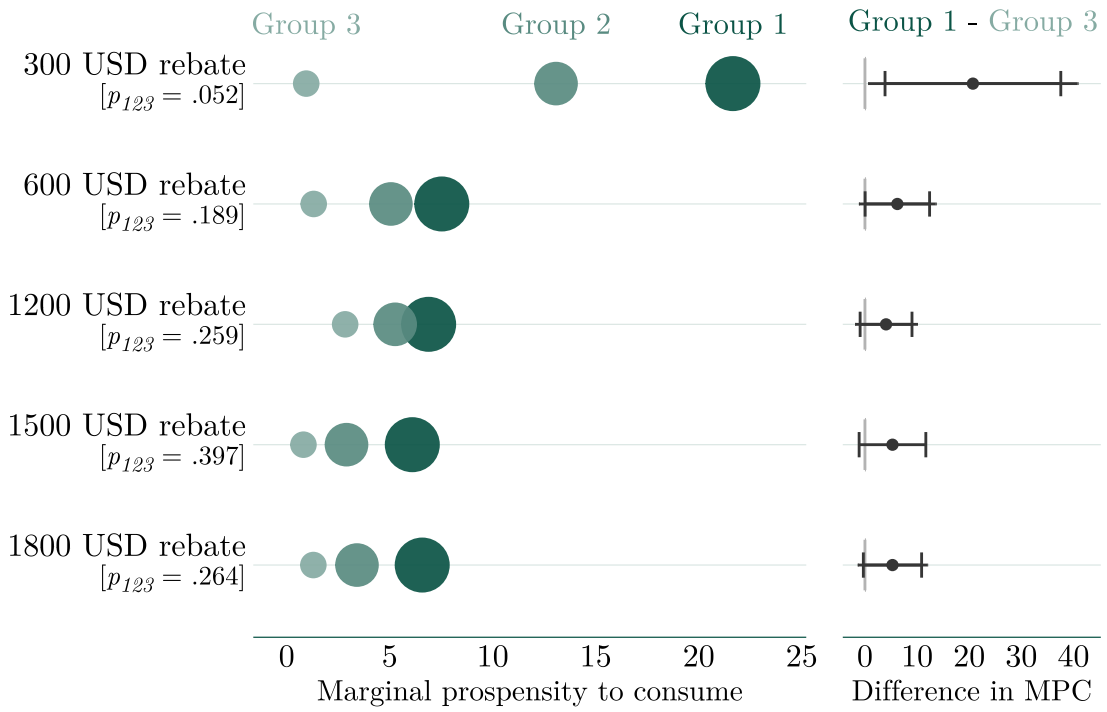
which is negative as long as $m'''(\cdot)$ and $n'''(\cdot)$ are sufficiently small (since only the bracketed term in the numerator is positive). □

Appendix Figure 1: ESP Spending Responses over Time by Timing of Payment



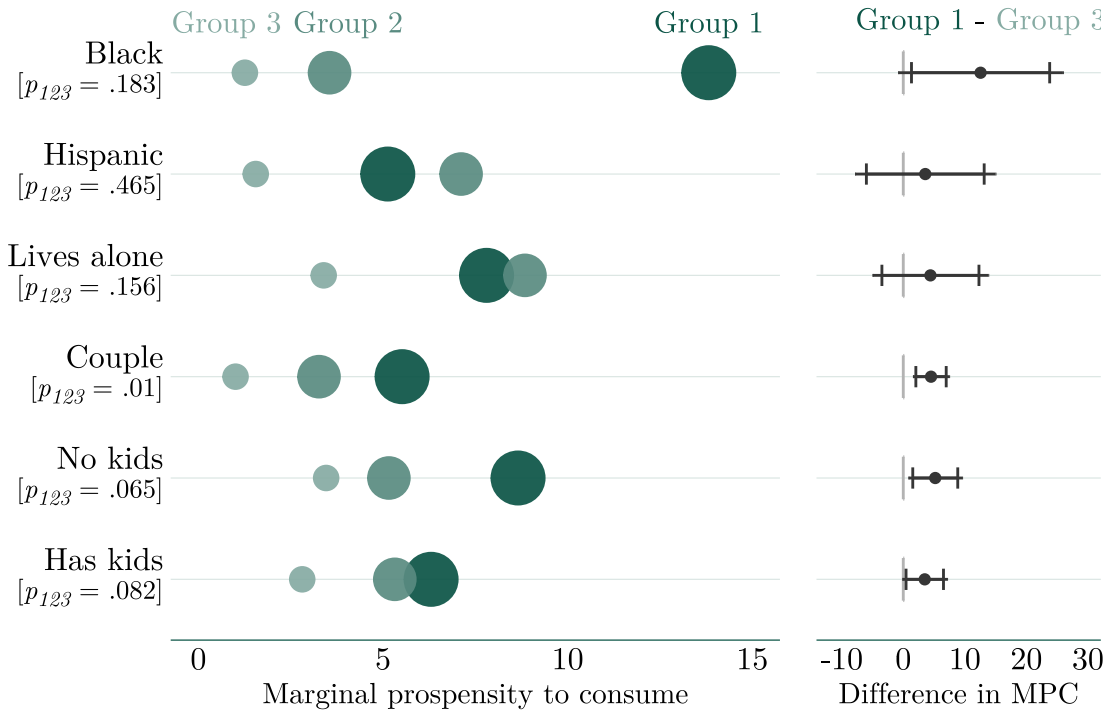
Note: This figure presents estimates from Equation (14) of the ESP spending response for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively. The horizontal axis denotes the number of weeks relative to the event of payment receipt. For $t \geq 0$, the figure depicts the cumulative t-week spending impact Γ^w_{t+1}, measured in dollars, among households in Group w. For $t < 0$, the figure displays estimates of γ^w_t, the impact of ESP receipt on spending in periods prior to the event. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Figure 2: MPC by Timing of Payment—Heterogeneity by Rebate Amount



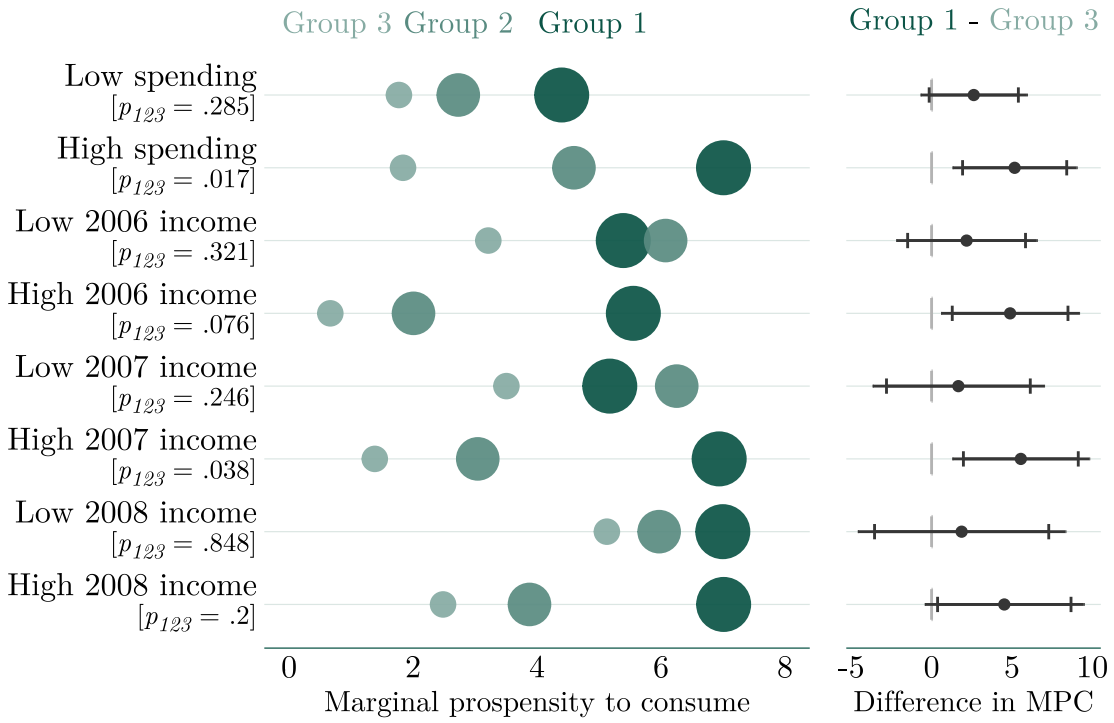
Note: Each row presents estimates from Equation (2) in Supplementary Appendix A.2 of the marginal propensity to consume in response to ESPs over a four-week period for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively, for households receiving the most common rebate amounts. The p-value labeled p_{123} corresponds to the null hypothesis of equality across groups. The panel on the right displays the difference in spending between Group 1 and Group 3, along with a 95 percent confidence interval (black line) and 90 percent confidence interval (vertical endpoints). See Supplementary Appendix A.1 for details on the subsamples. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Figure 3: MPC by Timing of Payment—Heterogeneity by Demographic Characteristics



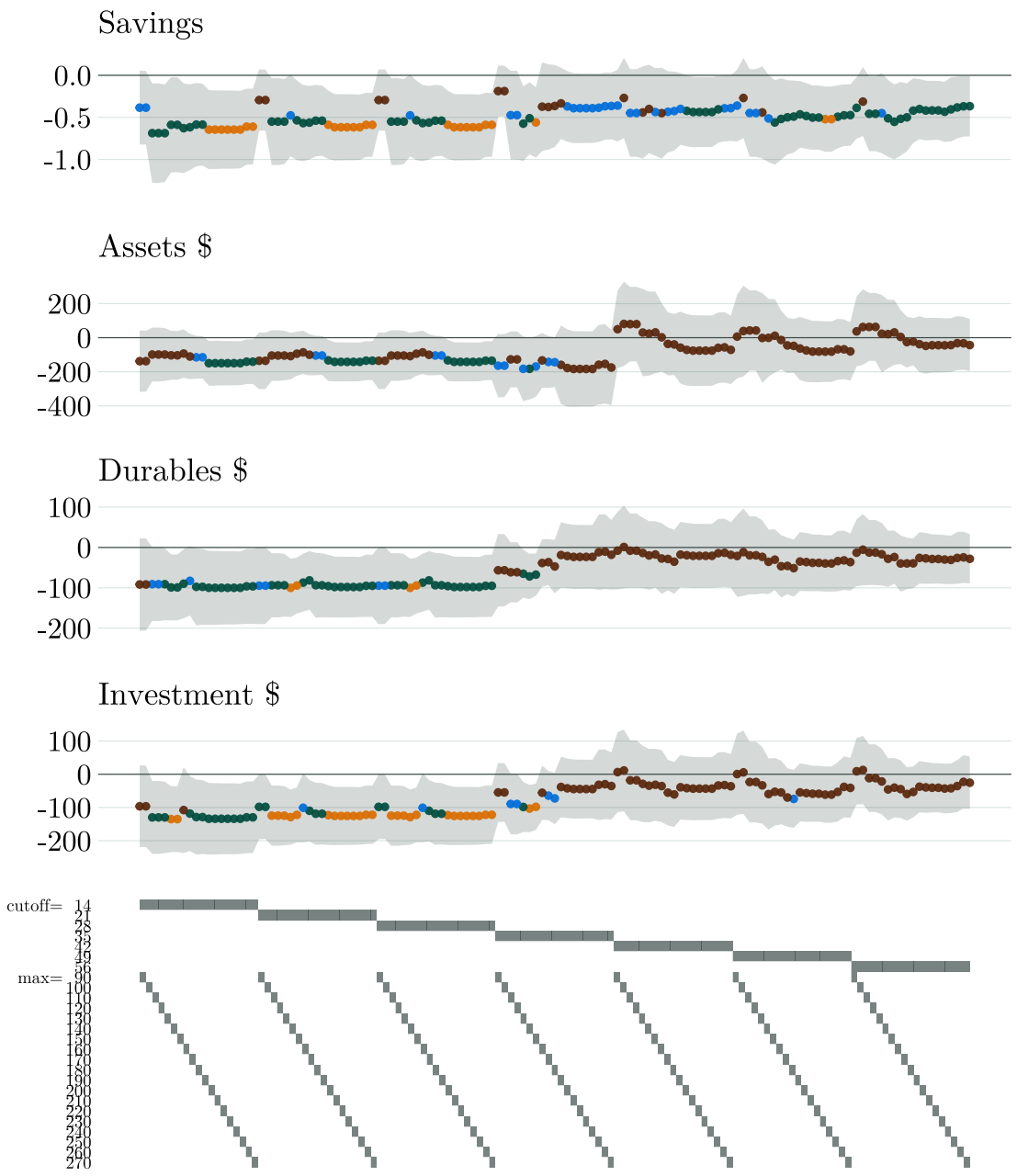
Note: Each row presents estimates from Equation (2) in Supplementary Appendix A.2 of the marginal propensity to consume in response to ESPs over a four-week period for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively, for a different subsample of households. The p-value labeled p_{123} corresponds to the null hypothesis of equality across groups. The panel on the right displays the difference in spending between Group 1 and Group 3, along with a 95 percent confidence interval (black line) and 90 percent confidence interval (vertical endpoints). See Supplementary Appendix A.1 for details on the subsamples. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Figure 4: MPC by Timing of Payment—Heterogeneity by Income and Spending



Note: Each row presents estimates from Equation (2) in Supplementary Appendix A.2 of the marginal propensity to consume in response to ESPs over a four-week period for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively, for a different subsample of households. The p-value labeled p_{123} corresponds to the null hypothesis of equality across groups. The panel on the right displays the difference in spending between Group 1 and Group 3, along with a 95 percent confidence interval (black line) and 90 percent confidence interval (vertical endpoints). See Supplementary Appendix A.1 for details on the subsamples. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Figure 5: Impact of Shorter Wait for Cash Transfers (Kenya)—Difference in differences



Note: Each specification corresponds to a different definition of the treatment group (short waiting times) and the comparison group (long waiting times), with "cutoff" denoting the threshold for defining a short waiting time and "max" denoting the maximum number of days of waiting time in the comparison group. See Figure 4 for additional information. Details about the estimation approach appear in Section 4.2. Colors denote statistical significance at the 1 percent (orange), 5 percent (green), and 10 percent (blue) levels.

Appendix Table 1: Timing of 2008 US tax rebates

Payments by electronic funds transfer		Payments by paper check	
Last two digits of taypayer SSN	Date by which payment funds are deposited	Last two digits of taypayer SSN	Date by which payment check is in mail
00–20	May 2	00–09	May 16
21–75	May 9	10–18	May 23
76–99	May 16	19–25	May 30
		26–38	June 6
		39–51	June 13
		52–63	June 20
		64–75	June 27
		76–87	July 4
		88–99	July 11

Note: Reproduced from Parker *et al.* (2013).

Appendix Table 2: Balance tests for direct deposit households

	EFT date			
	Group 1	Group 2	Group 3	p-value
Rebate amount ($)	1,008.33	1,022.78	1,025.63	0.6917
Known since Feb	0.51	0.49	0.49	0.5312
Known since Mar	0.18	0.19	0.19	0.9009
Known since Apr	0.11	0.13	0.13	0.5421
Less than expected	0.13	0.12	0.13	0.6111
Baseline average spending ($/week)	154.52	154.92	154.00	0.9424
Baseline maximum spending ($/week)	453.56	451.27	458.40	0.7328
Baseline spending frequency (weeks)	0.81	0.83	0.81	0.2986
Liquidity	0.56	0.56	0.57	0.8189
Savings habit	0.55	0.59	0.60	0.0603
Regrets purchases	0.41	0.40	0.40	0.7794
Financial plan	0.46	0.49	0.47	0.2186
Plans vacations	0.56	0.60	0.60	0.1061
No vacations	0.17	0.16	0.16	0.5260
Household size	2.63	2.69	2.69	0.5092
Married	0.61	0.62	0.63	0.3649
Lives alone	0.23	0.22	0.23	0.7960
No kids	0.63	0.61	0.62	0.5541
Has kids under 6	0.14	0.16	0.15	0.3055
Hispanic	0.07	0.08	0.08	0.2995
Nonwhite	0.17	0.19	0.17	0.2105
Female head age	49.33	48.78	48.55	0.3730
Male head age	49.97	49.46	49.07	0.2894
Female head HS grad	0.86	0.87	0.88	0.2417
Male head HS grad	0.72	0.72	0.73	0.6307
Female head college grad	0.28	0.29	0.30	0.5565
Male head college grad	0.25	0.25	0.25	0.9196
Income <$15k	0.08	0.06	0.06	0.0733
Income $15k–$30k	0.18	0.18	0.16	0.0722
Income $30k–$50k	0.26	0.26	0.27	0.5885
Income $50k–$70k	0.21	0.20	0.20	0.8168
Income $70k–$100k	0.21	0.23	0.23	0.1906
Income ≥$100k	0.07	0.07	0.08	0.5363

Note: This table presents summary statistics for households receiving direct-deposit payments in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively. See Supplementary Appendix A.1 for details on the variable definitions. The p-values in the final column correspond to the null hypothesis of equality across groups. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Table 3: Balance tests for paper check households

	Check date			
	Group 1	Group 2	Group 3	p-value
Rebate amount ($)	869.90	826.48	849.02	0.0117
Known since Feb	0.43	0.42	0.43	0.8571
Known since Mar	0.19	0.15	0.14	0.0003
Known since Apr	0.16	0.17	0.18	0.2549
Less than expected	0.11	0.11	0.09	0.0082
Baseline average spending ($/week)	142.26	133.17	135.09	0.0089
Baseline maximum spending ($/week)	411.12	390.73	391.37	0.1049
Baseline spending frequency (weeks)	0.84	0.84	0.85	0.7858
Liquidity	0.68	0.69	0.69	0.6899
Savings habit	0.63	0.67	0.68	0.0090
Regrets purchases	0.40	0.38	0.40	0.2514
Financial plan	0.53	0.54	0.55	0.6443
Plans vacations	0.55	0.51	0.53	0.0258
No vacations	0.19	0.21	0.19	0.1991
Household size	2.31	2.19	2.19	0.0109
Married	0.59	0.57	0.56	0.3678
Lives alone	0.28	0.31	0.32	0.0293
No kids	0.77	0.82	0.81	0.0019
Has kids under 6	0.08	0.06	0.06	0.0212
Hispanic	0.06	0.06	0.06	0.6700
Nonwhite	0.16	0.17	0.16	0.6384
Female head age	55.67	58.87	58.08	0.0000
Male head age	55.79	59.20	58.21	0.0000
Female head HS grad	0.85	0.84	0.84	0.8248
Male head HS grad	0.67	0.66	0.66	0.8339
Female head college grad	0.24	0.21	0.23	0.0392
Male head college grad	0.20	0.19	0.21	0.4092
Income <$15k	0.08	0.11	0.10	0.0212
Income $15k–$30k	0.23	0.26	0.23	0.1303
Income $30k–$50k	0.26	0.26	0.27	0.6338
Income $50k–$70k	0.19	0.16	0.17	0.1272
Income $70k–$100k	0.19	0.16	0.17	0.1039
Income ≥$100k	0.05	0.06	0.05	0.6948

Note: This table presents summary statistics for households receiving paper-check payments in the first three weeks (Group 1), weeks 4–6 (Group 2), and weeks 7–9 (Group 3) of the disbursement period, respectively. See Supplementary Appendix A.1 for details on the variable definitions. The p-values in the final column correspond to the null hypothesis of equality across groups. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Table 4: ESP Spending Responses by Timing of Payment—Pre-Rebate Differences

	Group 1	Group 2	Group 3
Panel A: Relative to all households			
Period -4	0.87	-0.70	-0.89
	(5.02)	(2.15)	(2.94)
Period -3	-2.79	3.00	-2.21
	(4.80)	(2.90)	(2.68)
Period -2	0.96	-0.49	0.82
	(4.60)	(2.43)	(2.91)
Period -1	-7.14	-1.91	-0.59
	(4.65)	(3.16)	(3.60)
Panel B: Relative to households receiving paper checks			
Period -4	0.93	-0.65	-0.98
	(5.21)	(2.39)	(2.93)
Period -3	-2.76	2.81	-2.28
	(4.71)	(2.36)	(2.78)
Period -2	0.90	-0.61	0.81
	(4.96)	(2.27)	(3.09)
Period -1	-7.16	-2.03	-0.86
	(4.97)	(3.04)	(3.34)
Panel C: Relative to households receiving paper checks on scheduled dates			
Period -4	1.80	-0.17	-0.66
	(4.14)	(2.04)	(2.79)
Period -3	-2.43	2.89	-0.54
	(4.66)	(2.30)	(3.28)
Period -2	0.96	1.02	0.90
	(4.97)	(2.28)	(3.20)
Period -1	-5.81	-2.06	-2.00
	(4.93)	(4.03)	(4.47)
Panel D: Relative to households receiving paper checks in July			
Period -4	0.80	0.80	-1.70
	(4.97)	(2.36)	(2.70)
Period -3	-1.58	1.98	-1.45
	(4.86)	(2.45)	(2.71)
Period -2	0.27	0.43	1.83
	(4.06)	(1.65)	(2.68)
Period -1	-6.39	-0.79	-3.42
	(4.95)	(3.57)	(4.49)

Note: This table presents estimates of γ_k^w from alternative specifications, described in Supplementary Appendix A.3, for households receiving EFTs in the first (Group 1), second (Group 2), and third (Group 3) week of May, respectively. Standard errors reported in parentheses are adjusted for clustering at the household level and obtained from a block-bootstrap procedure with 100 replicates. Calculated based on data from The Nielsen Company (US) LLC and provided by the Marketing Data Center at the University of Chicago Booth School of Business.

Appendix Table 5: Balance Tests for Households Receiving UCTs at Different Times

	Group 1	Group 2	p-value
Panel A: Household characteristics			
Age	35.99	35.27	0.8215
Married	0.70	0.76	0.5475
Children	3.00	3.00	0.7613
Household size	4.97	4.97	0.8216
Education	8.77	8.83	0.8493
Panel B: Baseline consumption			
Total	176.99	185.77	0.9553
Non-durables	173.87	182.78	0.9560
Alcohol	1.20	1.38	0.9240
Tobacco	1.18	0.69	0.6709
Panel C: Baseline assets			
Savings	17.81	14.75	0.3550
Land	1.76	1.19	0.3216
Total	371.77	349.51	0.7296
Durables	178.24	180.52	0.6279
Livestock	175.72	154.23	0.4189
Small livestock	36.17	26.28	0.0809
Cows	120.00	103.65	0.6577
Birds	19.55	24.30	0.1920
Agricultural tools	9.95	7.59	0.2534
Furniture	107.38	109.58	0.6935
Appliances	4.73	6.69	0.6626
Bike	21.01	15.42	0.0064
Phone	25.02	28.16	0.4190

Note: The sample consists of 152 households receiving one-time lump-sum transfers of KES 24,000 (USD 384 PPP) between one and nine months from the GiveDirectly announcement visit (Haushofer and Shapiro, 2016). Group 1 consists of households that receive payments between one and four months after the announcement visit. Group 2 consists of households that receive payments between five and nine months after the announcement visit. See Supplementary Appendix B.1 for details on the variable definitions. The p-values in the final column correspond to the null hypothesis of equality across groups.

Appendix Table 6: Balance Tests for Immediate and Delayed Payment Treatments in Windfall Experiment

	Immediate	Delayed	p-value
Panel A: Household characteristics			
Male	0.68	0.65	0.5674
Married	0.64	0.62	0.6491
Household size	4.69	4.72	0.9757
Acres of land	1.53	1.44	0.4220
Value of non-fixed assets	1121.11	1166.17	0.8977
Asset index	-0.16	-0.15	0.9464
Distance to branch (km)	3.70	3.70	0.4475
Hyperbolic	0.23	0.24	0.8491
Patient now, impatient later	0.21	0.29	0.1003
Impatience (switching point out of 6)	2.85	2.95	0.6212
Panel B: Savings and expenditure			
NBS account	21.68	19.80	0.7205
Formal savings	42.51	43.89	0.9232
Informal savings	51.94	54.46	0.6828
In-kind savings	96.72	104.47	0.7273
Total financial assets	101.37	99.82	0.8789
Total savings	206.32	205.32	0.9801
Total expenditures	68.83	67.27	0.9056
Food	31.94	32.09	0.9539
Non-durables	13.75	11.01	0.1478
Durables and investments	14.35	13.20	0.8089
Transfers and fees	9.52	8.16	0.6728
Unplanned food	2.76	2.90	0.7157
Unplanned non-durables	1.04	0.77	0.3578

Note: The sample consists of 474 households receiving MK 25,000 (USD 176.50 PPP) windfalls from the field experiment by Brune *et al.* (2017). The immediate treatment consists of 156 households receiving payments via cash or direct deposit without delay. The delay treatment consists of 318 households that receive payments after a one-day delay (158 households) or after an eight-day delay (160 households). The p-value corresponds to the null hypothesis of equality between the immediate and delayed payment treatments, based on a regression with village and week-of-first-survey fixed effects as in Brune *et al.* (2017). All values are reported in USD PPP adjusted using the 2014 exchange rate 141.64 MK/USD. See Supplementary Appendix C.1 for details about variable definitions.

Appendix Table 7: Impact of Non-Immediate Windfall on Savings

	1-day delay	8-day delay	p-value
NBS account	-11.33	-1.18	0.2034
	(7.32)	(7.16)	
Formal savings	-0.47	12.27	0.5998
	(12.34)	(14.04)	
Informal savings	5.56	17.97	0.2255
	(10.56)	(10.56)	
In-kind savings	-0.65	137.95	0.0003
	(24.36)	(36.57)	
Total financial assets	8.84	32.50	0.2716
	(18.90)	(20.60)	
Total savings	-3.29	159.39	0.0005
	(31.89)	(47.74)	

Note: Each row presents estimates of Equation (3) in Supplementary Appendix C.2 using the sample of the 474 households described in Appendix Table 6 for a different form of savings. The first column presents the estimate of β_1 (the causal impact of receiving the windfall with a one-day delay relative to receiving the windfall immediately), and the second column presents the estimate of β_8 (the causal impact of receiving the windfall with an eight-day delay relative to receiving the windfall immediately). Formal savings consist of balances in NBS bank accounts (the bank that facilitated the experiment), other bank or microfinance institution accounts, and employee-based Savings and Credit Cooperatives (SACCOs). Informal savings consist of balances in Rotating Credit and Savings Associations (ROSCAs), village savings clubs (*kalabu yosunga ndalama*), cash that is not for living expenses kept at home or in a secret hiding place or given to someone else for safe keeping. In-kind savings consist of advance purchases of farm inputs, business inventory, and bags of maize. Total financial assets consist of formal and informal savings combined. Total savings consist of total financial assets combined with in-kind savings. All values are reported in USD PPP adjusted using the 2014 exchange rate 141.64 MK/USD. Standard errors are reported in parentheses. The data come from the survey questions displayed in Supplementary Appendix Figure 1.