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Consumer spending during unemployment: Positive and normative implications

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Consumer Spending During Unemployment: Positive and Normative Implications
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Abstract

We study the spending of unemployment insurance (UI) recipients using de-identified data from nearly 200,000 bank accounts. Spending on nondurables falls by 6% at the onset of unemployment, is largely stable during UI receipt, and then falls by an additional 13% at benefit exhaustion. Using cross-state variation, we show that spending responds to the level of UI benefits and drops exactly when UI benefits are exhausted.

We explore the positive and normative implications of the drop in spending at UI exhaustion. From a positive perspective, our finding that spending responds to a large and predictable income drop sharpens an existing puzzle of the empirical excess sensitivity of spending to income, which is at odds with predictions from rational models. A model which includes hand-to-mouth consumers (Campbell and Mankiw 1989) as well as a model of inattentive consumers (Gabaix 2016) are able to generate a drop at exhaustion. In normative terms, because spending is so much lower after UI exhaustion than during UI receipt, the consumption-smoothing gains from extending UI benefits are at least three times as big as the gains from raising the level of UI benefits.

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1 Introduction

How does consumer spending evolve during an unemployment spell? Understanding the path of spending during this particularly stressful period in a household's financial life is important for explaining fundamental household decisions and for designing an appropriate policy response. However, this question has been difficult to answer precisely in prior work because the existing data sources on spending during unemployment are mostly small, infrequent surveys. The goal of this paper is to document the monthly path of spending during unemployment in the U.S. and to assess its positive and normative implications.

Using de-identified bank account data, we find that spending responds immediately to decreases in income, both at the onset of unemployment and even at the largely predictable exhaustion of unemployment insurance (UI) benefits. From a positive perspective, we explore the implications of our findings for different theoretical models of consumption. We show that the sensitivity of spending to income that we document is inconsistent with the standard benchmark buffer stock model. However, it is consistent with a model which includes hand-to-mouth consumers (Campbell and Mankiw 1989) as well as a model of inattentive consumers (Gabaix 2016). From a normative perspective, we examine the implications of our results for optimal UI policy. Because spending is so much lower after benefit exhaustion than during UI receipt, we find that the consumption-smoothing gains from extending UI benefits are at least three times greater than from increasing the level of UI benefits.

To document the path of spending, we worked with the JPMorgan Chase Institute (JPMCI) to construct a new de-identified panel dataset with monthly income and spending. The dataset is based on the universe of Chase consumer checking, saving, and credit accounts, aggregated to the monthly level. Spending is measured from debit and credit card transactions, cash withdrawals, and electronic transactions captured through the bank account. Our analysis sample includes nearly 200,000 households who received direct deposit of UI benefits into their bank accounts in 20 U.S. states between January 2014 and June 2016.

Spending drops at the onset of unemployment and drops more in states with low UI benefits. Spending on nondurables falls by 6.0%. The size of the drop is similar to estimates from Gruber (1997) based on food spending, though our estimates are substantially more precise, thanks to a larger sample size. We divide states based on the level of weekly UI benefits. Spending drops by 4.6% in high-benefit states compared to 7.3% in low-benefit states. The timing of the spending response suggests that higher UI benefits cause higher spending. There is an empirical one-month lag from job loss until the start of UI benefits and the spending response to higher UI benefits occurs only after UI payments have begun.

The finding that spending drops more in low-benefit states is useful for three reasons. First, we can use this variation to construct what is to our knowledge the first quantitative estimate of the marginal propensity to consume (MPC) nondurables out of UI payments.

Each additional dollar of UI raises spending on nondurables by 38 cents. Second, we use this substantial MPC to show that the drop in current income at onset is large enough to explain the entire spending drop at onset. We also directly assess, and reject, alternative explanations for the drop in spending at onset based on a drop in permanent income or an increase in home production. Third, we use this empirical fact as an over-identification test for the theoretical consumption models in Section 4.

Spending drops sharply again at UI benefit exhaustion. We analyze job seekers eligible for six months of benefits. Spending declines modestly during UI receipt and then drops by 13% in the month when UI benefits are exhausted. A large drop in spending is surprising because the exhaustion of UI benefits is predictable. This finding is novel because previously-available data were not sufficiently high-frequency to measure the drop in the precise month of benefit exhaustion.

Detailed expenditures by category suggest that the drop in spending at benefit exhaustion reflects a decline in consumption. One particular strength of the JPMCI data is rich detail on twenty-four expenditure categories. Spending drops on necessities such as groceries, medical copayments, and drugstores by about 30% more than the average drop in total nondurables. The drop in spending is persistent, so households are not simply eating previously-purchased nonperishables and delaying medical payments by a month. In contrast to the large drop in spending on necessities, nondurable spending categories which reflect financial commitments such as insurance and utility bills show only small declines in spending at exhaustion (Chetty and Szeidl 2007). Durable spending follows the same pattern, with expenditures on commitments such as mortgages and auto loans showing small declines.

The drop at exhaustion passes robustness checks designed to address concerns about internal and external validity. The drop in spending is not offset by additional spending out of other household (e.g. spousal) bank accounts. Cross-state evidence suggests the drop at six months is caused by benefit exhaustion, rather than being driven by an unobserved event at six months of benefit receipt. For example, in Florida, where benefits last only four months, we document a sharp drop in spending after four months of benefit receipt. With respect to external validity, most UI recipients have substantial prior labor force attachment and therefore are very likely to have a bank account. In fact, UI recipients in the JPMCI data are similar to external benchmarks for total household income, spending, debt payments, checking account balances and age.

The second part of our paper exploits the mean path of spending during unemployment as a simple, transparent way to test between alternative theoretical consumption models. The benchmark buffer-stock consumption model predicts no excess drop in spending at benefit exhaustion. Intuitively, the probability of UI benefit exhaustion is rising with each additional month of unemployment and households should gradually cut their spending in order to prepare for this largely predictable event. To make this point quantitatively, we study a model with endogenous consumption in the tradition of Deaton (1991) and Carroll (1997) and endogenous job search as in Mortensen (1977) and DellaVigna et al. (2016). We compute the optimal path of spending in a household model calibrated to match liquid assets, income levels, and job-finding rates in the JPMCI data. This calibrated model does a good job of predicting the level of spending at the date of UI benefit exhaustion but fails to predict the drop in spending at UI benefit exhaustion.

Viewed through the lens of our rational model, the drop in spending at benefit exhaustion sharpens the longstanding "excess sensitivity" puzzle. Numerous papers have documented that spending responds to predictable changes in income. Two of the most prominent examples are the drop in spending at retirement and the rise in spending upon receipt of expected tax rebates.[1]

Economists disagree as to whether the drop in spending at retirement reflects a failure of consumption smoothing, but the source of this disagreement is not applicable to our setting. Banks et al. (1998) argue that explaining the drop requires the systematic arrival of negative information at retirement.[2] Aguiar and Hurst (2005) question this interpretation and show that retirees are substituting time for money in home production of food. This ambiguity does not apply to benefit exhaustion because it is a change in income without any change in labor force status or time available.

One popular theory for interpreting excess sensitivity to tax rebates – liquidity constraints – is not applicable to benefit exhaustion. Several economists have developed models which exhibit excess sensitivity because some agents happen to be close to their liquidity constraint when an economic shock arrives (Gourinchas and Parker 2002, Kaplan and Violante 2014, Carroll et al. 2016). This explanation does not apply in our context. Because the agent does not need to borrow to prepare for exhaustion; the only technology that is needed is a bank account. Even a liquidity-constrained agent with no assets at the onset of unemployment will gradually cut her spending in anticipation of benefit exhaustion because agents can save their UI benefits to prepare for the predictable shock of benefit exhaustion.

In addition to being inconsistent with home production and liquidity constraints, two other features of the decision problem around exhaustion make it difficult for any rational expectations parameterization to match the drop in spending. First, exhaustion is a sufficiently large shock to income that even a highly impatient agent with a 10% *monthly* discount rate will cut spending before benefit exhaustion.[3] Second, any force which makes

[1]Examples using tax rebates and refunds include Hsieh (2003), Johnson et al. (2006), Parker et al. (2013), Baugh et al. (2013), Souleles (1999), Shapiro and Slemrod (2009) and Kueng (2015). Baker and Yannelis (2015) and Gelman et al. (2015) examine the spending response to an unanticipated, temporary loss of income: the federal government shutdown. Gelman et al. (2014) and Pagel and Vardardottir (2016) examine the spending response to payday.

[2]Bernheim et al. (2001) document that food spending drops at retirement particularly for low-asset households and interpret this as low-asset households being unprepared for retirement. Stephens and Toohey (2016) argue that both food spending and food consumption drop at retirement.

[3]A similar lesson emerges in the context of a beta-delta model as in Laibson et al. (2015). For high values of β, agents cut spending before exhaustion. For lower values of β, spending does drop sharply at benefit

long-term unemployment more painful through lost productivity strengthens the incentive to prepare for exhaustion.

We examine two alternative models that are able to generate a drop in spending at benefit exhaustion.[4] Our "spender-saver" model based on Campbell and Mankiw (1989) features heterogeneous agents, some of whom cut their spending dramatically at benefit exhaustion. The model assumes the population is a mix of three types of agents: forward-looking agents with no borrowing constraint (permanent income consumers, Friedman 1957), forward-looking agents with an exogenous borrowing constraint (buffer stock consumers), and hand-to-mouth consumers who set their consumption equal to income in each month. This hybrid model is able to match the path of spending because the hand-to-mouth consumers sharply cut consumption around onset and exhaustion, while the presence of the buffer stock agents best matches the gradual decline in spending during UI receipt. The distribution of types which best fits the path of mean spending has 30% of agents as hand-to-mouth, 50% of agents as permanent income consumers and 20% of agents as buffer stock consumers.

We also examine a model by Gabaix (2016) where agents are inattentive to future income changes. In his model, agents face a cognitive cost of planning for future income changes. This leads them to act as if changes will be smaller than they actually are. Implemented in our context, this leads households to rationally set their consumption during unemployment as if the income loss at benefit exhaustion is smaller than the true income loss. Because agents underestimate the size of the income drop at benefit exhaustion, they cut their spending sharply at benefit exhaustion. This model is able to match the drop in spending at onset and the drop at exhaustion. However, this model has two shortcomings. First, it predicts too large of a drop in the two months prior to benefit exhaustion compared to what we see in the data. Second, it is unclear from a conceptual standpoint whether rational inattention is the most appropriate frame for a such a large and salient change in income as UI benefit exhaustion.

Using an over-identification test we provide further evidence against the benchmark buffer stock model and in support of both behavioral alternatives. The test exploits differences across states in UI benefit generosity and the fact that payment of UI benefits typically begin one month after job loss. Both spender-saver and inattention models, evaluated at the parameters implied by the path of mean spending during unemployment, predict that spending in states with higher benefits should rise not at job loss, but at the arrival of UI benefits. The data are consistent with this prediction. However, this test rejects the rational buffer stock model as well as a model with over-optimism. We further explore whether the distribution of the spending drop at benefit exhaustion or heterogeneity in asset hold-

exhaustion, but that model predicts far too large of a spending drop at the onset of unemployment.

[4] We consider and reject a third model which features a drop at benefit exhaustion due to over-optimism. This model requires agents to be far too optimistic about finding a job precisely in the month that UI benefits are exhausted. We reject this model because these beliefs are inconsistent with survey evidence documenting persistent over-optimism among UI recipients in Spinnewijn (2015) and an over-identification test discussed below.

ings can distinguish between the spender-saver and inattention models; we conclude that although these tests are promising for future work, our particular data is unsuitable for their implementation.

The final part of the paper examines the normative implications of our results for optimal UI policy. The consumption implementation of the canonical Baily (1978)-Chetty (2006) formula for the optimal level of UI benefits requires the spending drop during unemployment as an input.[5] Researchers calibrating this formula have typically relied on the Panel Survey of Income Dynamics (PSID), which has two shortcomings for this purpose.[6] The first shortcoming is that until recently the PSID covered only food and housing spending. Researchers have raised concerns that the measured drop in food expenditure might overstate the drop in nondurable consumption due to home production (Shimer and Werning 2007) or fail to capture a larger drop in unmeasured consumption categories (Chetty and Szeidl 2007). The second shortcoming is that the survey is administered infrequently and has an ambiguous reference period, making it difficult to assess if survey responses about spending coincide with unemployment (Chodorow-Reich and Karabarbounis 2016). Our estimates address these concerns by estimating the share of the spending drop attributable to work-related expenses, decomposing household expenditure into twenty-four detailed categories, and using monthly data. Our results confirm that Gruber (1997)'s estimates for the welfare gain from additional UI benefits based on food spending in the PSID generalize to all nondurable spending.

Our results also enable us to estimate the welfare gain from extending the duration of UI benefits. Although most prior work on optimal UI benefits focused on the level of UI benefits as the key policy parameter, a newer strand of the literature has examined the optimal path of benefits.[7] Although there is substantial research estimating the fiscal cost of extensions, we are not aware of any paper that has quantified the welfare gains from small extensions.[8]

We find that the welfare gains from improved consumption-smoothing due to extending the duration of UI benefits are at least three times as large as from raising the level of UI benefits. This conclusion holds both in a modified version of the Baily-Chetty formula and

[5]The spending drop is also an input into macro models of the business cycle. Four recent papers have focused on changes in precautionary savings motives as an amplification mechanism for business cycle fluctuations (Sterk and Ravn 2013, McKay and Reis 2016, Ragot et al. 2016, Haan et al. 2016). The strength of the precautionary savings motive in these models depends upon the drop in consumption during unemployment. Recent papers focusing specifically on UI include Kekre (2016), Landais et al. (2013), Hagedorn et al. (2016), Chodorow-Reich and Karabarbounis (2016), and Coglianese (2016).

[6]A recent innovation in this literature is the use of annual income and asset data in tax records by Kolsrud et al. (2015) to measure the evolution of consumption.

[7]Schmieder and von Wachter (2016), Kekre (2016), and Kolsrud et al. (2015) develop theoretical frameworks for valuing extensions of UI benefits.

[8]Recent papers estimating the cost of extensions include Nekoei and Weber (2016) and Schmieder et al. (2012). The paper which comes closest to doing estimating the gains is Kolsrud et al. (2015). They analyze the optimal path of UI benefits in Sweden, where exhaustion is not relevant because there is no time limit on benefit receipt.

in the three structural models discussed above. The economic intuition for our result is that long-term unemployment is a state of the world where consumption is much lower and marginal utility is much higher; benefit extensions target this high marginal utility state of the world effectively. This calculation about the relative welfare gains from benefit level increases and benefit duration extensions does not consider that increased UI generosity may discourage job search.

The total welfare impact – which includes both the gains from improved consumption-smoothing and the losses from job search distortions – is more positive from UI duration extensions than from UI level increases across all scenarios we consider. Our data are not well-suited for analyzing job search distortions, so we use estimates from a recent literature review by Schmieder and von Wachter (2016). The job search distortions per dollar spent on extending UI benefits are modestly larger than from raising UI benefit levels. After incorporating these distortions, we find that there are absolute welfare gains from extending UI benefits in the inattention model and little change in welfare from extending UI benefits in either the spender-saver and buffer stock structural models or when applying the modified Baily-Chetty formula. In contrast, raising the level of UI benefits has a welfare loss across all models, consistent with analyses in prior literature using consumption moments to evaluate the welfare implications of raising UI benefit levels (Kolsrud et al. 2015, Kroft and Notowidigdo 2016).

The paper proceeds as follows. Section 2 describes the JPMCI data set and why it is suited for measuring how unemployment affects spending. Section 3 shows that spending is highly sensitive to the level and duration of UI benefits, including a sharp drop at benefit exhaustion. Section 4 compares predictions from different consumption models to the data. Section 5 evaluates the consumption-smoothing gains from UI benefits. Section 6 concludes.

2 JPMCI Data and External Validity

2.1 Analysis Sample

The sample for this paper consists of de-identified bank records drawn from the universe of households with a Chase bank account. Farrell and Greig (2015) report that there are 27 million households with a checking account in the JPMCI data. We focus on the subset with a bank account in states where UI benefits are paid by direct deposit. There are 20 U.S. states where Chase has physical branches and UI benefits are paid by direct deposit.[9] The unit of observation is household-by-month, from September 2013 through June 2016. We study households which did not receive any UI payments in 2013 and received at least one month of UI benefits between January 2014 and June 2016. From January 2014 onward, the potential UI benefit duration was 6 months in 17 states and less than 6 months in Florida,

[9] Appendix Figure A.1 shows a map of the 20 states. Appendix Table A.1 provides basic summary statistics on the sample.

Michigan and Georgia. Our primary analysis sample uses the 17 states which offered exactly 6 months of benefits.

The JPMCI dataset only flags UI recipients who were paid by direct deposit.[10] Nearly all states offer UI recipients a choice between receiving benefits by direct deposit or prepaid debit cards. Data from Saunders and McLaughlin (2013) show that share of UI recipients paid using direct deposit in our 20 states is 45%. As a robustness check to address questions about the external validity of estimates for direct deposit recipients, we separately show results in states with low and high shares of UI recipients receiving direct deposit.

Our primary analysis sample imposes two restrictions on the sample of JPMCI UI recipients. The first restriction is motivated by the fact that 28% of banked households have checking accounts at multiple banks (Welander 2014). To limit the sample to households which use Chase as their primary bank account, JPMCI recommended limiting the analysis sample to households with at least five monthly checking account "outflows." An outflow is any debit to a checking account including a cash withdrawal at an ATM, an electronic payment, a paper check or a debit card transaction. We select households who have five outflows in each month from three months prior to their UI spell to three months after their UI spell. This criteria retains 65% of household-months and is conservative in that it probably drops some households who do bank primarily with Chase. Our key empirical result that spending drops at benefit exhaustion also holds in the larger sample without this restriction.

The second restriction is to limit the sample to households with a single contiguous UI spell. This restriction is necessary because we define UI exhaustees based on the number of weeks of benefits received and benefit duration measured in weeks is only available in the JPMCI data for contiguous UI spells. This criteria retains 82% of household-months for a final sample size of 186,487 households and 5.4 million household-months. As a robustness check, we verify that the spending drop at the onset of unemployment is similar for households with one UI spell and households with multiple UI spells.

In some cases, we observe spending for a Chase account belonging to a household member (e.g. a spouse) who is not receiving UI, which is useful for understanding whether households increase spending out of other bank accounts during unemployment. The JPMCI data include two definitions of households. The first, more narrow definition considers a household to include all bank accounts that are administratively linked. Most people link their bank accounts administratively when they get married, making it easy for spouses to access each others' accounts (Bank TD 2014). The second, broader definition includes other adults in the family whose accounts are not administratively linked. If two Chase customers got married and did not administratively link their bank accounts, the JPMCI

[10] Errors in transaction classification lead to measurement error of UI receipt. To overcome this measurement error, we define UI recipients as households that received at least two UI benefit payments. We also require that UI payments must have an amount and frequency which is reasonable given UI program rules – less than $3,000 per month and fewer than six checks per month.

data would only classify them as part of a single household under the broader household definition. Because marriage partner selection is very unlikely to be related to prior bank usage, spending behavior out of unlinked household accounts at Chase is likely to be similar to spending behavior out of unlinked household accounts at other banks. The JPMCI database is structured around the narrow definition and this is what we use in most of our analysis, but we analyze our most important results using the broad definition as well. In any case, the definitions coincide for 79% of households.

2.2 Variables: Constructing Spending, Income, Assets and Liabilities

Spending – Our analysis focuses primarily on the nondurable spending subset of outflows because it offers a better approximation of consumption flows than total spending, which includes durables (Browning and Crossley 2009). The definition of nondurable spending captures three components which together make up 50 percent of outflows: (1) debit and credit card spending (an average of $1,541 per month, 28% of total outflows), (2) cash withdrawals ($622, 11%) and (3) bill payments ($623, 11%).[11] The other half of outflows is made up of consumer debt payments (14%), transfers to external accounts (6%), and uncategorized outflows (30%). One particular strength of credit and debit card spending is that all transactions are categorized using a four-digit Merchant Category Code issued by the Internal Revenue Service. This means that the JPMCI sample contains a granular view of the economic hardships imposed by unemployment.

Income – Our analysis focuses on the checking account inflows we observe most clearly: labor income and government transfers. the definition of income captures two components which together make up 63% of inflows: (1) payroll paid using direct deposit (59% of inflows three months prior to onset of UI) and (2) government income (4%). The remainder of inflows is transfers from outside savings and investment accounts (12%), other income (3%) and uncategorized inflows (22%). Uncategorized inflows, which are often paper checks, cannot be assigned to income or savings. Because total checking inflows are difficult to interpret, they are not the focus of our analysis.

We take two additional steps to clean the data. First, to eliminate seasonality, inflation, secular trends, and business cycle fluctuations, all results for income and spending are presented relative to a comparison group. The control group is households in the analysis sample that did not exhaust UI, analyzed in months when they were employed and not receiving UI.[12] Second, to reduce the influence of outliers, we winsorize each variable at the 95th percentile of positive values for that variable.

Assets – The JPMCI data do not directly measure total liquid assets, but do contain

[11] This definition of nondurable spending includes spending on Chase credit cards at the time goods are purchased, rather than when the credit card bill is paid, which may be months later. Mean monthly Chase credit card spend is $263. This definition of nondurable spending excludes Chase card spending at stores which primarily sell durables such as furniture or electronics.

[12] This approach is similar to Fadlon and Nielsen (2015). Formally, with i as a household, t as a month, and $y_{it,raw}$ as the original data, $\bar{y}_t^{control} \equiv \frac{1}{n_t}\sum_i y_{i,t}^{control}$, $\bar{y}^{control} \equiv \frac{1}{n}\sum_t \sum_i y_{i,t}^{control}$, the analysis variables in this paper are $y_{it} = y_{it,raw} - \left(\bar{y}_t^{control} - \bar{y}^{control}\right)$.

two coarse measures of liquid assets. The first measure is balances in checking and savings deposit accounts at Chase. Savings accounts are responsible for a very small share of liquid assets among U.S. consumers, so going forward we simply refer to the combined measure of checking and saving deposit accounts as "checking account balances." These balances offer an incomplete measure of a household's assets for two reasons. First, many consumers have external sources of liquid assets. In the Survey of Consumer Finances (SCF), the median balance in a household's primary checking account is $1,500 and median total liquid assets for an employed household are $4,900. Second, checking account balances overstate the liquid assets available to handle an economic shock because they partly serve to cover transactions during the month. Prior to the onset of unemployment, median monthly outflows are $4,000, meaning that a typical household has enough funds in their checking account to cover less than two weeks of expenses.

Our second liquid asset measure is an estimate of the household's total liquid assets based on an internal JPMC statistical model. This model uses a combination of checking account activity and third-party data sources to construct an estimate of total liquid assets. Unfortunately, this variable is not well-suited for studying high-frequency movements in a household's asset position. In Section 3.2, we study heterogeneity in the spending drop during unemployment by estimated liquid assets at the onset of unemployment.

Liabilities – For the 42% of households with Chase credit cards, we observe revolving balance on Chase credit cards, new purchases on Chase credit cards, and credit limits on Chase credit cards.

2.3 Representativeness

Our results in the JPMCI data seem likely to generalize to the broader population of UI recipients. Most UI recipients have substantial prior labor force attachment and therefore are very likely to have a bank account. Ninety percent of households reporting UI income in the past year in the SCF had a bank account at the time of the survey. Table 1 compares the representativeness of the JPMCI sample to external benchmarks in terms of income, spending, checking account balances and age.

When we compare the JPMCI spending data to external benchmarks, we find under-coverage of total nondurables, while we find better coverage of specific nondurable categories and debt payments. Our measure of spending on nondurables is 94% of the Consumer Expenditure Survey (CEX) benchmark and 44% of the Bureau of Economic Analysis' Personal Consumption Expenditures (PCE) benchmark. We believe that our true coverage of spending is somewhere between these two numbers: the CEX is too low because of under-reporting and PCE is too high because it includes the consumption of very wealthy households who are not relevant for our study. For specific nondurables, JPMCI spending is 144% of the CEX benchmark for groceries, 132% for food away from home, 120% for gas, and 119% for utilities. The best public use dataset for measuring monthly debt payments is the SCF. JPMCI spending is 112% of the SCF benchmark for mortgage payments, 104% for auto loan payments and 63% for credit card payments.[13]

The remaining rows in Table 1 show that JPMCI UI recipients have similar income, age and checking account balances to external benchmarks. We measure the distribution of household income in the 12 months prior to UI receipt using the Survey of Income and Program Participation (SIPP). In the JPMCI data, we rescale checking account income into pre-tax dollars. Figure 1 shows that the distribution of income in these two datasets is quite similar. Table 1 shows that mean household income in JPMCI is 101% of the SIPP benchmark and that mean age is 41.1 years in JPMCI compared to 44.3 years in the SIPP. The median checking account balance in the JPMCI sample is $1260, which is 84% of the SCF balance in the household's primary checking account.[14]

3 How UI Affects Consumer Spending

In this section, we develop a new set of empirical facts about consumer spending during unemployment. Our primary goal is to estimate the path of mean spending from the onset of unemployment through benefit exhaustion for a typical UI recipient. Section 3.1 documents this path, which we then use in Section 4 as a simple, transparent empirical target for theoretical consumption models. Our secondary goal is to uncover the mechanisms driving the path of spending. Section 3.2 shows that the spending drop at onset is smaller in states with more generous UI benefits. This is useful for three reasons: it is the first estimate of the MPC on nondurables out of differences in UI benefit levels; we use this substantial MPC to show that the drop in current income at onset is large enough to explain the entire spending drop at onset; and we use it in an over-identification test of the theoretical models. We also directly assess, and reject, alternative explanations for the drop in spending at onset based on a drop in permanent income or an increase in home production. In Section 3.3, we devote particular attention to the drop in spending at UI benefit exhaustion because this feature of the data is what differentiates between alternative theoretical models. This section also discusses five robustness checks to assess internal and external validity of the drop at exhaustion.

3.1 Path of Income and Spending During Unemployment

Income drops sharply at the start of an unemployment spell and would likely drop much more but for the availability of UI benefits. The top panel of Figure 2 shows labor income by completed UI duration. The bottom panel shows labor income, and labor plus UI income for an evolving sample of those continuing unemployment. Prior to onset, all future UI recipients are included in the bottom panel. Define $\bar{y}_t = \frac{1}{n}\sum_i y_{i,t}$ where i is a household and t is months since UI receipt. In month $t = 0$, everyone who gets UI through month 1

[13] Appendix Table A.2 provides additional detail comparing spending between JPMCI and external benchmarks.

[14] Appendix Tables A.3 and A.4 provide additional statistics comparing income and checking account balances in the two samples. The algorithm for rescaling post-tax dollars into pre-tax dollars is described in Appendix Table A.3.

is included, in month $t = 1$, everyone who gets UI through month 2 is included, and so on. Formally, each point is in Figure 2 is estimated as

$$\Delta y_t = \frac{\sum_{i \in \text{UI duration} > t} y_{i,t} - y_{i,t-1}}{\sum 1(i \in \text{UI duration} > t)} \quad (1)$$

$$\bar{y}_t = \Delta y_t + \bar{y}_{t-1}. \quad (2)$$

Figure 2 contains two lessons about household income at the start of an unemployment spell. First, the data suggest that many people start receiving benefits one month after job separation. Figure 2 shows that labor income is nearly constant in the months leading up to receipt of UI and then falls sharply in the month before UI benefit receipt. This empirical regularity is important for measuring the MPC out of UI benefits in Section 3.2. Second, labor income does not drop to zero because some households have another member who continues to earn labor income. Table 2 shows the evolution of income during unemployment. After taking into account UI benefits and the labor income of other household members, the average drop in measured household income is \$470.[15]

Figure 3 provides visual evidence of the sensitivity of consumption to income by depicting the path of spending at the onset of unemployment. This path mirrors the path of income from Figure 2 in four ways. First, spending drops sharply at onset, coincident with the drop in labor income. The spending drop occurs *before* UI benefits start and we exploit this feature of the data as a placebo test in Section 3.2.1. Second, for job seekers with a short unemployment spell, income and spending recover immediately on re-employment. Third, for job seekers with a long unemployment spell, both income and spending remain depressed while unemployed. Fourth, for job seekers who exhaust UI benefits, there is a sharp drop in income and spending. We analyze this drop extensively in Section 3.3.

Our estimates of the drop in spending during unemployment are quantitatively in line with prior estimates for the U.S. using survey data from the U.S., but are five times as precise as the state-of-the-art estimates.[16] Gruber (1997) reports that food spending falls by 6.8%.[17] Although Gruber's empirical specification does not generate a standard error for this statistic, Hendren (2016) reports a comparable estimate with standard error of 0.5%.

[15]The ratio of UI benefits to the drop in labor income implies a replacement rate of 66%. This apparent 66% replacement rate is larger than typical statutory UI pre-tax replacement rates, which are around 45% in the US. Two factors explain nearly all of the gap in measured replacement rates: differential tax treatment of UI benefits and labor income payment method. First, UI checks are not subject to withholding, whereas a typical paycheck will have 7.65% deducted in payroll taxes and perhaps 15% in income tax withheld. Second, we are only able to detect labor income paid by direct deposit in the JPMCI data; we have calculated using the SCF that about 15% of labor income is paid by paper checks and pre-paid debit cards rather than by direct deposit.

[16]See Browning and Crossley (2001), Bloemen and Stancanelli (2005) and Kolsrud et al. (2015) for estimates for Canada, the United Kingdom and Sweden, respectively. These estimates are difficult to compare to ours because UI benefits are more generous in these countries.

[17]Several authors have replicated this estimate: Chetty and Szeidl (2007), Kroft and Notowidigdo (2016), East and Kuka (2015), Chodorow-Reich and Karabarbounis (2016), Saporta-Eksten (2014) and Hendren (2016). Other estimates of the spending drop during unemployment include include Browning and Crossley (2001), Bloemen and Stancanelli (2005), Hurd and Rohwedder (2016) and Kolsrud et al. (2015).

It is ambiguous which is the correct reference period in the PSID. If the reference period is unemployment onset, then our estimates which are comparable show that spending drops by 6.0% on all nondurables (Table 2, standard error: 0.1%) and 6.2% on food (Table A.5, standard error: 0.1%). If the reference period is an annual time horizon then our comparable estimates are 6.4% on nondurables and 4.3% on food (Appendix Table A.6). In either case, our estimates are more precise.

To better understand the drop in consumption, we investigate the role of liquid assets and borrowing in smoothing this drop. Liquid assets appear to help households smooth. Households with lower estimated liquid assets at onset show larger drops in spending (Appendix Figure A.3).[18] In contrast, households do not appear to use borrowing as a means of smoothing the drop. Unemployed households with a credit card on average borrow only $20 per month on their Chase credit card (Appendix Figure A.2), offsetting less than 10% of the consumption drop.[19] Both of these observations motivate modeling choices we make in Section 4.

3.2 UI Benefit Levels Affect Spending Only When UI Payments Begin

To understand how UI benefit levels affect the path of spending, we compare states with high and low UI benefits. Specifically, we rank states based on the fraction of household income replaced by UI benefits and divide the states at the median by the total number of UI recipients into two groups. To ensure that job seekers received UI for the entire month in which spending is measured, we limit the sample to job seekers that received at least two full months of UI benefits and study spending in the second month of UI receipt. High benefit states are CO, ID, KY, NJ, NV, OR, TX, UT, WA and WV. Low benefit states are AZ, IL, LA, NY, OH, OK, WI. High benefit states replace an additional 5.1% ($199) of household income, as shown in the top panel of Figure 4 and in Table 3.

High- and low-benefit states are similar on observables that might be expected to affect the size of the spending drop during unemployment. The amount of labor market risk as measured by the unemployment rate is similar: 5.7% in high-benefit states versus 5.6% in low-benefit states during our sample period. The labor income loss post-unemployment is similar: after 15 months, income has recovered to 79% of the pre-onset mean in high-benefit states versus 81% in low-benefit states. The non-UI safety net is actually more generous in low-benefit states, with spending of $1,950 per capita compared to spending of $1,700 per capita in high-benefit states. Because these states show balance on ex ante observables, an explicit procedure to ensure balance on these observables such as Currie and Gruber (1996) would yield similar conclusions.

[18] This is consistent with Kawano and LaLumia (2016)'s finding that households with IRAs liquidate them during unemployment.

[19] Some prior research using public use datasets has found increases in credit card borrowing during unemployment (Sullivan 2008, Collins et al. 2016), while other work has found decreases (Bethune et al. 2015). Because of small sample sizes, it is challenging to make statistically precise statements about borrowing during unemployment using these datasets.

A related concern is that high- and low-benefit states might differ on unobservables which affect the size of the spending drop, and we exploit an institutional feature of the UI system to address this concern. There is usually a one-month lag between the onset of unemployment and the receipt of UI benefits, as discussed above. The bottom panel of Figure 4 shows that spending drops an equal amount in high- and low-benefit states before UI payments begin. Only after UI payments begin do these two series diverge.

After UI payments begin, spending drops much more in low-benefit states and the timing of the spending response suggests that this relationship is causal. From before onset through the second calendar month of UI benefit receipt, spending drops by 4.6% in high-benefit states compared to 7.3% in low-benefit states.[20] Translating to dollars, spending falls by $74 more in low-benefit states, implying a marginal propensity to consume (MPC) out of a permanent one dollar difference in UI benefits across states of 38 cents. The fact that the divergence in spending between high- and low-benefit states does not occur until after UI payments begin suggests that the relationship between benefit levels and spending is causal.

Our estimated response of food spending to UI benefits is within the range of prior estimates. Gruber (1997) and East and Kuka (2015) estimate that a 10 percentage point increase in the UI replacement rate raises food spending by 2.7% and 0.8% respectively using the PSID.[21] Our comparable statistic is that a 10 percentage point increase in the UI replacement rate would raise a household's food spending by 2.3%.

3.2.1 Home Production, Permanent Income Loss Do Not Explain Drop

Why does spending drop at the onset of unemployment? Browning and Crossley (2001) describe three reasons why spending may fall at the start of an unemployment spell – a temporary income loss, a decrease in work-related expenses, and a permanent income loss. Although the event study plots in Figures 2 and 3 provide suggestive evidence in favor of the temporary income explanation, the MPC at onset provides more definitive evidence. A back of the envelope calculation shows that the $170 spending drop at onset can be accounted for by the $470 drop in income ($\$470 \times 0.38 = \$179$).

A substantial literature has focused on consumers substituting time for money to explain lifecycle expenditure patterns (Aguiar and Hurst 2013) and business cycle fluctuations (Nevo and Wong 2015). In our context, four of the five expenditure categories with the largest

[20] Asymptotic methods for handling clusters can lead to misleading standard errors when the number of clusters is small. Table 3 reports a p-value from a permutation test (see e.g. Fisher 1935, Ganong and Jaeger 2016) for the hypothesis that the spending response is equal in low- and high-benefit states of 0.12. With only 17 states, the permutation test does not have good power against economically reasonable values for the MPC; we would have needed to find an MPC of 52 cents in order to reject the null with $p = 0.05$.

[21] These two papers do not report a MPC per dollar of UI benefits. Their analysis focuses on unemployment by household heads rather than by all household members. UI replaces a larger fraction of household income when the head is unemployed, which suggests that the estimated MPC on food in the JPMCI sample may be larger than the implied MPC based on the PSID estimates. Empirical results from McKee and Verner (2015) and DiMaggio and Kermani (2016) also suggest a large MPC out of UI benefit levels. However, Browning and Crossley (2001) estimate that a 10 percentage point increase in the UI replacement rate raises total spending by only 0.7%.

spending drops at unemployment are department stores (clothing), flights and hotels, food away from home, and transportation, all of which seem to be plausibly work-related (Appendix Table A.7). Building on Aguiar and Hurst's methodology, we analyze a subset of work-related expenditure categories in the JPMCI data.[22] Spending drops by 10% for the work-related categories compared to around 6% for the rest of nondurables.

Our estimates imply a small role for home production in explaining the decline in spending on work-related categories during unemployment. A larger drop for work-related categories could occur because of increased time available for home production or because these spending categories are luxuries with a high elasticity of spending to income. We can disentangle these two channels because people in high- and low-benefit states have the same increase in time availability due to unemployment, but different-sized drops in income. Consider a hypothetical scenario where the household had increased time for home production due to unemployment, but no change in household income. Table 3 estimates an MPC on work-related categories of 10 cents. Extrapolating linearly to an increased-time-only counterfactual, spending on work-related categories would have fallen by ($\$63 - \$470 \times 0.10 =$) \$16, which is only 25% of the total \$63 decline in spending on work-related categories.

Two pieces of evidence suggest that the drop in spending at the onset of unemployment is also not explained by permanent income losses. First, job seekers in our sample lose about \$9,000 of income in the first twenty-four months of unemployment, which is a small amount in terms of lifetime income. From six months onward, income is trending upward and it is unclear how persistent income losses are after twenty-four months.[23] Second, the permanent income loss is very similar in high- and low-benefit states. If permanent income losses played a big role in explaining the drop in spending at onset, then we would not expect the level of temporary UI benefits to be so influential in determining spending levels.

3.3 Benefit Exhaustion: Nondurables Spending Drops Sharply

Benefit exhaustion coincides with a dramatic, precisely estimated drop in spending. Exhaustion of monthly UI benefits generates a large, predictable and sustained drop in income.[24] Labor income growth replaces only a modest share of the lost UI benefits.[25]

[22] We define a spending category as work-related if it exhibits a larger-than-median drop at retirement (Aguiar and Hurst 2013). Appendix Figure A.4 illustrates this methodology and shows which spending categories are defined as work-related.

[23] Appendix Figure A.5 shows that after twenty-four months labor income plus government transfers have recovered to 95% of their pre-onset mean. This finding may seem surprising in light of prior work by Jacobson et al. (1993) and similar results in Couch and Placzek (2010), Wachter et al. (2009), Davis and von Wachter (2011), and Flaaen et al. (2016). This prior work has largely focused on high-tenure workers who separate in mass layoffs, who tend to have larger earnings losses than the typical UI recipient.

[24] The top panel of Appendix Figure A.6 demonstrates that the drop is predictable. It shows labor income + UI for job seekers unemployed for at least 1, 2, 3, 4, 5 and 6 months respectively. With each additional month of unemployment, average income shows an increasing drop at month 6. Someone who has been unemployed for 5 months will on average see their income drop by 16% in month 6. The bottom panel shows the path of spending. The news that average income will drop by 16% does not affect spending.

[25] Appendix Figure A.7 shows the path of labor income around exhaustion. Labor income rises for three reasons. First, some UI recipients would have found jobs even if benefits continued. Second, other household

Altogether, income drops by $1,100 at benefit exhaustion and nondurable spending drops by 9.3%. This sharp drop in spending at exhaustion is the key empirical fact which differentiates the benchmark buffer stock model from the behavioral models in Section 4.

The drop in spending for a jobseeker who fails to find a job in the sixth (and final) month of benefit receipt is larger than the unconditional drop for all UI recipients who receive six months of benefits measured in Table 2 because of re-employment at exhaustion. Twenty-seven percent of job seekers in our data find a job in the month that UI benefits are exhausted.[26] Figure 3 shows that spending is constant at re-employment for those who find a job in month 5. If 27% of the sample that finds a job after six months has constant spending, then the mean drop in spending for those who remain unemployed is actually 12.7% (9.3%/0.73). We use this 12.7% spending drop as the empirical target for the model in Section 4.

The drop in spending at exhaustion appears to reflect a change in a household's actual consumption bundle from the prior month. Table 4 decomposes the drop in checking account outflows into twenty-four different categories.[27] Categories linked to necessities exhibit sharp drops. For example, grocery spending drops by 13.9%, medical out-of-pocket spending drops by 12.8% and drug store purchases drop by 13.2%. Drops in these categories are substantially larger than the average 9.3% drop in spending on all nondurables at exhaustion documented for the same sample in Table 2.

The sharp drop in grocery spending at exhaustion probably reflects a deterioration in diet quality. Aguiar and Hurst (2005) compare the diets of employed and unemployed people, controlling for a wide variety of observables, and report a similarly-sized gap in spending on groceries between the employed and unemployed (9-15%) to the drop we see at exhaustion. They estimate that unemployment causes a five percentage point increase in the share of households consuming any lunch meat and a nine percentage point decrease in the share of households consuming any fresh fruit.

In contrast, households appear to prioritize their most important financial commitments at exhaustion and these categories show much smaller declines. Table 4 shows that the drop in nondurable spending is smallest for utility and insurance payments. Durable spending

members may increase their labor supply (Cullen and Gruber 2000, Stephens 2002, Rothstein and Valetta 2014, Blundell et al. 2016, Kawano and LaLumia 2014). Third, search effort and job-finding rates are higher at benefit exhaustion (Katz and Meyer 1990, Schmieder et al. 2012, Card et al. 2007, Krueger and Mueller 2010, DellaVigna et al. 2016).

[26]We calculate the job-finding rate in the month that benefits are exhausted by comparing the path of mean labor income for people who exhaust UI to people who exit UI in five months (and presumably have found a job) using the labor income series in Figure 2. For a jobseeker who exits UI in five months, mean labor income jumps by 45 percentage points of its pre-onset value in the two-month window around UI exit. It does not recover to 100% in part because some new jobs do not pay by direct deposit. In comparison, for UI exhaustees, mean labor income jumps by 12 percentage points in a two-month window. Taking the ratio (12/45) implies a 27% job-finding rate in the month benefits are exhausted. To the best of our knowledge, this is the first estimate of the job-finding rate for UI recipients at benefit exhaustion in the U.S.

[27] Appendix Figure A.8 shows a timeseries for three alternative spending definitions.

follows the same pattern, with expenditures on commitments such as mortgages and auto loans showing small declines. There is little evidence to suggest that benefit exhaustion does immediate damage to a household's long-term financial health. These empirical results are consistent with the presence of consumption commitments as suggested by Chetty and Szeidl (2007).

3.3.1 Robustness Checks on Drop at Exhaustion

Causality Using Potential Benefit Duration – Comparing states with different potential benefit durations suggests that the drop in spending at 6 months is caused by the drop in UI benefits. UI benefits lasted 4 months in Florida from January 2014 through June 2015, compared to 6 months in most states. We compare people who received 4 months of benefits in Florida to the subset of our primary analysis sample in 6-month states who received benefits for at least 4 months. The top panel of Figure 5 shows that UI benefits in Florida were a smaller share of income and ended sooner than in 6-month states. The bottom panel shows that the path of spending mirrors the path of income. Spending falls discretely at 4 months in Florida and at 6 months in 6-month states.

There are two additional sources of variation in potential benefit duration in our data. Florida offered 3.5 months of benefits from July 2015 through December 2015 and then offered 3 months of benefits for the rest of our sample period. Beyond Florida, there are two other states in our sample – Michigan and Georgia – which offered less than 6 months of benefits. Appendix Figure A.9 shows that spending also drops when benefits expire for other time periods in Florida as well as in Georgia and Michigan. Because there are fewer observations in these states and time periods, our estimates are less precise.

Other Household Bank Accounts – Spending patterns out of other household (e.g. spousal) bank accounts reject the hypothesis that the drop in spending at exhaustion reflects substitution to a different bank account. In Section 2.1, we explain how the JPMCI dataset can capture spending for two customers who form a household unit without administratively linking their bank accounts. Spending out of other accounts is constant at benefit exhaustion (see Appendix Figure A.10). Because only about one-quarter of households have accounts at multiple institutions, the fact that spending is constant out of spousal accounts leads to a very small bias in the estimates discussed above. Incorporating the fact that spending is constant in other household accounts for the 28% of households with outside bank accounts at benefit exhaustion changes the unconditional drop at exhaustion from 9.3% to 8.9%.

Direct Deposit – A cross-state comparison of the drop at exhaustion suggests that the results for UI beneficiaries paid by direct deposit are likely to generalize to the broader population of UI recipients. Appendix Figure A.11 compares the size of the spending drop at exhaustion (normalized by the income loss at exhaustion) to the share of UI recipients in a state that are paid by direct deposit. The share of UI recipients paid by direct deposit varies widely, from 15% to 70% in states in the JPMCI data. Because there is no clear relationship between the drop at exhaustion and direct deposit usage, it seems unlikely that the direct deposit screen is an important source of bias.

Time Aggregation – One complication for estimation is that in the monthly JPMCI data, a household that exhausts benefits halfway through the month will see their spending drop over a two-calendar-month period. Examining the subsample of households whose last UI check was paid on the 21st of the month or later guarantees that the income "seam" coincides with the monthly intervals in the bank data. Appendix Figure A.11 shows that the two-calendar-month drop for non-seam households is of very similar size to the one-calendar-month drop for seam households. This motivates our interpretation of the two-calendar-month spending drop for all exhaustees as an accurate estimate of the drop in spending from one month to the next at benefit exhaustion.

Heterogeneity by Covariates – We examine heterogeneity in the drop at exhaustion for thirteen subgroups (Appendix Table A.8). The drop in spending is always statistically significant, suggesting that our findings hold quite broadly across UI exhaustees.

4 Positive Implications for Consumption Models

High-frequency data on the path of spending offers a simple, clear empirical target for testing between alternative consumption models. A predictable drop in temporary income from the expiration of UI is a novel laboratory to study predictions from these models. As Jappelli and Pistaferri (2010) note in their review article, only a few empirical papers study predictable income drops other than retirement (Shea 1995, Souleles 2000, Baker and Yannelis 2015, and Gelman et al. 2015) and we are not aware of any quantitative consumption model which has studied a predictable drop in temporary income.

We first evaluate the benchmark buffer stock model, which predicts that spending will decline gradually during unemployment, contrary to the sharp drop in spending that we see in the data. Next, we show that several extensions of the buffer stock model are also unable to match the path of spending. Finally, two behavioral models previously used to explain job search behavior – beta-delta and over-optimism – do not match features of the data.

Viewed through the lens of our rational model, the drop in spending at benefit exhaustion sharpens the longstanding "excess sensitivity" puzzle in two ways. Prior attempts to reconcile empirical evidence of excess sensitivity with rational models have relied on liquidity constraints and home production. Liquidity constraints have been used to explain why spending would rise after the predictable arrival of a tax rebate. However, liquidity constraints cannot explain why spending would fall at exhaustion. To prepare for the drop at benefit exhaustion, agents only need a saving technology such as a bank account to prepare for a drop in income. A different strand of the literature has suggested that the drop in spending at retirement may be attributable to increased home production. Because benefit exhaustion is a change in income without a change in the agent's time budget, the observed drop in spending is unlikely to be explained by a change in home production.

Two models are consistent with the spending drop at benefit exhaustion: a model with heterogeneous consumers, some of whom are hand-to-mouth, and a model with inattentive consumers. Using an over-identification test we provide further evidence against the benchmark buffer stock model and in support of both behavioral alternatives.

4.1 Baseline Model Setup and Parameterization

We calibrate a finite-horizon buffer stock model of consumption, savings and job search. Agents choose their level of consumption each month, c_t, and their job search effort if unemployed, s_t, to maximize their expected discounted flow of lifetime utility. We assume agents have Constant Relative Risk Aversion (CRRA) utility over consumption $u(c_t)$ and that exerting search effort is associated with strictly increasing and convex disutility cost $\psi(s_t)$ as in Chetty (2008) and DellaVigna et al. (2016). Agents earn a monthly return of R on their beginning of month assets a_t. The only risk to income z_t comes from unemployment; this risk is partially mitigated by UI benefits, which expire after six months.[28] Income follows a Markov process Π based on exogenous separations from employment and endogenous job search during unemployment. The agent's problem in month t can be written as

$$\max_{\{c_t, s_t\}} \mathbb{E} \sum_{n=0}^{T-t} \delta^n (u(c_{t+n}) - \psi(s_{t+n})) \tag{3}$$

$$\text{subject to } c_t + a_{t+1} = Ra_t + z_t \tag{4}$$

$$c_t \geq 0 \tag{5}$$

$$a_{t+1} \geq -b_t \tag{6}$$

$$Ra_T + z_T - c_T \geq 0 \tag{7}$$

where δ is the monthly discount factor, $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, $\psi(s) = k\frac{s^{1+\xi}}{1+\xi}$ when unemployed and $\psi = 0$ when employed, z_t evolves according to transition matrix $\Pi(s_{t-1})$, T is the number of months in the agent's life, and b_t is the borrowing limit. The last inequality is a budget balance condition at the end of life.

We solve the household problem recursively using the method of endogenous gridpoints suggested in Carroll (2006). This generates optimal consumption paths and search effort for a given set of parameters.[29] We calibrate the model using the JPMCI data and preference parameters summarized in Table 5.

[28] We analyze UI recipients eligible for six months of benefits. In Section 3.1, we documented that the decline in household income occurs one month *before* UI receipt begins because of a time lag between job separation and the beginning of UI receipt. To match this feature of the data in the model, we assume that UI benefits last seven months rather than six months.

[29] The combination of asset level and employment status determines beginning-of-period cash on hand $m_t = Ra_t + z_t(e)$, which is formally how the model is solved.

We choose income and assets at onset to match the JPMCI data. We normalize income to 1.00 in the employed state. Household income is 0.83 while receiving UI benefits and 0.54 after UI benefit exhaustion.[30] We do not observe total liquid asset holdings in the JPMCI data, so we estimate them using an adjustment factor from the SCF. Specifically, we estimate assets as a share of income according to the following expression: $a_0^{data} = \frac{\text{Total liquid assets}_{SCF}}{\text{Checking account balance}_{SCF}} \cdot \frac{\text{Checking account balance}_{Chase}}{\text{Pre unemployment monthly income}_{Chase}} = 0.66$. We assume agents cannot borrow ($b_t = 0$), which matches the near-absence of additional credit card borrowing during unemployment documented in Section 3.1. We relax this assumption in Section 4.3.

We choose parameters for the cost of job search (k, ξ) to match the job-finding rate in the JPMCI data. The job-finding rate – as measured by the UI exit rate – is 23% in months 2, 3 and 4 of UI receipt and 27% in month 5. The job-finding rate in month 6, when benefits are exhausted, is 27%, as discussed in Section 3.3. The job-finding rate in the JPMCI data is in line with administrative data on the time-path of UI exit rates in the U.S. (Meyer 1990, Card and Levine 2000) as well as Austrian data on re-employment around benefit exhaustion in Card et al. (2007). We choose an exogenous separation rate to UI of 3.25% in order to match the 11.5% of households with an unemployed member during 2014 (Bureau of Labor Statistics, 2014).

We choose preference parameters and features of the environment using standard values for household consumption models. For the preference parameters δ and γ we choose standard values of 0.996 (translating to an annual discount rate of 5%), and 2.0. In Section 4.3, we estimate these two parameters as a robustness check and find $\hat{\delta} = 0.998$ and $\hat{\gamma} = 1.5$. We choose a monthly real interest rate of 0.25%, which translates to an annual interest rate of 3%. We consider a time horizon of 240 months, corresponding to a middle-aged worker with 20 years left in her career.

4.2 Baseline Buffer Stock Model Predictions Compared to Data

The model's predictions match some features of the data during unemployment, but not the sharp drop in spending at benefit exhaustion. Figure 6 visually compares the model to the data.[31] We define the empirical counterpart to the model's predictions as the path of nondurable spending shown in Figure 3.[32] The model does a good job of matching the spending drop at the onset of unemployment. The model also does a good job of matching the evolution of the job-finding rate (Appendix Figure A.12).

After the onset of unemployment, two forces push the agent to cut her spending with

[30] Our household income concept includes labor income from all household members, capital income, and government transfers. Labor income does not fall to zero at exhaustion because of these other income sources.

[31] Section 4.3 considers a version where we estimate the preference parameters rather than using calibrated values.

[32] Alternative methods for measuring the spending path – such as using total expenditures instead of nondurables or using the path of spending for ex-post exhaustees instead of the pooled sample – yield similar results.

each passing month: news and asset decumulation. With each additional passing month of unemployment, information about the path of future income is gradually revealed (Appendix Figure A.6). The asset drawdown is similarly gradual. The agent cuts spending gradually because the forces causing her to cut spending grow stronger with each month. As a result, there is no excess drop in spending when UI benefits run out in the model. We document in the next section that any model with rational expectations will also fail to predict the sharp drop in consumption at exhaustion observed in the data.

4.3 Alternative Models That Do Not Match Spending Path in Data

The top four panels of Figure 7 demonstrate that seven alternative parameterizations which maintain the assumption of time-consistent rational expectations behavior are unable to match the path of spending, and in particular the sharp drop in consumption at exhaustion.

Changes in liquid assets at onset or in the borrowing technology available to households do not generate a sharp drop at exhaustion, as shown in Panel A. The starkest example is to consider spending for an agent with *zero* assets at the start of unemployment. Although the decline in spending during unemployment is larger, this agent exhibits the same qualitative behavior as the baseline parameterization of gradually cutting spending to prepare for exhaustion. Instead of consuming all her UI benefits and drawing down liquid assets, she saves an increasing portion of her benefits each month.[33] The other extreme is to consider a permanent income consumer who can borrow against her future income at interest rate R. A "natural borrowing constraint" (Aiyagari, 1994) arises because the agent must pay all her debts before death and have positive consumption in every period.[34] This agent only cuts her spending by a little bit during unemployment because because she has good access to credit. Similarly, we examine spending for an agent who can do unsecured borrowing at monthly rate $R = 1.015$ up to 2.25 months of income.[35] This agent cuts spending slightly less than in the benchmark model.

Adopting more pessimistic scenarios for labor market risk does not generate a sharp drop at exhaustion, as shown in Panel B. We adopt the stark assumption that all jobs found before exhaustion pay the same as the pre-unemployment job and exhaustion brings with it a 10% *permanent* income loss, which is at the upper end of estimates in the literature.[36] We

[33] In the Kaplan and Violante (2014) model, the availability of a high-return illiquid asset with a transaction cost leads agents to hold relatively few liquid assets. It seems likely that an agent in their model with few liquid assets who did not access her illiquid asset would behave similarly to the agent with zero assets at onset in our model.

[34] In any period, the natural borrowing constraint is the present discounted value of the minimum possible future income flows, which are bounded below by the income value for an agent who has exhausted UI benefits. Formally, we set $b_t = \sum_{s=0}^{T-t-1} \frac{z_{min}}{R} \left(\frac{1}{R}\right)^s$ where z_{min} equals the income for an agent who has exhausted UI benefits.

[35] This borrowing limit is calibrated to match the SCF, following Kaplan and Violante (2014).

[36] Abraham et al. (2016) report that medium-term re-employment earnings in the U.S., including zeros, are 10% lower for someone unemployed three quarters relative to someone unemployed for one quarter.

also consider an alternative scenario where after exhaustion agents have a 50% chance of getting a job at their old wage and a 50% chance of getting a job where permanent income is 10% lower. At exhaustion, the agent learns which state of the world she is in. The model's predictions are essentially unchanged. Although permanent income substantially affects consumption when an agent has a liquid buffer, it matters little when assets are depleted.

Changing preference parameters such as risk aversion and the discount factor does not generate a sharp drop at exhaustion, nor does introducing heterogeneity in the discount factor, as shown in Panels C and D. Instead of calibrating the discount factor and risk aversion parameter, we use a quadratic minimum distance measure to estimate $\hat{\theta} \in (\delta, \gamma)$ in an attempt to explicitly match the path of spending:

$$\hat{\theta} = \arg\min_{\tilde{\theta}} \sum_{t=-2}^{8} (c_t - \hat{c}_t(\tilde{\theta}))^2. \tag{8}$$

We estimate $\left(\hat{\delta}, \hat{\gamma}\right) = (0.998, 1.5)$. Because these two parameters do not change the predictability of benefit exhaustion, they do not remediate the model's failure to match the spending drop at benefit exhaustion, as shown in Panel C. An alternative parameterization in the spirit of Krusell and Smith (1998) treats the path of spending as the mean from three types of agents: $\hat{c}_t(w_1, w_2) = w_1 \; c_t^{\text{buffer-stock}} + w_2 c_t^{\text{perm inc}} + (1 - w_1 - w_2) c_t^{\text{impatient}}$. The first two spending series reflect the baseline model and the model of a permanent income consumer. The third reflects a buffer stock agent with a monthly discount factor δ of 0.9. This model best fits the data when 30% of consumers are standard buffer-stock agents, 45% are permanent income consumers, and 25% are impatient. The addition of an impatient type does not improve the fit of the model much because even an agent who is impatient by the standards of the existing consumption literature will still prepare for exhaustion. In Section 4.4, we consider a model with heterogeneity where the third type is a hand-to-mouth agent, and we show that this assumption does generate a sharp drop at exhaustion.

The bottom two panels of Figure 7 examine behavioral models which have been fruitfully applied to explain job-finding behavior (DellaVigna and Paserman 2005, DellaVigna et al. 2016, Spinnewijn 2015).

The naive beta-delta model cannot quantitatively match the path of spending, as shown in Panel E.[37] We show that neither $\beta = 0.4$ nor $\beta = 0.7$ are consistent with the empirical path of spending. A β of 0.7 roughly matches the size of the drop at exhaustion well, but the drop in spending before exhaustion is quantitatively too large. With a β of 0.4, agents fully exhaust their assets while receiving UI such that there is a sharp drop at benefit

When conditioning on positive earnings, the decline is only 1.6%. Schmieder et al. (2016) show that re-employment wages in Germany fall by about 10% during the first six months of unemployment. They conclude that one-half to two-thirds of the cross-sectional relationship between wages and duration in their data is causal.

[37] In the beta-delta model, the consumers maximization problem corresponds to $\max_{\{c_t, s_t\}} \mathbb{E}\left[u(c_t) - \psi(s_t) + \beta \sum_{n=1}^{T-t} \delta^n (u(c_{t+n}) - \psi(s_{t+n}))\right]$ rather than equation (3).

exhaustion, without much drop in the preceding months. However, the model predicts that agents use up all of their assets while receiving UI and the predicted spending drop is now far too large. We also investigate whether a mixture of beta-delta and standard hyperbolic discounters can match the data. However, when we estimate weights on a mixture of types with $\beta = \{0.4,\ 0.7,\ 1.0\}$ we find that 100% of the weight is placed on the patient type with $\beta = 1$.

Another possibility is that spending drops suddenly at benefit exhaustion because job seekers have overly optimistic beliefs about their chance of finding a job. We conduct two exercises to evaluate this theory. First, we calibrate our model to match the over-optimism in surveys documented in Spinnewijn (2015), as shown in Panel F.[38] Relative to the baseline model, persistent over-optimism means that agents cut spending by too little early on during unemployment and then, having run down their assets, make larger cuts to their spending later on. However, there is no excess drop at benefit exhaustion. Second, it is possible to estimate the subjective job-finding probabilities implied by spending behavior in the data. The path of spending implies a belief of a 71% chance of finding a job exactly in the month of exhaustion. However, these implied beliefs are inconsistent with the over-optimism at onset documented by Spinnewijn (2015) as well as an over-identification test discussed in Section 4.4.3.[39]

4.4 Alternative Models That Match The Spending Drop At Exhaustion

We examine two models that are able to generate a sharp drop in spending at benefit exhaustion. The first model treats the mean path of spending as the weighted average of heterogeneous consumers. This model generates a drop because some consumers are "hand-to-mouth", meaning that they set consumption equal to income each month. The second model studies a representative agent who prepares inadequately for benefit exhaustion. This model generates a spending drop because the agent does not pay attention to how much income will drop at benefit exhaustion.

4.4.1 Spender-Saver

We evaluate a "spender-saver" model in the spirit of Campbell and Mankiw (1989). The top panel of Figure 8 shows the path of spending for three consumer types: buffer stock (path from Figure 6), permanent income agents (path from Panel A of Figure 7) and hand-to-mouth, who set $c_t = y_t$. We treat the path of spending in the data as the mean

[38] In his sample, jobseekers' report their median expected time to find a job is 8 weeks, while the median actual time to find a job is 23 weeks. Converting to monthly job-finding probabilities, this implies job seekers are too optimistic about their chance of finding a job each month by 21 percentage points, or a factor of 2.75. We evaluate a model where job seekers incorrectly perceive a (25%+21%=) 46% chance of finding a job each month. A model where the perceived job-finding rate is (2.75*25%=) 69% yields even more extreme results.

[39] Appendix Figure A.13 plots these beliefs. They also do not match work-in-progress by Spinnewijn, Mueller and Topa (November 14, 2016, personal correspondence) that shows little change in jobseekers' optimism while searching.

from three types of agents:

$$\hat{c}_t(w_1, w_2) = w_1\ c_t^{\text{buffer-stock}} + w_2 c_t^{\text{perm inc}} + (1 - w_1 - w_2) c_t^{\text{hand-to-mouth}}. \tag{9}$$

We fit $\tilde{\theta} = (\hat{w}_1, \hat{w}_2)$ by minimizing equation 8.

The spender-saver model closely tracks the empirical path of mean spending during unemployment. The intuition for why the model fits well is that the mean path of spending is well-approximated by three line segments – a sharp drop at onset, a gradual drop during UI receipt and a sharp drop at exhaustion. The share of hand-to-mouth agents targets the sharp drops, the share of buffer stock agents targets the gradual drop during UI receipt, and the residual agents are assumed to be permanent income. Quantitatively, the weights which deliver the best fit to the spending data are 20% buffer stock agents, 50% permanent income agents and 30% hand-to-mouth agents.[40] For comparison, Campbell and Mankiw (1989) estimated that aggregate data on annual consumption were consistent with about 50% of agents being hand-to-mouth consumers and 50% being permanent income consumers. One question for future research is what micro-founded models can explain the behavior of the hand-to-mouth agents.[41]

4.4.2 Inattention

We apply the model of inattention or "sparsity" proposed by Gabaix (2016) to unemployment. In our implementation of Gabaix's model, agents solve the following Bellman equation, where j indexes state of the world:

$$\max_{c_t, s_t} u(c_t) - \psi(s_t) + \delta E V_j(a_{t+1}; \tilde{z}_{exhaust,j}) \tag{10}$$

subject to the constraints in equations 4, 5, 6, and 7. Agents correctly perceive income $z_{emp} = 1$ during employment and income of $z_{ui} = 0.83$ during UI receipt, but underestimate the size of the income drop at benefit exhaustion, so they perceive $\tilde{z}_{exhaust} > z_{exhaust} = 0.54$. While the rational agent solves the dynamic optimization problem with the correct income values z, the inattentive agent instead uses $\tilde{z}_{exhaust}$ to solve equation 10. This inattention is present only when she is employed or receiving UI benefits. Once UI benefits are exhausted, she correctly perceives the income level at exhaustion.

[40] These weights also deliver a good fit for the aggregate path of job search. We separately compute the optimal job search effort for each type. The hand-to-mouth types (Mortensen 1977) exert the most effort and have the largest increase in search effort over the spell. Appendix Figure A.12 shows job-finding rates generated by the model by averaging across all three types.

[41] The types we call "hand-to-mouth" are observationally equivalent to extremely impatient rational agents. When we estimate the discount factor for this group, the model delivers a *monthly* discount factor of 50%, meaning that these agents are indifferent between \$1 today and \$4,000 in twelve months. Another possibility is that a behavioral microfoundation like reference dependence could generate a very high sensitivity of spending to income (DellaVigna et al. 2016).

In Gabaix's model, perceived income $\tilde{z}$ emerges from a structural primitive $\bar{\kappa}$. The primitive $\bar{\kappa}$ reflects a cost of thinking and the interpretation of $\bar{\kappa}$ is the largest possible income shock for which the agent would not cut spending in advance at all. A single value for $\bar{\kappa}$ gives rise to different levels of attention $\{m_j\}$ in the months leading up to benefit exhaustion. In each state of the world j prior to benefit exhaustion, the agent solves equation 10 using a different value for perceived income at benefit exhaustion:

$$\tilde{z}_{exhaust,j} = 0.54m_j(\bar{\kappa}) + 0.83(1 - m_j(\bar{\kappa})). \tag{11}$$

The model nests a consumer who is fully rational with $m_j = 1$ and a consumer who is myopic about the risk of exhaustion with $m_j = 0$. The agent chooses an "optimal" level of attention by comparing the benefits of a Taylor approximation of the gains from attention around a default (inattentive) consumption plan to the cost of thinking. Following equation 75 in Gabaix (2016), we solve for $m_j(\bar{\kappa})$ as:

$$m_j(\bar{\kappa}) = \mathcal{A}\left(\frac{dc_j}{dm_j}c_j\right)^2 \frac{1}{\bar{\kappa}^2} \tag{12}$$

Online Appendix A.1 describes how we choose $\bar{\kappa}$ to fit the data.

Figure 9 shows the path of spending predicted by the inattention model where $\bar{\kappa}$ is chosen to match the spending drop at benefit exhaustion in the data. The model does a good job of matching the data at onset, the first four months of unemployment, and the drop at benefit exhaustion. However, the model predicts a modest cut in spending in the two months prior to benefit exhaustion which is not present in the data.[42] Because the spender-saver model has two parameters, while the inattention model has only one parameter, it is not surprising from an econometric perspective that it is easier for the spender-saver model to exactly match the path of mean spending.

Although the inattention model does come close to matching the data, the institutional circumstances around UI benefit exhaustion pose a challenge to the rational inattention story underlying the model. The rational inattention literature historically sought to explain why agents ignored small fluctuations in macroeconomic variables (Sims 2003, Reis 2006). In contrast, Gabaix's model seeks to also explain behavior around large predictable income losses such as benefit exhaustion and retirement. However, the income loss at benefit exhaustion is easily knowable -- it is equal to the size of the benefit check and UI agencies offer regular updates on the amount of benefits remaining. Furthermore, job seekers have ample time to think about their household financial decisions.

In order to justify the failure of preparing fully for benefit exhaustion as a rational response within the model, we estimate that the cognitive cost $\bar{\kappa}$ must equal 0.045. A cost

[42]The model also predicts a small spike in the job-finding rate after benefit exhaustion (Appendix Figure A.12). The JPMCI data are not definitive on this issue because bank account data are not well-suited for precisely measuring spikes in the job-finding rate.

of this size means that an inattentive agent would completely ignore an income shock of 4.5% or smaller until it arrived. To the best of our knowledge, this is the first estimate of $\bar{\kappa}$ based on household behavior.[43] It is outside the scope of this paper to examine whether such a cognitive cost is empirically justified, or if instead a more appropriate interpretation is that the inattention behavior in the Gabaix (2016) model is not fully rational.

4.4.3 Over-identification Test That Further Supports These Models

Using an over-identification test we provide further evidence against the benchmark buffer stock model and in support of both behavioral alternatives. The test is inconclusive in separating between the spender-saver model and the inattention model, though the inattention model does modestly better.

The empirical setting for the test exploits the one-month lag between job loss and receipt of UI benefits described in Section 3.2. We study the predicted spending out of UI benefits at the onset of unemployment in the context of the models from the previous section. We alter the economic environment in the baseline model by adding one month after job loss before benefits begin when income is 0.83. After that, income is 0.86 in states with high benefits and 0.80 in states with low benefits. Agents know if they live in a state with high or low benefits. Both the saver-spender and inattention models predict that spending responds after UI payments begin, which matches this feature of the data (Appendix Figure A.14). On this dimension, the inattention model appears to outperform the saver-spender model.

This test provides further evidence against alternative models. In the buffer-stock model, an agent who knows about the UI benefit level will update her spending before UI benefits start, which is not what we see in the data. Similarly, a model where agents have overly-optimistic beliefs about the job-finding rate at benefit exhaustion is unable to explain why spending responds to UI benefits only after UI payments begin.

In the Online Appendix, we discuss two strategies that could distinguish between these models which examine spending behavior by assets at onset and the distribution of the spending drop at benefit exhaustion. Neither of these tests is conclusive given the limitations of our data, but they are promising avenues for future work.

5 Normative Implications for Optimal UI

Our empirical results have the normative implication that the welfare gains through improved consumption-smoothing from extending the potential duration of UI benefits are substantially larger than the gains from increasing the level of UI benefits. Our estimates vary from three times more valuable to six times more valuable depending on the specification. After incorporating job search distortions, we continue to find that duration extensions have a more positive impact on welfare than UI level increases. Although most prior work

[43] Goldfarb and Xiao (2017) estimate a dollar cost of inattention for restaurant owners.

on optimal UI benefits focused on the level of UI benefits as the key policy parameter, a newer strand of the literature has examined the optimal path of benefits. Although there is substantial research estimating the fiscal cost of extensions, we are not aware of any paper that has quantified the welfare gains from small extensions.

Two complementary analyses of budget-neutral tax-financed policies both find that duration extensions are more valuable than level increases. The first analysis uses the consumption implementation of the canonical Baily-Chetty formula; it has the advantage of being highly transparent and the disadvantage of requiring rational behavior which we reject in Section 4. Our implementation draws on the formulas in Schmieder and von Wachter (2016) for valuing changes in potential duration versus changes in benefit levels and draws on Kolsrud et al. (2015) in considering the monthly evolution of consumption. The second analysis measures welfare using the structural models from Section 4, including the two behavioral models that are able to generate a drop in spending at UI benefit exhaustion.

We first calculate the welfare gains to increasing the level of UI benefits in terms of the Baily-Chetty formula. We consider a benefit level increase db which is financed by a tax increase $d\tau$ on employed agents. As in Section 4, $j \in \{1 \ldots 7\}$ reflects states where the agent is unemployed and receiving UI benefits. π_j is the fraction of time that agents are in each state. We approximate the welfare gains as

$$\frac{dW}{db} \approx \sum_{j \in \{1 \ldots 7\}} u'(c_{ui,j})\pi_j db - u'(c_{emp})\pi_{emp} d\tau. \tag{13}$$

Table 6 reports this welfare change normalized by a Lucas-type money metric: $\frac{d\tilde{W}}{db} = \frac{dW}{db}/u'(c_{emp})$. When there is a single unemployed state and no benefit exhaustion, $\frac{db}{d\tau} = \frac{\pi_{unemp}}{\pi_{emp}}$ and $\frac{d\tilde{W}}{db}$ collapses to the canonical Baily-Chetty formula $\frac{u'(c_{unemp}) - u'(c_{emp})}{u'(c_{emp})}$.

We next calculate the welfare gains to extending the duration of UI benefits in the same framework. Extending the potential duration of benefits by dP raises income by the benefit level b, is financed by taxes $d\tau$, and has welfare impact

$$\frac{dW}{dP} \approx u'(c_{exhaust})\pi_{exhaust} b dP - u'(c_{emp})\pi_{emp} d\tau. \tag{14}$$

Comparing a level increase and a duration extension of equal fiscal cost, extensions are 4.3 times as valuable in terms of welfare using the modified Baily-Chetty formulas. Absent behavioral response, a tax increase $d\tau$ of 0.136% on the employed state is sufficient to finance a one-month benefit extension dP or a 1.1 percentage point increase in household income db during UI receipt. We assume a CRRA utility function with a risk aversion parameter of 2. Implementing equations 13 and 14, Table 6 shows that private welfare is .017% higher under a benefit level increase and .075% higher under a benefit duration extension.

The intuition for why duration extensions have a larger impact than level increases is that spending is much lower after exhaustion. During UI receipt, spending is on average

7% lower than during employment. By UI benefit exhaustion, spending is 21% lower.

The finding that duration extensions are more valuable than level increases depends on our new empirical estimates that spending is much lower after benefit exhaustion, rather than our estimates of the spending level during UI or a specific value for risk aversion. Recall from Section 3.2 that our estimates of the spending drop during UI receipt are similar to Gruber (1997). As a result, it is unsurprising that implementing equation 13 with his estimates yields a similar gain from level increases (Table 6 row 2). Our results are also not driven by our choice of the risk aversion parameter: the ratio of the gains from a duration extension to the gains from a level increase varies from 4.1 to 5.2 as the risk aversion parameter rises from 1 to 4 (Table A.9).

A full evaluation of the welfare gains from each policy requires incorporating the job search distortions from extended durations and higher levels. Our data are not well-suited for analyzing job search distortions, so we use estimates from a recent literature review by Schmieder and von Wachter (2016). The median estimate from the papers they review is that for each additional dollar spent mechanically raising UI benefit levels, the government will spend an additional 35 cents on benefits because UI recipients will take longer to find a job. They define this 35-cent estimate as the "behavioral cost" of benefit level increases. For duration extensions, the median estimate is a 60-cent behavioral cost. To assess the welfare change including the job search distortions, we reevaluate equations 13 and 14, substituting $d\tau = 0.136\% \times 1.35 = 0.183\%$ for higher levels and $d\tau = 0.136\% \times 1.6 = 0.218\%$ for extended durations.

After incorporating job search distortions, there are welfare losses from increasing the level of UI benefits and approximately no change in welfare from extending UI benefits. This conclusion, which is reported in Table 6 columns 3 and 4 for $\gamma = 2$, is highly sensitive to the level of γ. At $\gamma = 1$, there are substantial welfare losses from increasing UI generosity, while at $\gamma = 4$ there are substantial gains from extending UI benefits (Appendix Table A.9).

As a complement to the Baily-Chetty analysis, we use a structural approach to consider the welfare implications inside our three models (rational, spender-saver, inattention) from the two types of changes to UI benefit generosity. This approach includes four steps. First, we simulate employment histories for 1000 agents indexed by i. Second, for this set of employment histories, we construct three income histories: the baseline z from Section 4.1, an alternative z^{level} with an increase in monthly benefit levels db of 1.1% financed by a tax increase $d\tau$ in the employed state, and an alternative $z^{duration}$ with a one-month extension of benefits dP financed by a tax increase $d\tau$ in the employed state. Third, we calculate consumption histories as $\{c(z_{it})\}$ under each of these income histories. Fourth, we evaluate the change in date-0 welfare (average discounted lifetime utility of consumption) relative to a money metric of a 1% increase in lifetime income.[44] For the level increase, this formula is

$$\Delta Welfare = \frac{1}{n_{agent}} \frac{\sum_{t=0}^{T} \sum_i \delta^t (u(c(z_{it}^{level})) - u(c(z_{it})))}{\sum_{t=0}^{T} \sum_i \delta^t (u(c(z_{it} + 0.01)) - u(c(z_{it})))}. \tag{15}$$

We use the same formula to evaluate the gains from extending durations, substituting $z^{duration}$ for z^{level}.

Implementing this structural approach, we find that the welfare gains from a duration extension are 3.2 times greater than from a level increase in the rational buffer-stock model, as shown in row 3 of Table 6. Agent optimization means that the estimates from the structural model differ from applying the Baily-Chetty implementation to the spending data in two ways. First, during UI receipt, the buffer stock agent exhibits a larger cut in spending than we see in the data, meaning that marginal utility and the gains from raising the level of UI benefits are higher. Second, the rational model captures the endogenous decrease in private saving associated with more generous UI benefits (Hubbard et al. 1995). Although the endogenous saving response does lead to reduced gains, particularly from benefit duration extensions, the conclusion that extensions are more valuable than level increases remains intact.

To use the structural approach to evaluate the welfare gains in the two behavioral models, we need to define a welfare criterion. Our welfare criterion uses alternative observed consumption behavior for the same income history, CRRA utility function, and discount factor δ as we use in equation 15 for the rational agent. This is a paternalistic assumption which requires justification. In the context of the spender-saver model, it is paternalistic with respect to the hand-to-mouth agents. For that group, it can be motivated by thinking of the decision to consume every period as a technological constraint that prevents saving and borrowing. In the context of the inattention model, where an agent spends as if she is unaware of future income risk, her behavior under the scenario where she was fully aware of future income risk seems like the appropriate normative criteria for evaluating welfare.

The conclusion that duration extensions have much larger welfare gains than level increases also holds in the two behavioral models using this structural approach. In the spender-saver model, the gains from extending benefits are 2.7 times larger, as shown in row 4. In the inattention model, the gains from extending benefits are 6.2 times larger, as shown in row 5. The gains are particularly large in the inattention model because the inattentive agent does too little precautionary saving and UI benefits substitute for precautionary saving.

As with the Baily-Chetty approach, incorporating job search distortions in the structural approach does not change the conclusion that benefit duration extensions have a more

[44] Our estimated welfare gains in this section do not include utility from reduced job search effort. We omit these gains because the results are sensitive to the parameterization of the search cost function and there is little consensus in the literature over the appropriate values for these parameters. Instead, our normative calculations use a model with an exogenous job-finding rate which matches the JPMCI data.

positive impact on welfare than benefit level increases. To incorporate job search distortions we re-evaluate equation 15 using $d\tau = 0.136\% \times 1.35 = 0.183\%$ for the increase in UI benefit levels and $d\tau = 0.136\% \times 1.6 = 0.218\%$ for the extension of UI durations. The structural buffer stock model yields similar conclusions to the Baily-Chetty implementation in terms of the welfare change after including job search distortions. Again, there is a welfare loss from increasing UI benefit levels and approximately no change from extending UI benefits. Since the distortions estimated by Schmieder and von Wachter (2016) are fiscal parameters not dependent on a specific model of behavior, they are equally appropriate for adjusting $d\tau$ for the behavioral models as they are in the context of the rational buffer stock model. We find that after incorporating these distortions, the inattention model shows welfare gains from extending UI benefits, while the spender-saver model shows a small decrease in welfare. In both cases these welfare changes from extending benefit durations are more positive than those from increasing benefit levels.

6 Conclusion

This paper documents the path of spending during unemployment using high-frequency bank account data. Spending is highly responsive to the level of UI benefits and drops sharply at benefit exhaustion. This drop is inconsistent with the rational buffer stock model and sharpens the puzzle of the excess sensitivity of consumption to income. Two behavioral models are consistent with the drop at benefit exhaustion. Low spending after exhaustion implies that across all models we consider, the gains from extending UI durations are three to six times larger than the gains from increasing the level of UI benefits.

One empirical finding which would be interesting to explore further is that households do not seem to borrow much during unemployment. For example, households on average only borrow \$20 per month on Chase credit cards during unemployment. Because unemployment is a mostly temporary shock to income, the rational buffer stock model predicts a large increase in credit card utilization for households with few liquid assets (Herkenhoff 2015). The absence of credit card borrowing we observe among unemployed households is particularly striking against the backdrop of widespread credit card borrowing by U.S. consumers overall (Laibson et al. 2015).

Another interesting area for future research is that the behavior of households who exhibit excess sensitivity is poorly understood. For example, in the spender-saver model, better asset data could be used to understand whether there are some households that actually set consumption equal to income every month. In the inattention model, it would be interesting to understand whether households deliberately ignore upcoming income changes and what psychological foundations might explain this behavior.

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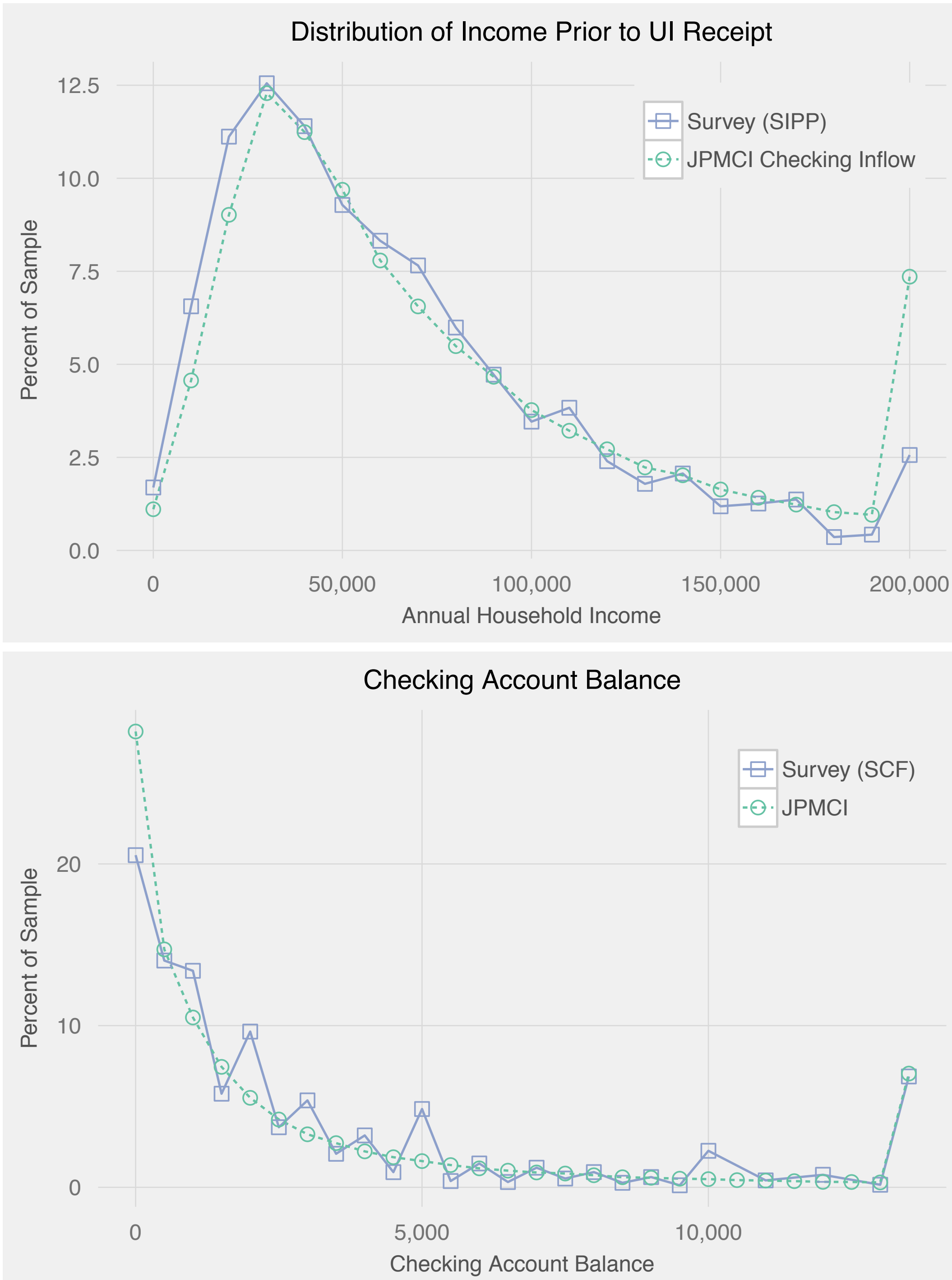
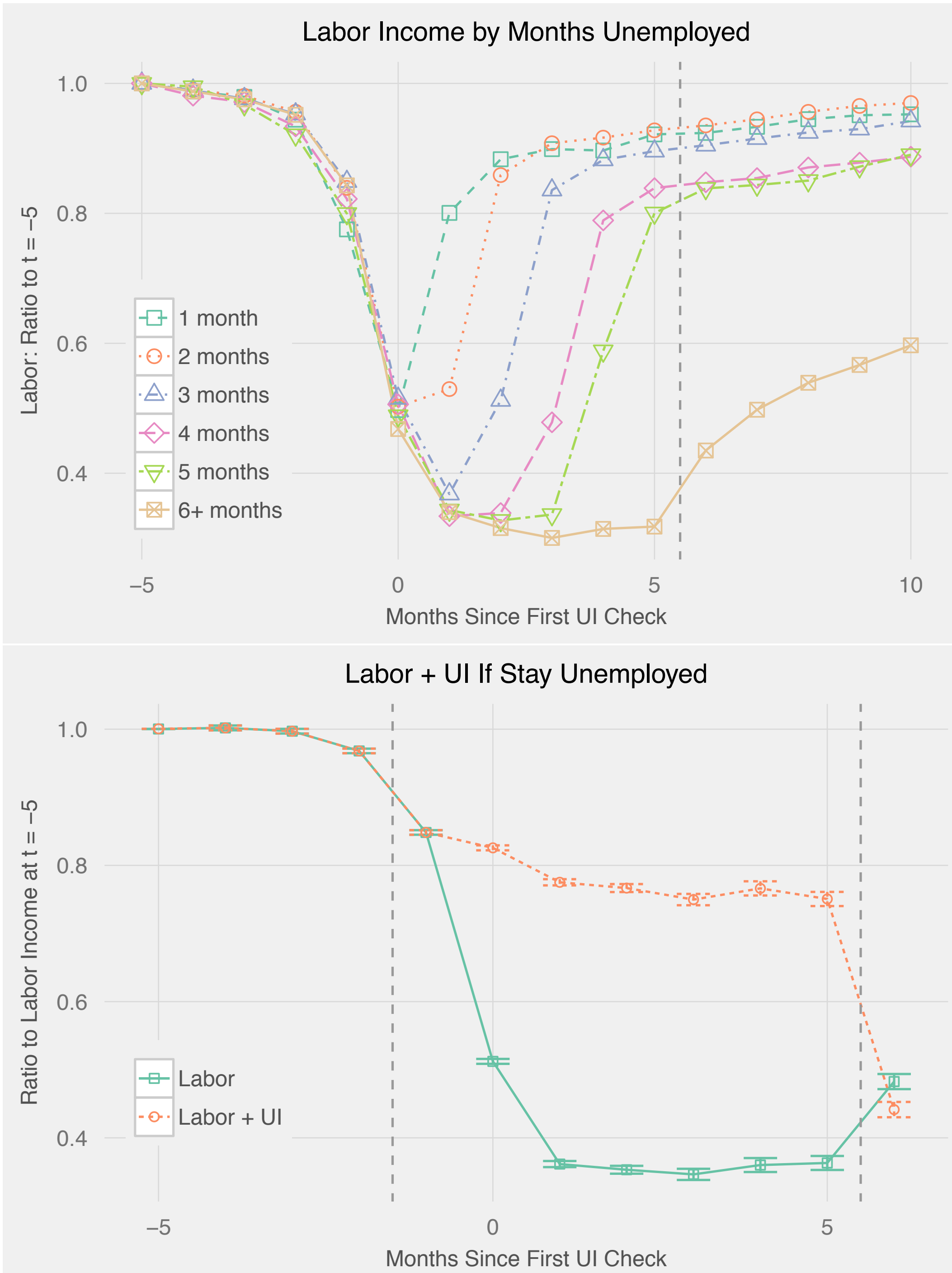
Figure 1: Representativeness



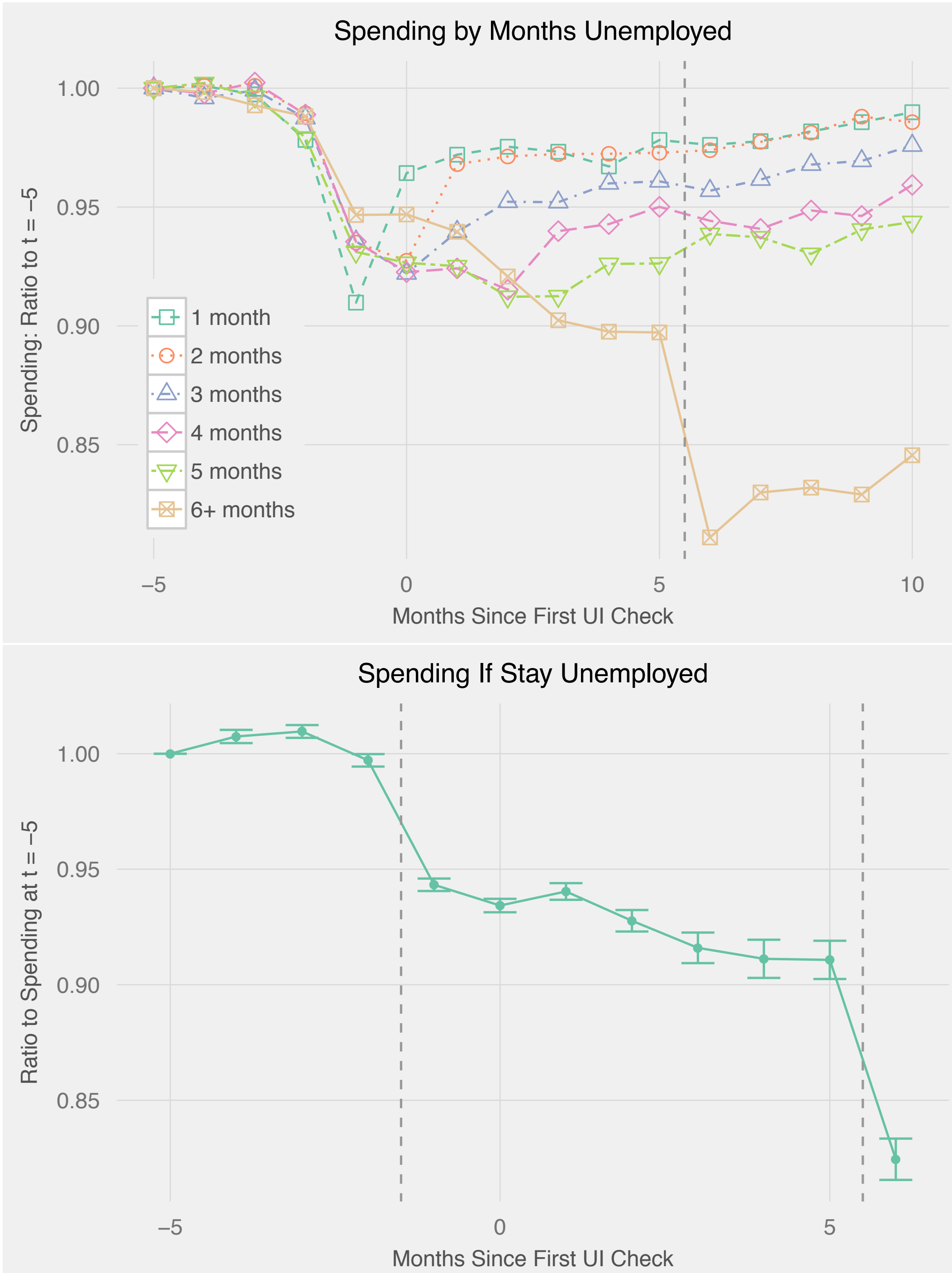
Notes: The top panel plots the distribution of pre-tax household income in the year prior to UI receipt in the 2004 Survey of Income and Program Participation and in the JPMCI data. The bottom panel plots the distribution of checking account balances in the 2013 Survey of Consumer Finances, and in the JPMCI data three months prior to UI receipt. See Section 2.3 for details.

Figure 2: Event Study: Income at UI Onset



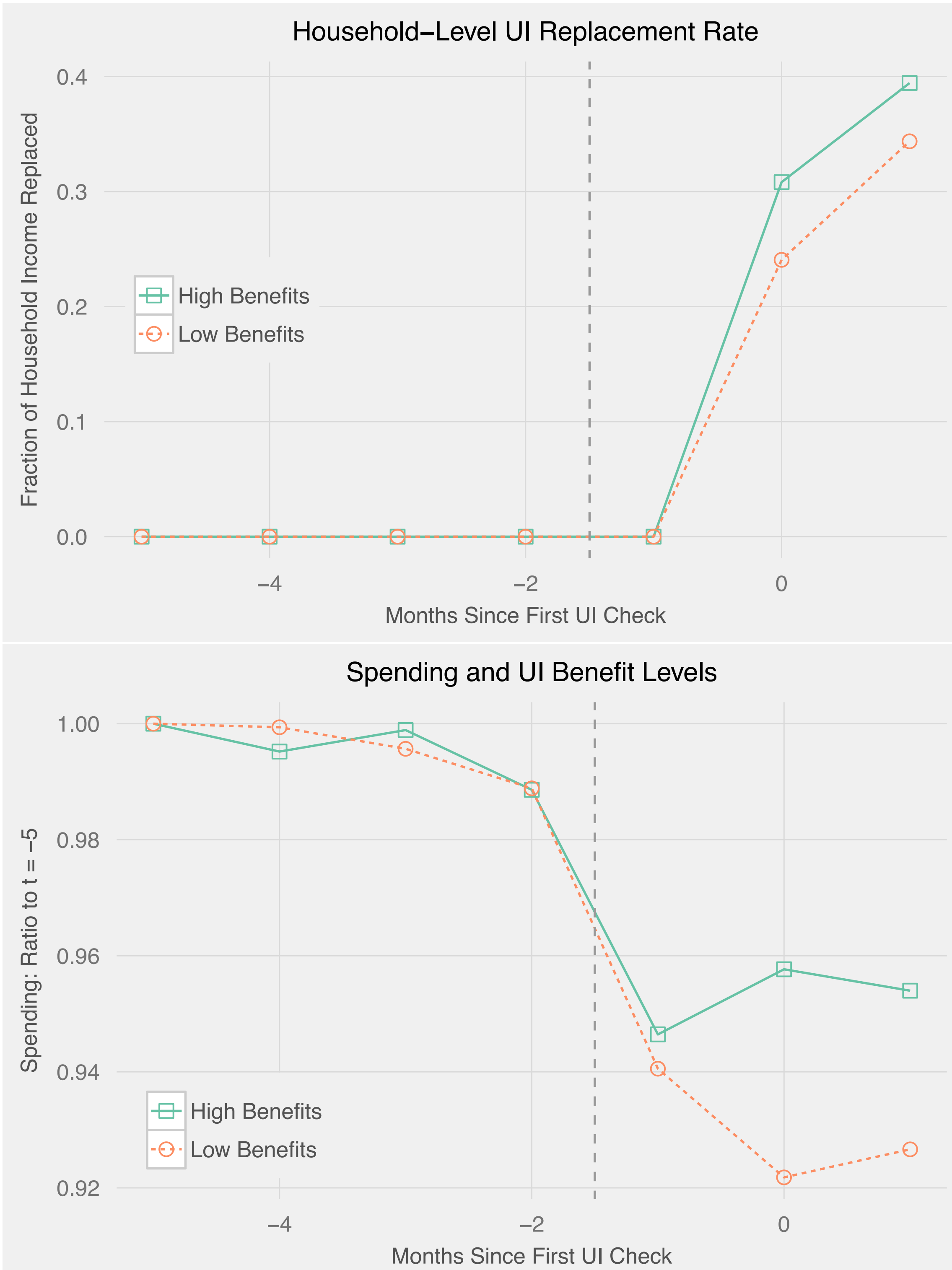
Notes: The top panel plots labor income as a function of completed UI duration. Mean labor income is positive during UI receipt because sometimes other household members continue to receive labor income. The vertical line marks UI benefit exhaustion. The bottom panel plots average labor and UI income for the subsample that stays unemployed. In months $t = \{-5, -4, -3, -2, -1, 0\}$, this includes everyone who receives UI at date 0. In month $t = 1$, this includes only households who continue to receive UI and excludes households who received their last UI check in month 0. In month $t = 2$, this excludes households who received their last UI check in month 0 or month 1, and so on. The vertical lines mark the onset of unemployment and UI benefit exhaustion. Horizontal bars denote 95% confidence intervals for change from the prior month from equation 2.

Figure 3: Event Study: Nondurable Spending at UI Onset



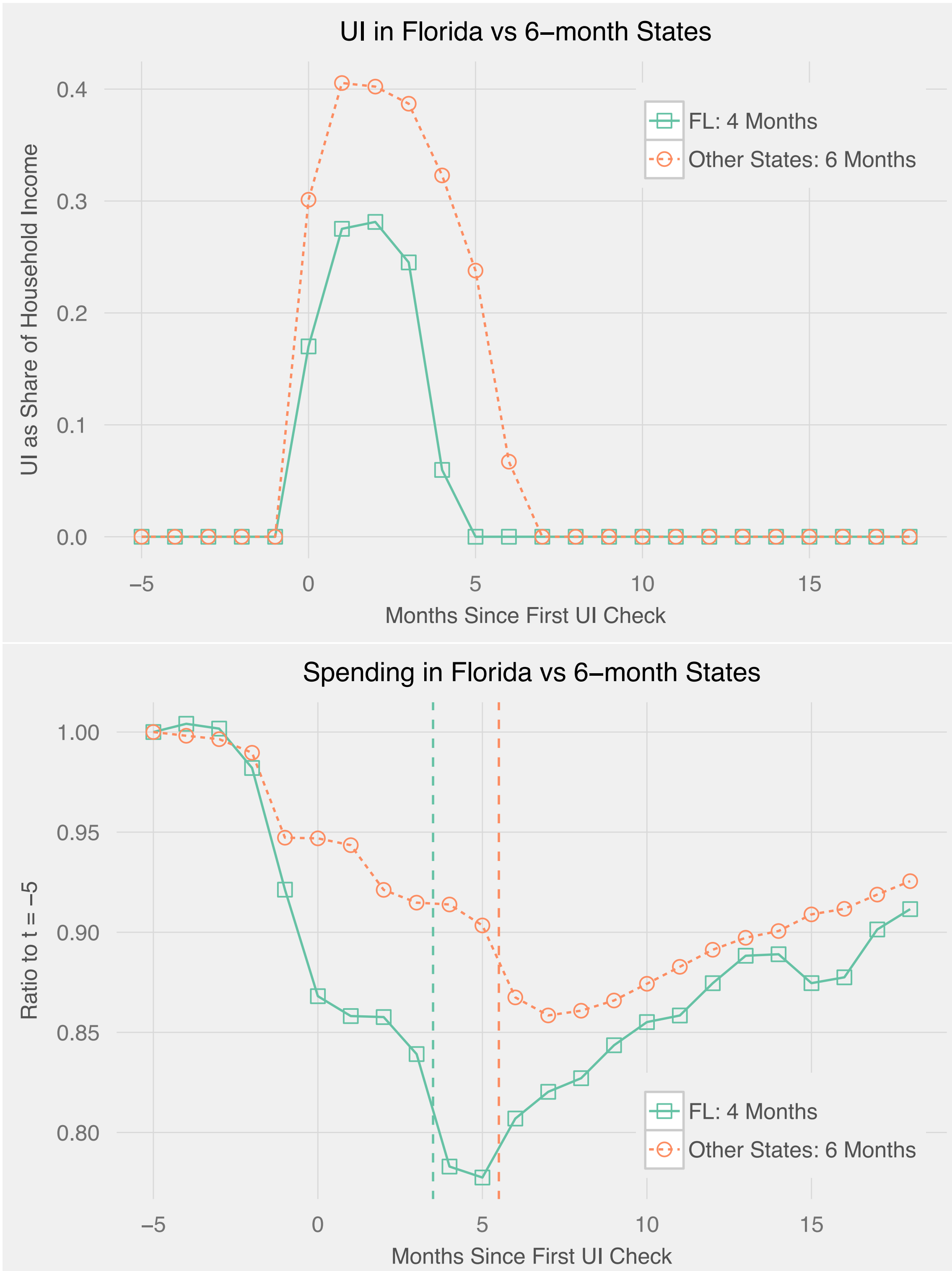
Notes: The top panel plots spending as a function of completed UI duration. The vertical line marks UI benefit exhaustion. The bottom panel plots spending for the subsample that stays unemployed. In months $t = \{-5, -4, -3, -2, -1, 0\}$, this includes everyone who receives UI at date 0. In month $t = 1$, this includes only households who continue to receive UI and excludes households who received their last UI check in month 0. In month $t = 2$, this excludes households who received their last UI check in month 0 or month 1, and so on. The vertical lines mark the onset of unemployment and UI benefit exhaustion. Horizontal bars denote 95% confidence intervals for change from the prior month from equation 2.

Figure 4: Spending and UI Benefit Levels



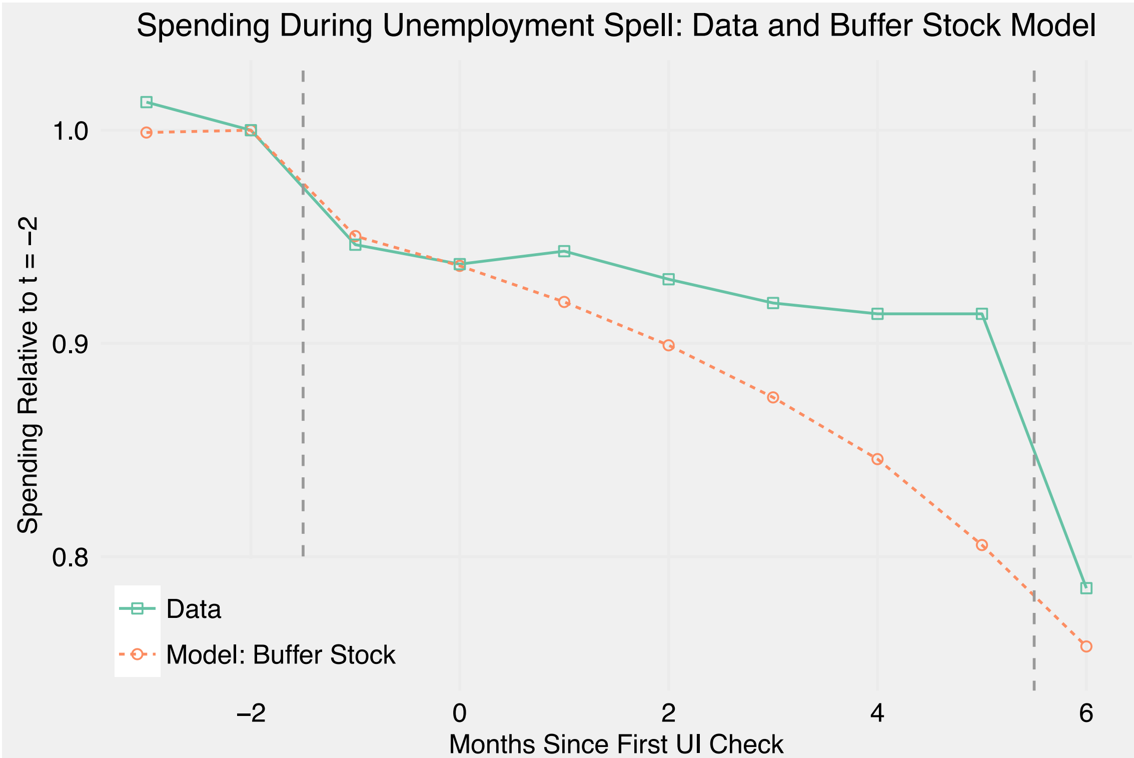
Notes: This figure shows event studies around the onset of unemployment for states with high and low UI benefits as a fraction of household income. High benefit states are CO, ID, KY, NJ, NV, OR, TX, UT, WA and WV. Low benefit states are AZ, IL, LA, NY, OH, OK, and WI. The top panel shows mean UI as a share of household income. The bottom panel shows mean nondurable spending. The vertical line marks the onset of unemployment. Spending falls before UI benefits begin because it typically takes one month to file a UI claim and start receiving benefits.

Figure 5: Spending and Potential UI Benefit Duration



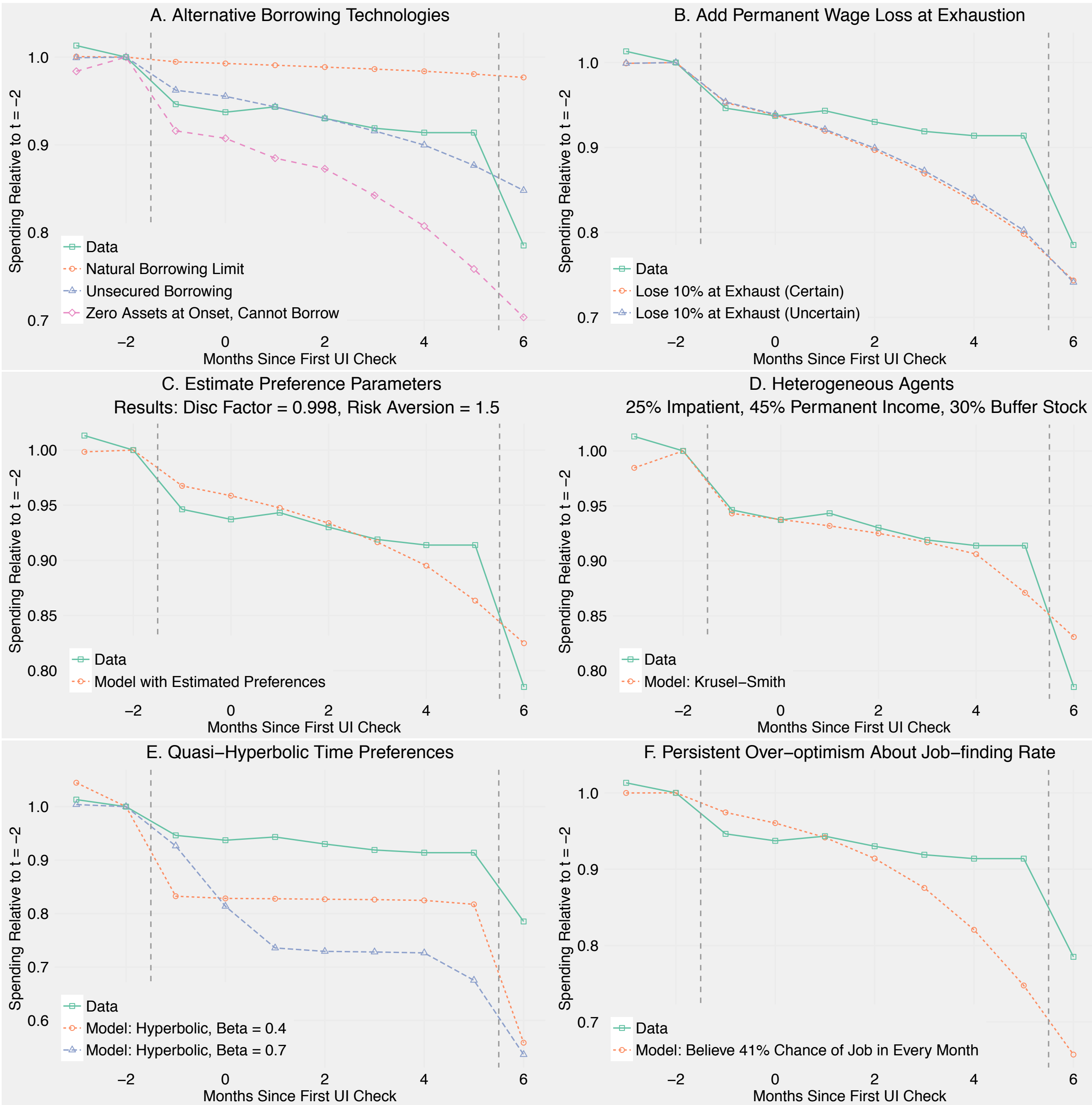
Notes: Although most states offer up to 6 months of benefits, Florida offered a low weekly benefit for up to 4 months from January 2014 through June 2015. This figure analyzes job seekers who received benefits for exactly 4 months in Florida and at least 4 months in 6-month states. The top panel shows mean UI benefits. The bottom panel shows mean nondurable spending. The vertical lines mark exhaustion in Florida and possible exhaustion in the 6-month states.

Figure 6:



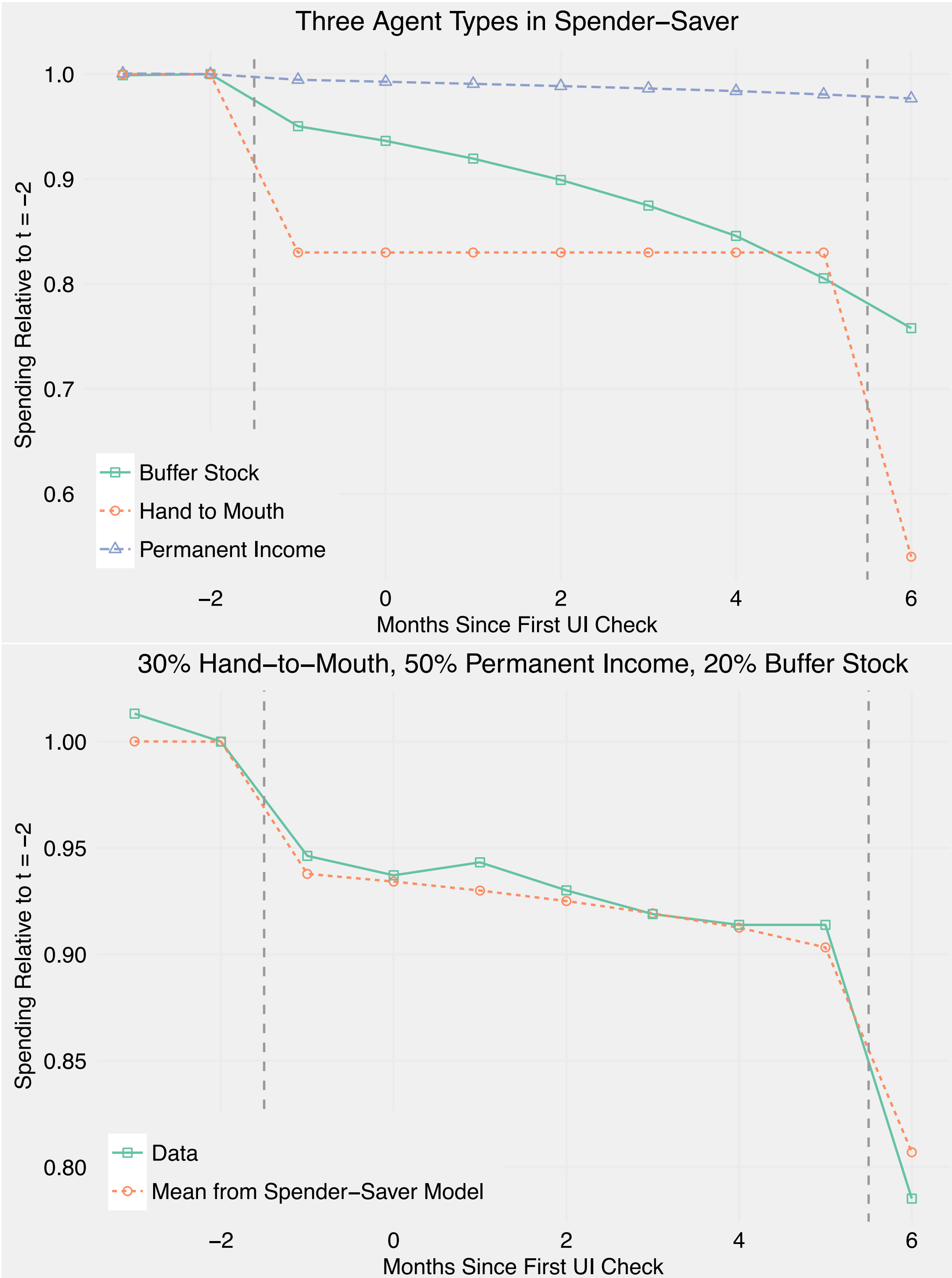
Note: This figure plots spending during an unemployment spell in the JPMCI data (green squares) and the predictions of a rational buffer stock model (red circles). The JPMCI data series mirrors Figure 3, except spending in month 6 is adjusted as discussed in Section 3.3. The model series is described in Section 4.

Figure 7: Alternative Models Which Do Not Fit Spending Path



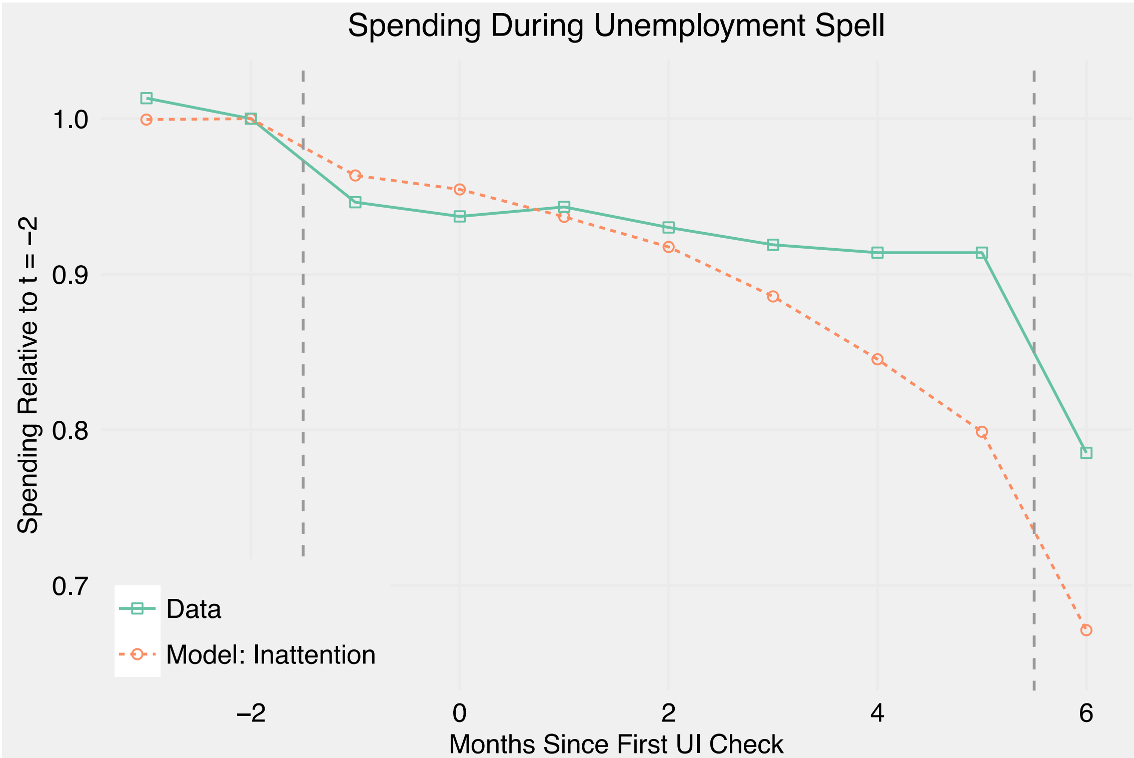
Note: This figure shows predicted spending from several alternative model parameterizations. None match both the level of spending at benefit exhaustion and also the sharp drop in spending at benefit exhaustion. Panel A shows the effect of having zero assets and of adding alternative borrowing technologies. Panel B assumes that permanent income is 10% lower for any job found after benefit exhaustion. Panel C estimates the discount factor and risk aversion parameters. Panel D assumes three types of agents – permanent income consumer, buffer stock, and impatient (10% monthly discount rate) – and estimates the weights on these types. Panel E plots a behavioral model with quasi-hyperbolic time preferences for two values of beta. Panel F plots a behavioral model where job seekers have over-optimistic beliefs of the job-finding rate parameterized to Spinnewijn (2015). See Section 4.3 for details.

Figure 8: Spender-Saver Model



Note: The top panel shows predicted spending for a buffer stock consumer, a hand-to-mouth consumer and a permanent income consumer. The bottom panel shows the data and predicted spending from a model that assumes a population with these three types of agents and estimates the weights on each type which best fit the data. See Section 4.4.1 for details.

Figure 9: Inattention Model



Note: The figure shows the data alongside predicted spending from an inattention model by Gabaix (2016). In this model, agents have a cost of thinking about the future which leads them to act as if the income loss at benefit exhaustion is smaller than the true income loss. See Section 4.4.2 for details.

Table 1: Representativeness

Category	Statistic (1)	JPMCI (2)	Benchmark (3)	Ratio (2) / (3) (4)	Benchmark Source (5)
Spending ($)					
Total Nondurables	Mean	1,797	1,912	94%	CEX
Total Nondurables	Mean	1,797	4,130	44%	BEA
Groceries	Mean	475	331	144%	CEX
Food Away From Home	Mean	290	219	132%	CEX
Fuel	Mean	262	218	120%	CEX
Utilities	Mean	371	312	119%	CEX
Mortgage	Mean	1,536	1,368	112%	SCF
Auto Loan	Mean	484	465	104%	SCF
Credit Card	Mean	1,010	1,613	63%	SCF
Income (Pre-tax Direct Deposit + Paper Checks, $)					
Labor Earnings	Mean	5,014	5,750	87%	SIPP
Total Income	Mean	6,334	6,290	101%	SIPP
Age	Mean	41.1	44.3	93%	SIPP
Checking Account Balance ($)	Median	1,260	1,500	84%	SCF
Number of U.S. States	N	20	50	--	--

Notes: This table compares the representativenessness of the JPMCI sample prior to unemployment to external benchmarks from the Consumer Expenditure Survey for 2013 (CEX), Bureau of Economic Analysis' Table 2.3.5 for 2013 (BEA), Survey of Income and Program Participation for 2013 (SIPP), and the Survey of Consumer Finances for 2013 (SCF). All income and spending varibles are monthly. For spending, the first two rows analyze the subset of nondurables measured in both JPMCI data and external datasets. To ensure comparability to external benchmarks, spending estimates for specific categories are adjusted for the fact that some purchases are made with cash or a non-Chase credit card (see notes to Appendix Table A.2 for details). Labor income is adjusted for the fact that some earnings are paid by paper check rather than direct deposit (see notes to Appendix Table A.3 for details).

Table 2: Income and Spending at Onset, During UI Receipt, and Benefit Exhaustion

	Pre-Onset Mean ($)	Two-Month Change at Onset[a]	Monthly Change During UI Receipt[b]	Two-Month Change at Exhaustion[c]
	(1)	(2)	(3)	(4)
Income [Direct Deposit Labor + UI[d]] (%[e])	3,265	-0.144	-0.022	-0.341
		(0.002)	(0.001)	(0.003)
Income [Direct Deposit Labor + UI[d]] ($)	3,265	-470	-73	-1,113
		(6)	(2)	(11)
Nondurable Spending (%[e])	2,831	-0.060	-0.007	-0.093
		(0.001)	(0.0004)	(0.003)
Nondurable Spending ($)	2,831	-169	-20	-262
		(4)	(1)	(8)
n		182,269	537,978	35,578

Notes: Standard errors are shown in parentheses underneath regression coefficients and are clustered by household.

a. Each observation is a household. Onset is defined as difference from three months before the first UI payment to one month before the first UI payment.

b. Each observation is a household-month.

c. Each observation is a household. Exhaustion is defined as difference from one month before the last UI payment to one month after the last UI payment for benefit exhaustees. The sample is exhaustees eligible for 26 weeks of benefits.

d. This definition of income is lower than the mean for labor earnings in Table 1 because it excludes labor income paid by paper checks and it is post-tax rather than pre-tax.

e. The dependent variable is the outcome variable as a percent of the pre-unemployment-onset mean.

Table 3: Income and Spending By UI Benefit Generosity

	Pre-onset Mean ($)[a] (1)	Low Benefit State Mean (% of col 1) (2)	High Benefit State Mean (% of col 1) (3)	Difference (col 3 - col 2) (4)	Permutation test p-value (5)	Marginal Propensity to Consume (6)
Income (% of Pre-Onset Total Income)						
UI Income	--	0.339	0.390	0.051	--	--
				(0.001)		
Spending (% of Pre-Onset Value)						
Nondurable Spending	2,757	0.927	0.954	0.027	0.12	0.384
				(0.004)		
Food Spending	453	0.956	0.977	0.021	0.25	0.050
				(0.005)		
Work-related Spending[b]	630	0.899	0.929	0.030	0.16	0.097
				(0.005)		
Total Checking Outflows	5,498	0.921	0.940	0.019	0.15	0.533
				(0.004)		
Placebo (% of Pre-Onset Spending)						
Nondurable Spending						
Post Job Loss, Pre-UI Receipt	2,757	0.941	0.945	0.004	--	0.083
				(0.004)		

Notes: n = 116,421 households. This table compares the evolution of income and spending as a function of UI benefit generosity. We divide states into two groups by based on the generosity of their UI benefits as a share of household income. We restrict the sample to households that received UI benefits for at least two months to ensure that they have at least one calendar month in which they received UI benefits in every week. Column 1 shows pre-onset means. Columns 2 and 3 show income and spending during the first full month of UI receipt in the first five rows. The last row in column 2 shows spending before UI receipt has begun as a placebo test. Column 4 contains a coefficient from a regression with a dummy for high benefit state and the asymptotic standard error in parentheses below the coefficient. Asymptotic methods can be misleading with only 17 clusters (states). Column 5 shows p-values from a permutation test (see Fisher 1935, Ganong and Jaeger 2016 and cites therein) for the hypothesis that the spending drop is equal in low- and high-benefit states which are constructed by computing the spending drop after randomly assigning states to the low- or high-benefit group. Column 6 shows the implied MPC out of permanent differences in UI benefits across states.

a. Pre-onset means are for the subset of households that received UI benefits for at least two months. Pre-onset means for the entire JPMCI sample are shown in Table A.1.

b. Work-related spending is defined in Section 3.2 and includes transportation and food away from home.

Table 4: Spending Decomposition for Households Who Exhaust UI Benefits

	Pre Onset $ (1)	Pre Exhaustion $ (2)	Post Exhaustion $ (3)	Change (col 3 - col 2) $ (4)	Change (col 3 / col 2) % (5)
Nondurables: Above-Average Drop					
Home Improvement	48.9	47.3	38.0	-9.3	-19.6%
Discount Stores	59.2	59.9	50.1	-9.8	-16.3%
Department Stores	19.7	17.1	14.7	-2.4	-14.1%
Other Retail	152.0	142.5	122.6	-19.9	-14.0%
Groceries	313.3	305.5	263.1	-42.4	-13.9%
Cash	667.3	554.9	480.3	-74.6	-13.4%
Drug Stores	39.5	35.9	31.2	-4.8	-13.2%
Medical Copay	36.4	30.6	26.7	-3.9	-12.8%
Entertainment	30.7	28.8	25.2	-3.6	-12.4%
Food Away From Home	201.4	174.8	153.2	-21.5	-12.3%
Online	43.3	39.8	35.8	-4.0	-10.1%
Professional & Personal Services	57.5	52.8	47.9	-4.9	-9.3%
Nondurables: Below-Average Drop					
Transportation	188.4	160.5	146.7	-13.8	-8.6%
Telecom	113.6	109.7	101.7	-8.0	-7.3%
Flights & Hotels	60.8	47.6	44.8	-2.8	-5.9%
Utilities	195.8	188.1	179.8	-8.3	-4.4%
Other Consumption	358.2	329.7	319.5	-10.2	-3.1%
Insurance	156.0	165.3	160.3	-5.0	-3.0%
Other Spending: (Ranked by Size of Drop)					
Uncategorized[a]	421.8	329.7	274.8	-54.9	-16.6%
Durables (Chase Card)	50.1	44.9	39.2	-5.7	-12.8%
Transfer to External Account	365.9	280.9	257.1	-23.9	-8.5%
Installment Debt	394.0	362.5	349.9	-12.6	-3.5%
Paper Checks	1,071.3	986.1	955.7	-30.5	-3.1%
Non-Chase Credit Card Bill	445.9	374.6	366.2	-8.4	-2.2%

Notes: n=32,662 households who exhausted UI benefits. This table decomposes the drop in spending during unemployment into twenty-five categories. Column 1 is three months prior to the first UI payment, column 2 is the month before UI exhaustion and column 3 is the month after UI exhaustion.

a. This category is constructed as the residual of checking account outflows and includes electronic transfers which cannot be assigned to a category.

Table 5: Model Parameters

Parameter	Value	Source
	Income and Assets	
	1.00 Employed	JPMCI
Income z_t	0.83 Unemp < 6 Months	JPMCI
	0.54 Unemp >= 6 Months	JPMCI
Initial Assets a_0	0.66	JPMCI with SCF
	Job Search	
Separation Rate	0.0325	BLS
Cost of Job Search k	5	JPMCI Target
Convexity of Job Search Cost ξ	2.5	JPMCI Target
	Other Preferences & Environment	
Monthly Discount Factor β	0.996	
Risk Aversion γ	2	
Borrowing Limit L	0	JPMCI Target
Monthly Interest Rate R	1.0025	Cagetti 2003

Notes: See Section 4.1 for details.

Table 6: Welfare Impact of Changes in UI Generosity

Welfare Change as an Equivalent Increase in Lifetime Income

	Gains (JPMCI Data)		Gains (JPMCI Data) + Distortion (Literature)		
	UI Benefits $\uparrow$ 1.1%	UI Duration $\uparrow$ 1 Month	UI Benefits $\uparrow$ 1.1%	UI Duration $\uparrow$ 1 Month	Ratio (col 2 / col 1)
	(1)	(2)	(3)	(4)	(5)
Baily-Chetty Approximation					
JPMCI Nondurables	0.017%	0.075%	-0.025%	0.003%	4.31
Gruber (1997) Food	0.018%		-0.024%		
Structural Model Simulation					
Buffer Stock Model	0.020%	0.063%	-0.022%	-0.008%	3.20
Spender-saver Model	0.022%	0.060%	-0.020%	-0.010%	2.73
Inattention Model	0.017%	0.108%	-0.024%	0.037%	6.24

Notes: We evaluate the welfare impact of budget-neutral tax-financed changes in the generosity of UI benefits as a percent of lifetime income for CRRA utility with risk aversion of 2. The first two rows show results using the Baily-Chetty approximation. The last three rows show results from three structural models. See Section 5 for details.

Column 1 considers a policy raises monthly benefits by 1.1% and raises taxes during employment by 0.136%; this tax revenue is sufficient to finance this increase in benefits if there is no job search distortion from increased UI benefits.

Column 2 considers a policy which extends potential UI benefit durations by one month and raises taxes during employment by 0.136%; this tax revenue is sufficient to finance this increase in benefits if there is no job search distortion from increased UI benefits.

Column 3 considers a policy which raises monthly benefits by 1.1% and raises taxes during employment by 0.183%; this tax revenue is sufficient to finance this increase in benefits when increased UI levels reduce job search at the median of the estimates reviewed in Schmieder and von Wachter (2016).

Column 4 considers a policy which extends potential UI benefit durations by one month and raises taxes during employment by 0.218%; this tax revenue is sufficient to finance this increase in benefits when extended UI durations reduce job search at the median of the estimates reviewed in Schmieder and von Wachter (2016).

A Online Appendix for Ganong and Noel "Consumer Spending During Unemployment: Positive and Normative Implications"

A.1 Estimating the Inattention Model (Gabaix 2016)

This appendix describes the estimation method used for the analysis in Section 4.4.2 and Figure 9. Let t index time since the start of unemployment. Define $\tilde{c}_t(\tilde{z})$ as the optimal path of consumption during unemployment for an agent who believes income at exhaustion is $\tilde{z}$. A value for attention $m \in [0,1]$ implies a perceived income level at exhaustion:

$$\tilde{z}(m) = z_{ui} - m \times (z_{ui} - z_{exhaust}). \tag{16}$$

Once benefit exhaustion has occurred, the agent correctly perceives her income. Let $\mathcal{A}$ be the attention function, $\frac{d\tilde{c}_t}{dm_t}$ is the response of consumption to more attention and $\bar{\kappa}$ be the structural parameter for cognitive cost. Section 10.2.2 of Gabaix (2016) implies that the equation for optimal attention m given cognitive cost $\bar{\kappa}$ is:

$$m_t^* = \mathcal{A}\left(\left(\frac{d\tilde{c}_t}{dm_t}\right)^2 \tilde{c}_t^2 \frac{1}{\bar{\kappa}^2}\right) \tag{17}$$

Gabaix recommends the sparse attention operator: $\mathcal{A}(x) = \max(1 - \frac{1}{x}, 0)$. Note that m_t appears on the left- and right-hand side of equation 17 so an iterative algorithm is needed to find m_t.

The algorithm for estimating $\bar{\kappa}$ is as follows:

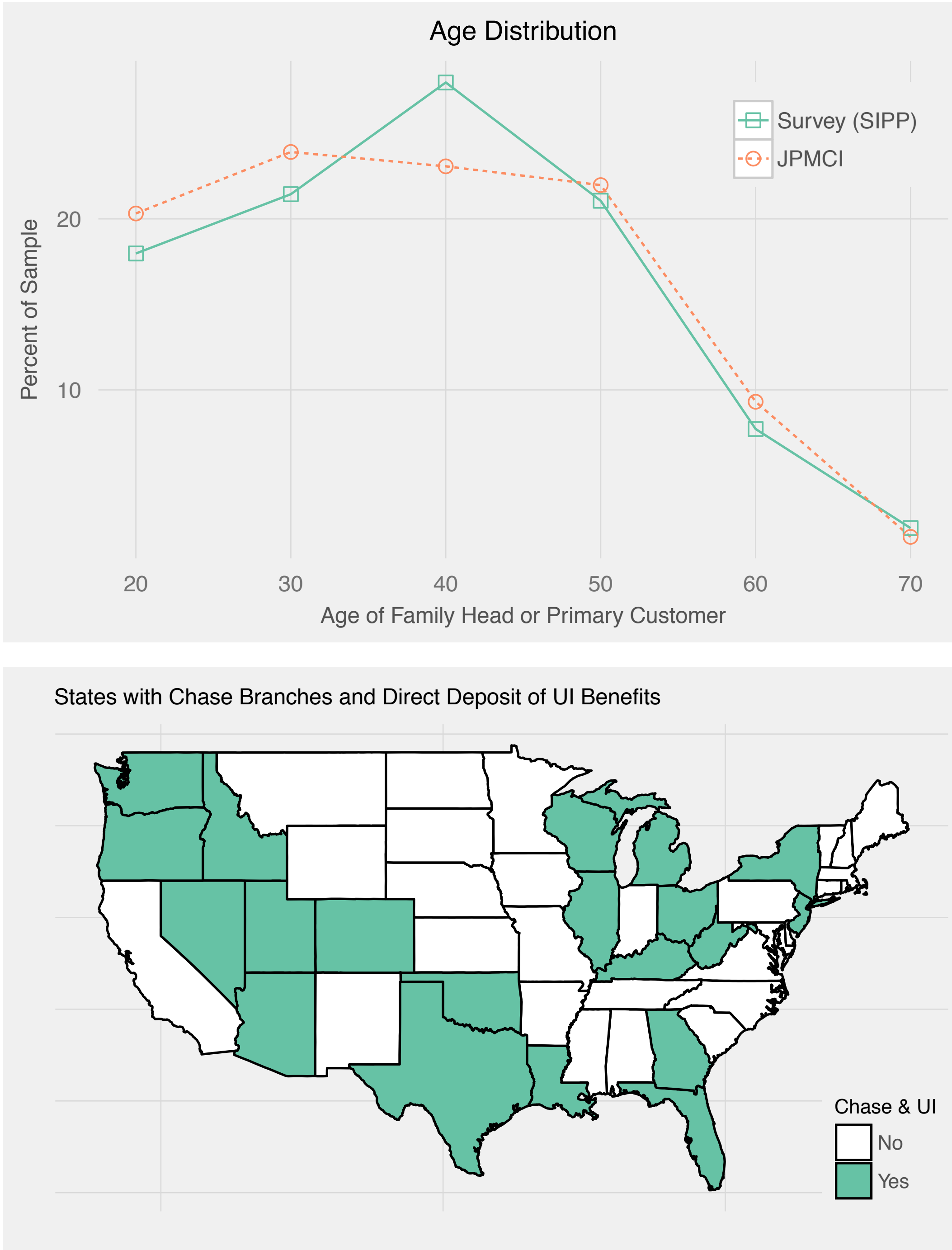
1. Compute $\tilde{c}_t(\tilde{z})$ as the consumption level in the case where UI benefits last forever, so perceived income $\tilde{z}$ at benefit exhaustion is equal to income during UI receipt z_{ui}.
2. Compute $\frac{d\tilde{c}_t(z_{ui})}{dm_t}$ as the change in consumption from additional attention.
3. For a grid of values $\bar{\kappa}$:
   (a) For a seed value of $\tilde{z}$, compute $\tilde{c}_t(\tilde{z})$.
   (b) Compute optimal attention $m_t^*(\frac{d\tilde{c}}{dm}\tilde{c}, \bar{\kappa})$ using equation 17.
   (c) Calculate perceived income at exhaustion $\tilde{z}_t(m_t^*)$ using equation 16. Perceived income $\tilde{z}_t$ falls as t gets larger.
   (d) At each date t, the agent forms a consumption plan c_t^* using the perceived $\tilde{z}_t$.
   (e) If quadratic distance $\sum_t |\tilde{c}_t^*(\tilde{z}_t(m_t^*)) - \tilde{c}_t| < 0.003$ proceed to the next value in the grid $\bar{\kappa}$.
   (f) If not, return to step (a) with an alternate value of $\tilde{z}$.
4. Evaluate distance from generated $\{c_t^*(\bar{\kappa})\}$ to the data. In Section 4.4.2, we target the drop in spending at UI benefit exhaustion so $d(c_{data}, \tilde{c}) = |\frac{c_{data,7}}{c_{data,6}} - \frac{\tilde{c}_7}{\tilde{c}_6}|$ The $\bar{\kappa}$ which best fits the data is the one with the shortest distance to the data.

A.2 Testing Between Spender-Saver and Inattention

Ideally, it would be possible to use data on liquid assets to test between these the spender-saver model and the inattention model. The spender-saver model predicts that the 30% of households who set spending equal to income will have zero liquid assets. If we could find which households had zero liquid assets, we could assess whether these households cut spending by the amount of lost income. Unfortunately, it is difficult to use checking account balances to assess whether a household has zero liquid assets. A very low checking account balance may simply mean that a household keeps its liquid asset reserve elsewhere. Conversely, a few thousand dollars in a checking account may simply be what is needed to cover outflows within a month for a household that has a consumption policy of setting income equal to spending each month. Although checking balances are insufficient to identify which households are hand-to-mouth, there is some qualitative evidence that heterogeneity in asset holdings affects spending. In particular, we rank households based on their estimated liquid assets before the onset of unemployment. Spending drops are larger for low-asset households (Appendix Figure A.3). This is qualitatively consistent with the spender-saver model, but could also arise from a richer inattention model with heterogeneity in cognitive costs.

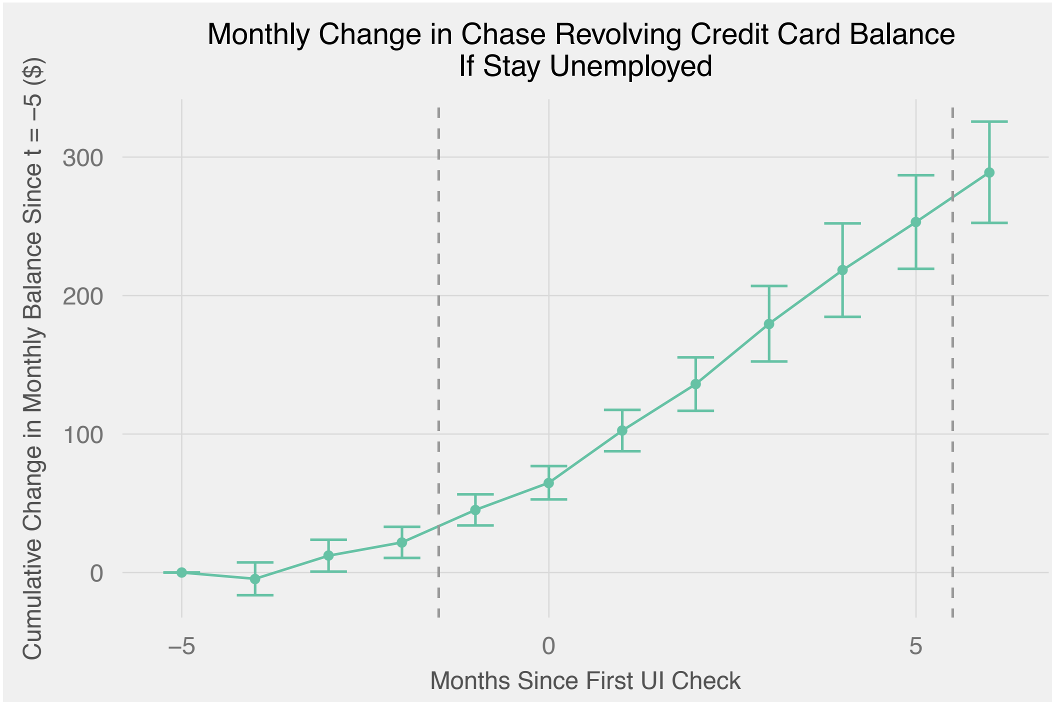
An additional test we consider is to examine the distribution of the spending drop at benefit exhaustion. The spender-saver model predicts that the 30% of households who set spending equal to income will cut their spending by the amount of lost UI benefits when payments run out. The distribution of the spending drop at exhaustion should have a point mass at the size of the income drop equal in size to the share of hand-to-mouth agents. Unfortunately, this test is uninformative because even when there is a sharp point mass in the income change distribution due to lost UI benefits, the distribution of the change in checking account inflows – which includes paper checks, transfers between accounts and other uncategorized transactions – is much more diffuse (Appendix Figure A.15). The spending drop at benefit exhaustion is also diffuse, but this does not reject hand-to-mouth behavior because of idiosyncratic noise from checking account inflows.

Figure A.1: Age and Geographic Distribution



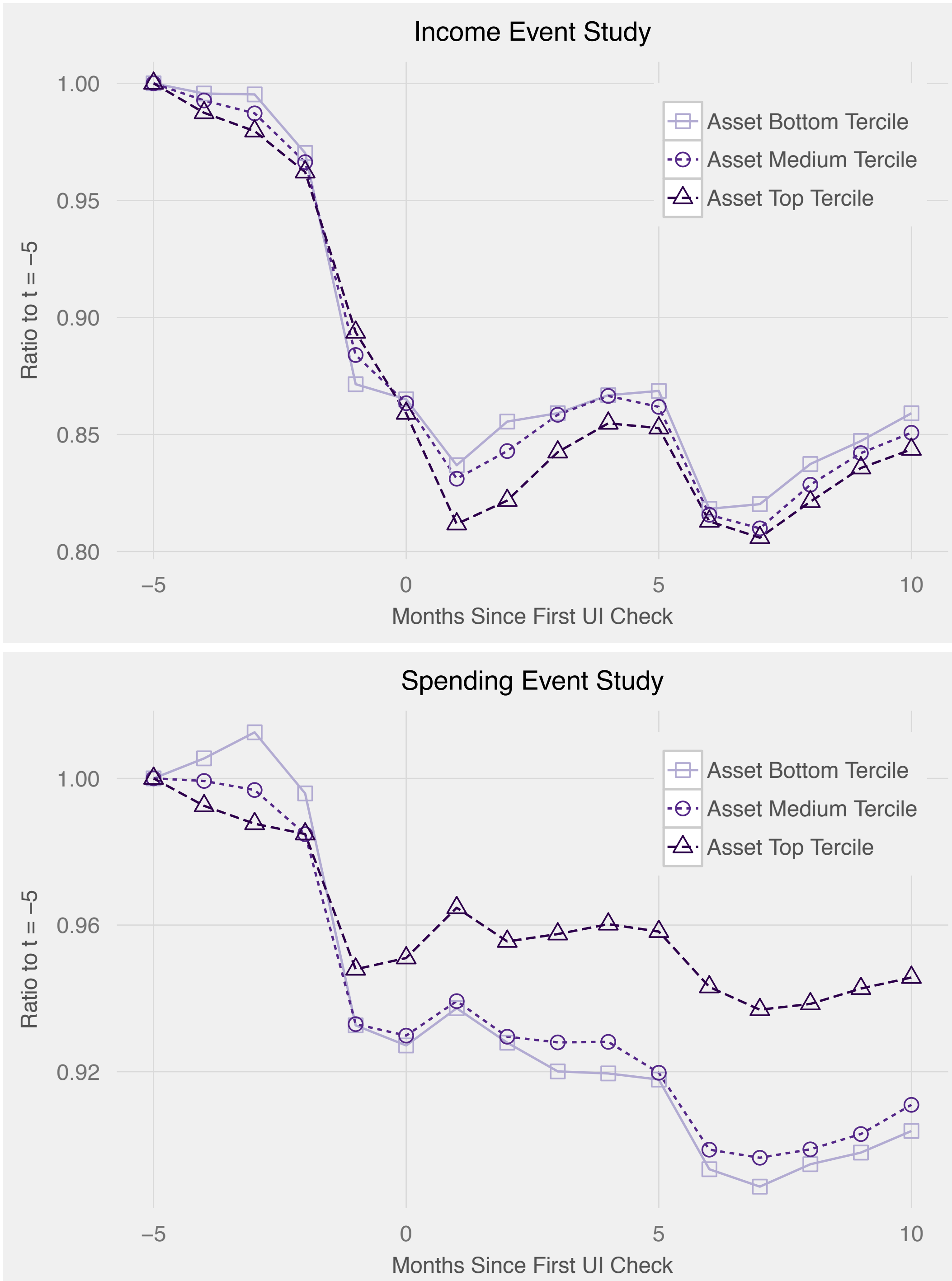
Notes: The top panel plots the age of household head for UI recipients in the Survey of Income and Program Participation and in the JPMCI data. The bottom panel shows the states in which the bank has physical branches and UI beneficiaries receive direct deposit of their benefits.

Figure A.2: Credit Card Borrowing



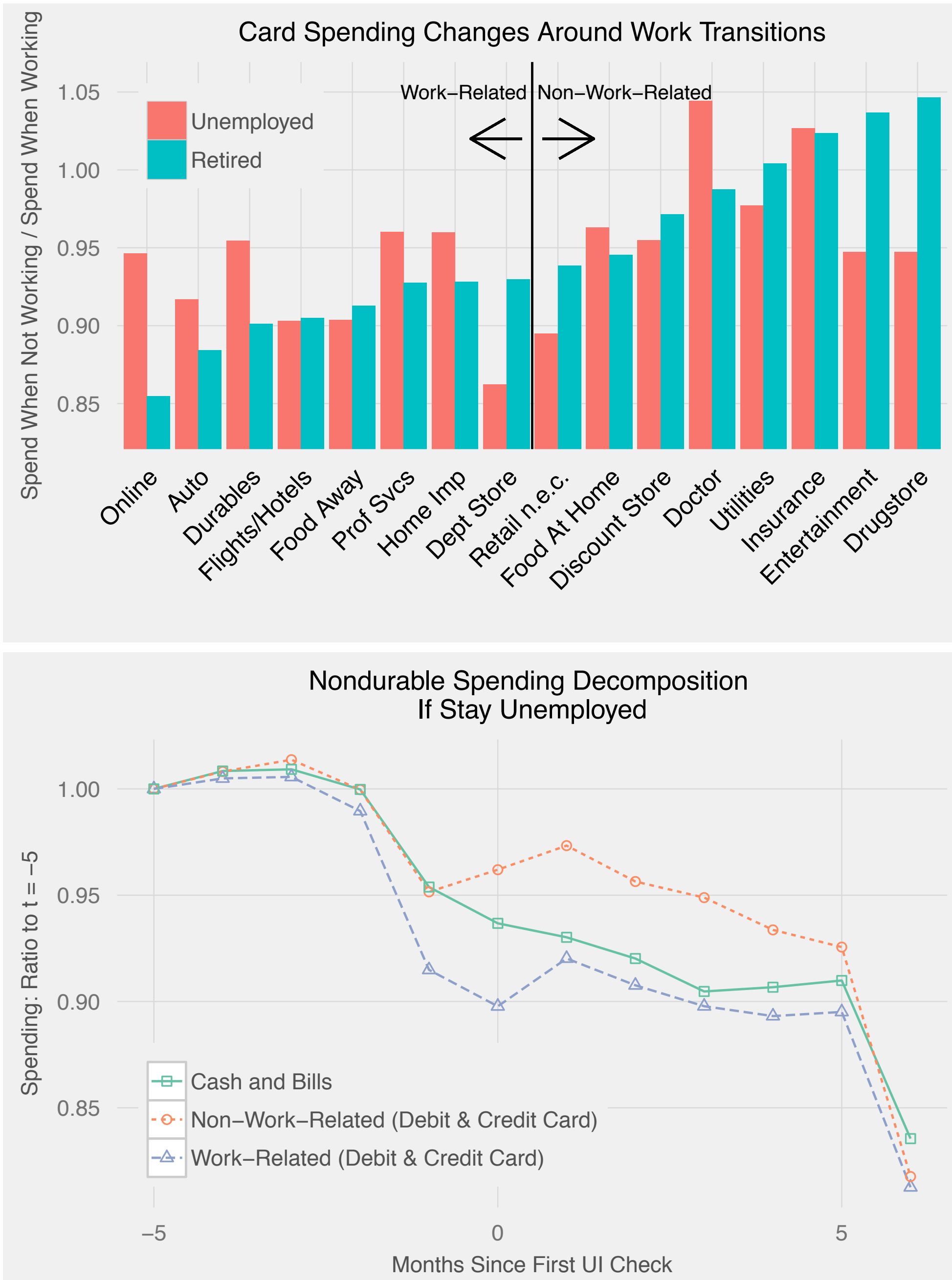
Notes: This figure plots the cumulative change in mean revolving Chase credit card balance relative to five months before UI receipt. 48% of Chase credit card holders have a revolving balance at the onset of unemployment and the conditional mean balance is \$5,160. In months $t = \{-5, -4, -3, -2, -1, 0\}$, this includes everyone who receives UI at date 0. In month $t = 1$, this includes only households who continue to receive UI and excludes households who received their last UI check in month 0. In month $t = 2$, this excludes households who received their last UI check in month 0 or month 1, and so on. The vertical lines mark the onset of unemployment and UI benefit exhaustion. Bars denote 95% confidence intervals for the change from the prior month from equation 2.

Figure A.3: Interpreting Onset: Event Study By Estimated Assets



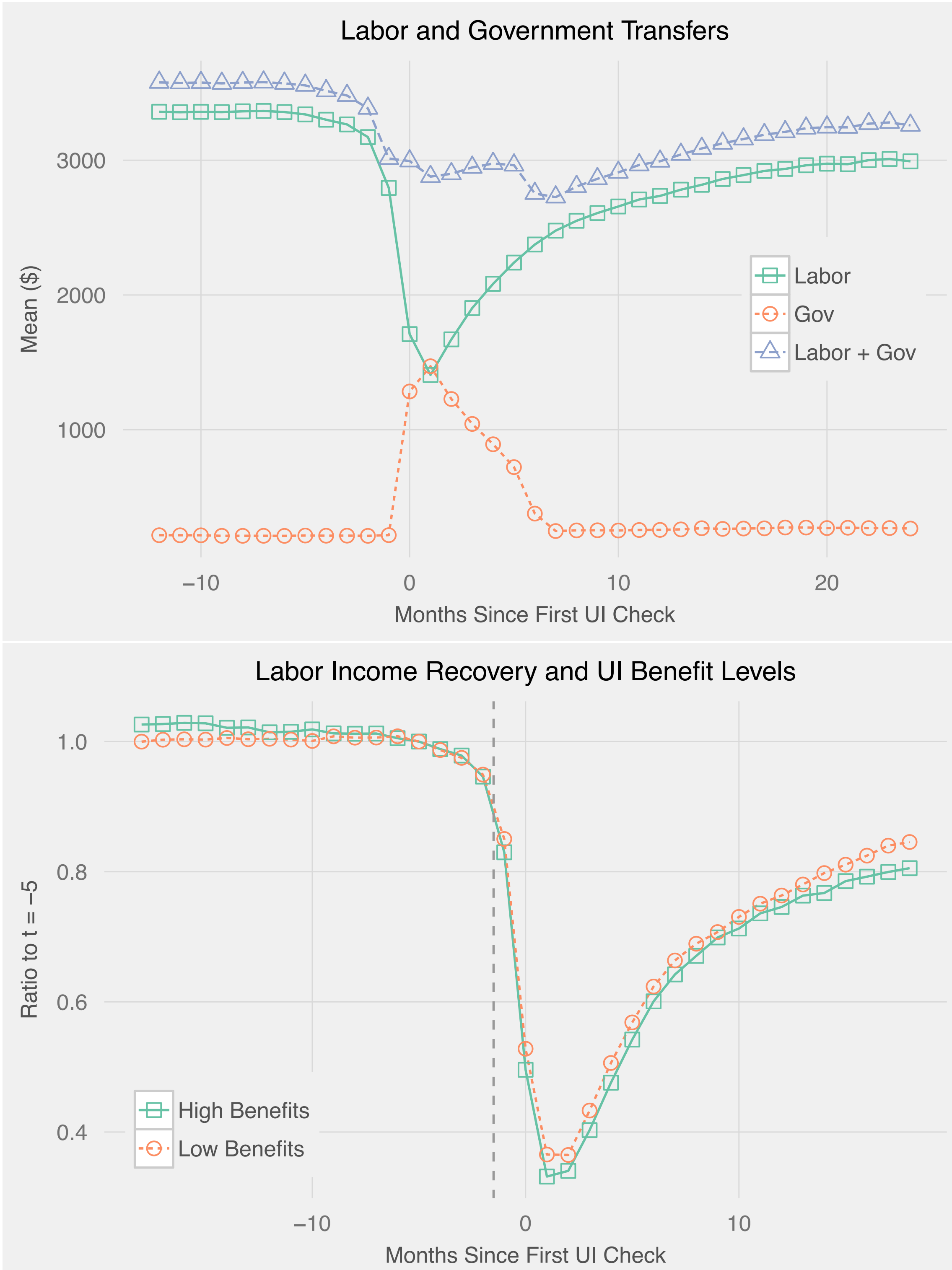
Note: This figure shows heterogeneity in the spending responses to unemployment by estimated liquid assets prior to the onset of unemployment. The top panel plots the path of income, which is the sum of labor income and UI benefits. The bottom panel plots the path of nondurable spending.

Figure A.4: Interpreting Onset: Work-Related Expenses



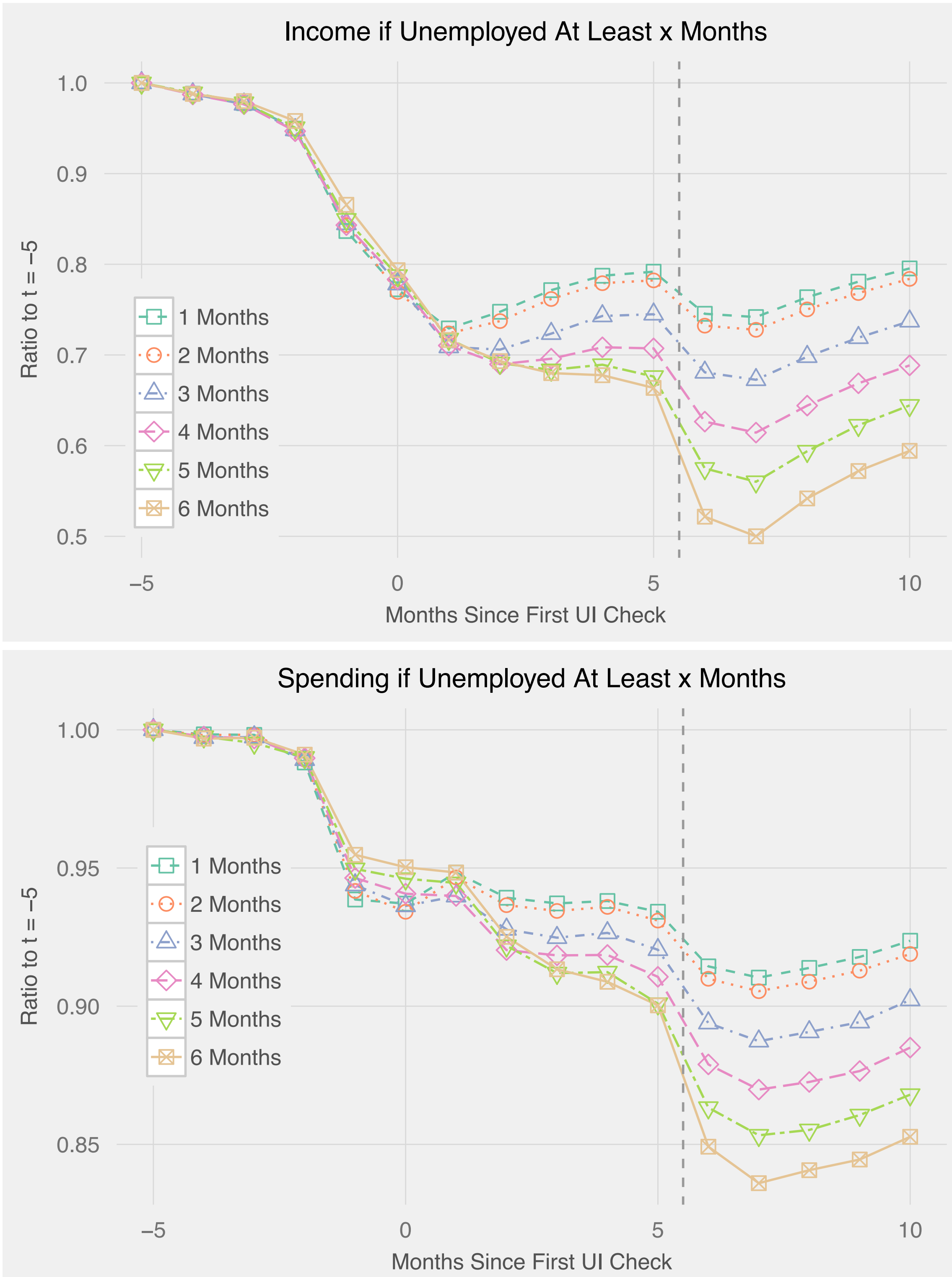
Note: The top panel compares the change in spending at retirement to the change in spending at the onset of unemployment for debit and credit card expenditures in 16 different merchant categories. We define retirement as a household aged 62 to 70 that begins receiving Social Security and limit the sample to households with $100,000 in estimated liquid assets so that the change in spending is attributable to increased home production and not financial considerations. We classify expenditure groups with drops greater than the median at retirement (to the left of the vertical line) as "work related." The bottom panel defines work-related expenses as those categories with an above-median drop at retirement and decomposes nondurable spending while unemployed into work-related expenditures on debit and credit card (26% of pre-onset nondurable spending), non-work-related expenditures on debit and credit card (30%) and cash withdrawals and bills (44%). In Section 3.2.1, we estimate that 75% of the drop in spending on work-related expenses at the onset of unemployment is attributable to the drop in income.

Figure A.5: Interpreting Onset: Labor Income Recovery in High and Low Benefit States



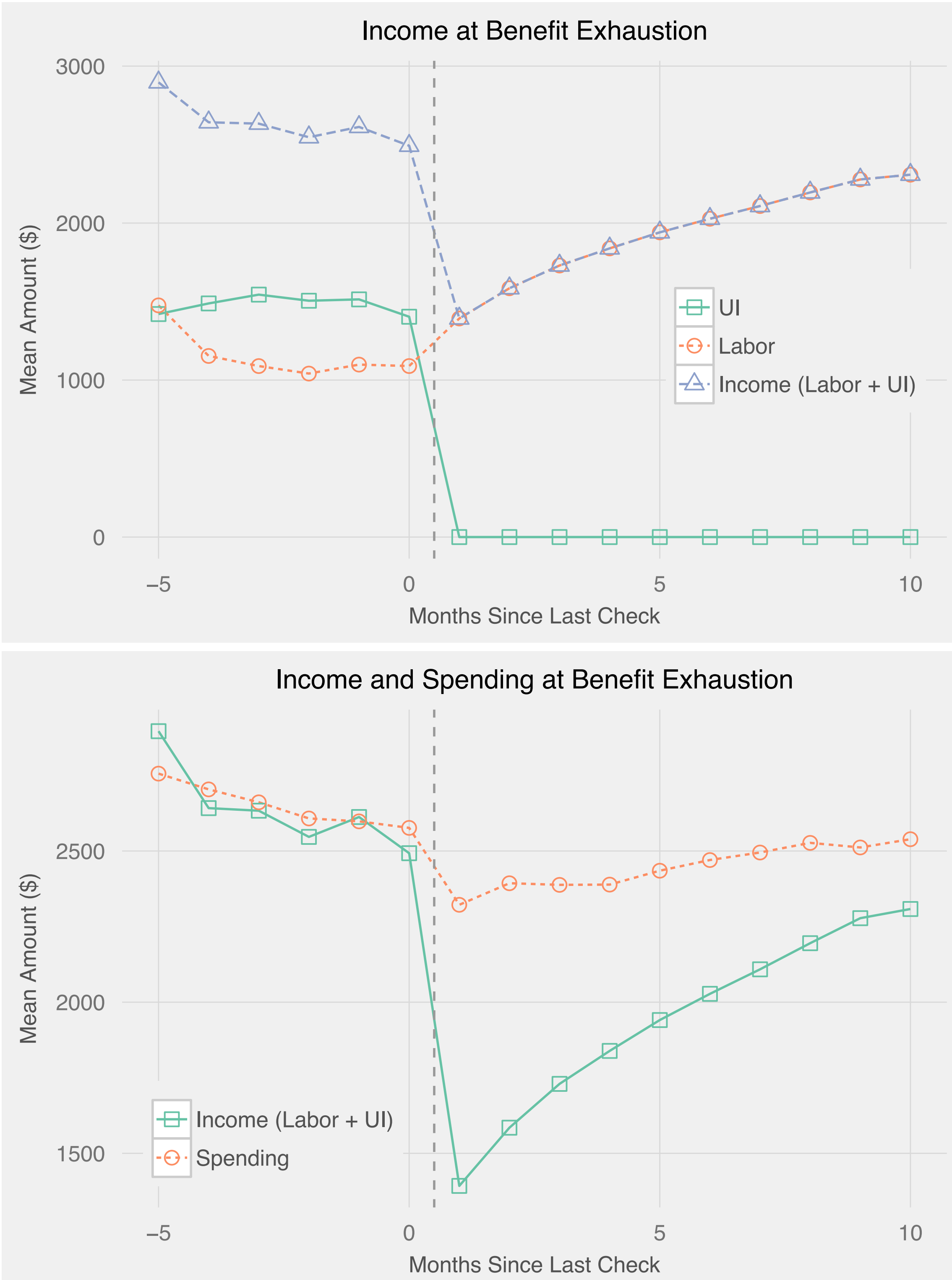
Note: The top panel plots the change in labor income and government transfers (UI, SSA, DI and tax refunds) for all UI recipients, relative to the first month in which they received a UI check. Two years after receipt of the first UI check, average income has recovered to 95% of its pre-onset mean. The bottom panel plots the path of labor income for the two groups of states depicted in Figure 4.

Figure A.6: UI Benefit Exhaustion: Income and Spending By Elapsed UI Duration To Date



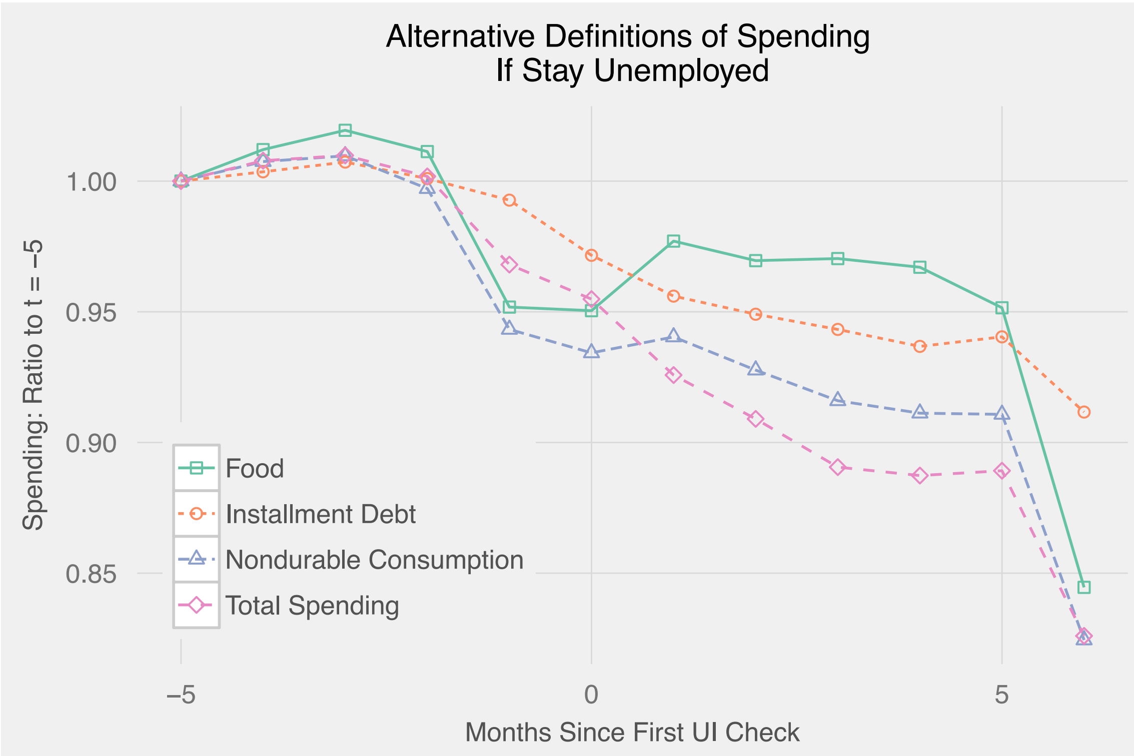
Note: The top panel shows income (labor income + UI) as a function of unemployment duration. The green squares are the path of income for every observation with UI receipt. The red circles are the path for job seekers unemployed at least two months. Each subsequent line restricts the sample to job seekers unemployed for an additional month. The bottom panel repeats the exercise for spending. The vertical line indicates benefit exhaustion.

Figure A.7: UI Benefit Exhaustion: Income and Spending



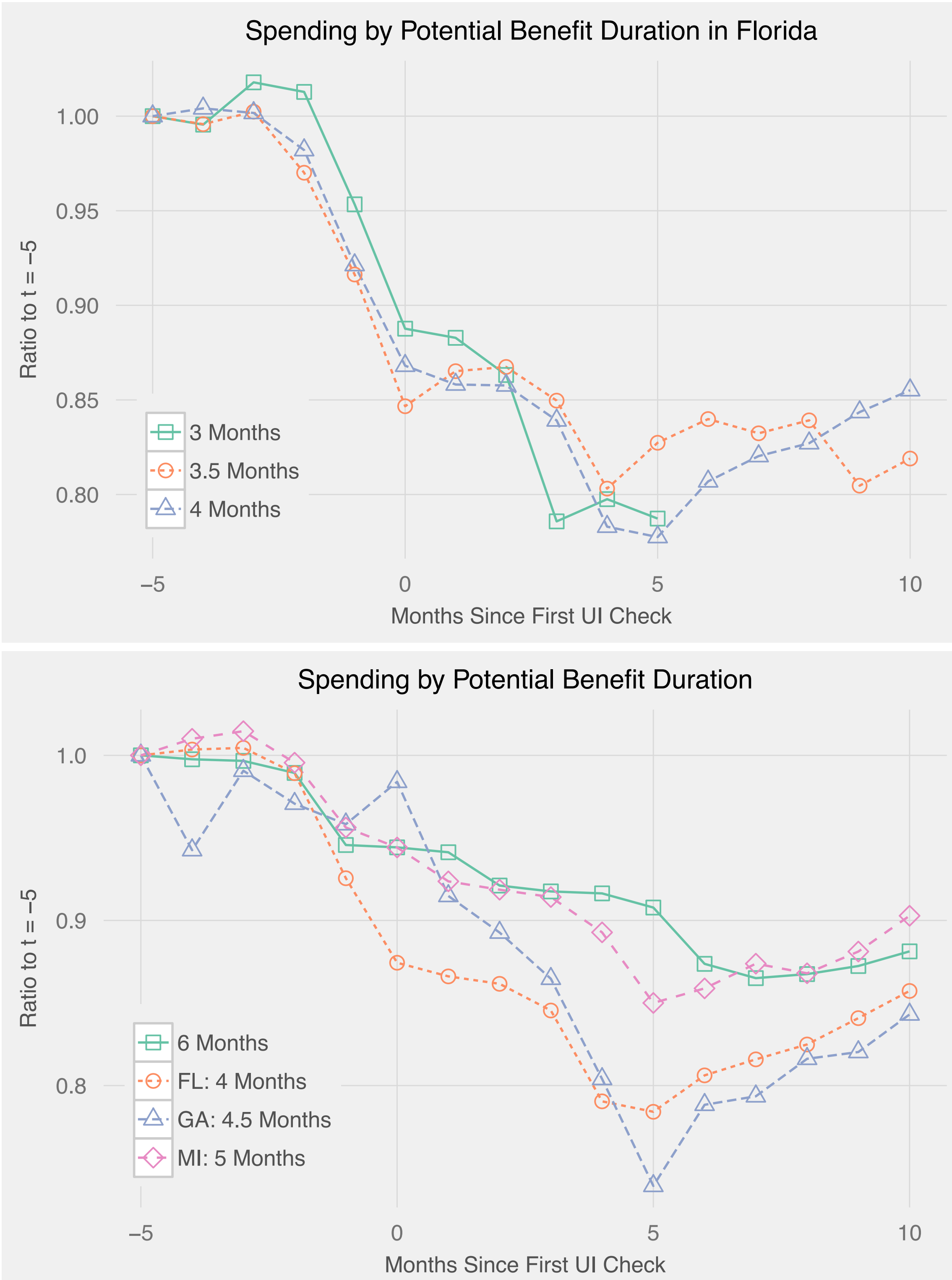
Notes: The top panel plots UI benefits and labor income relative to benefit exhaustion. The bottom panel plots the change in income (labor income plus UI) and spending around benefit exhaustion. See Section 3.3 for details.

Figure A.8: UI Benefit Exhaustion: Alternative Spending Definitions



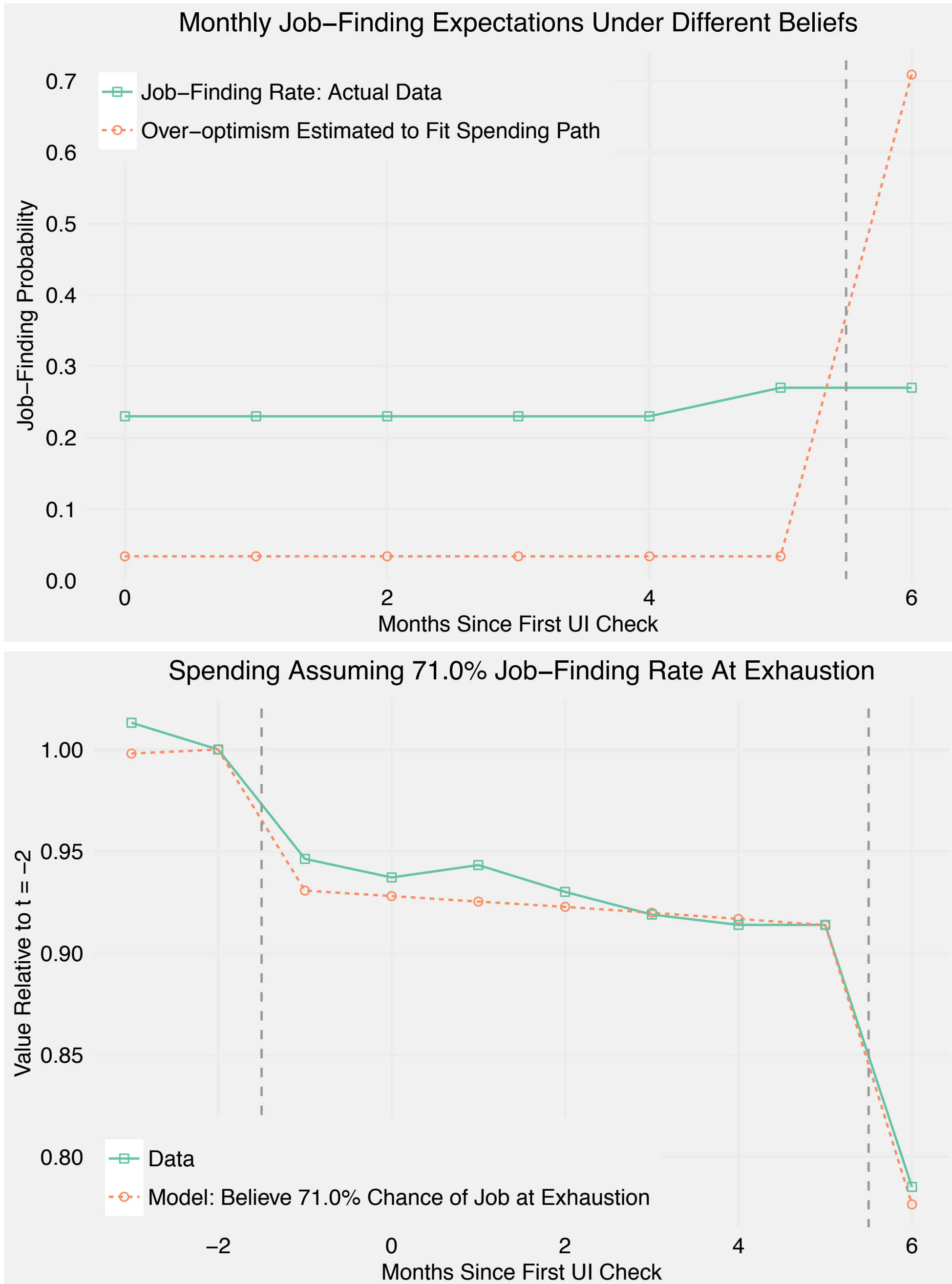
Note: This figure shows the evolution of four different definitions of spending using the methodology from Figure 3 to study job seekers who stay unemployed through benefit exhaustion. The blue triangles reflect the same spending series depicted in Figure 3. The other three lines indicate spending on groceries and food away from home (green squares), payments on mortgages, auto loans and student loans (red circles) and total checking account outflows (purple diamonds).

Figure A.9: UI Exhaustion Robustness: Spending by Potential Benefit Duration



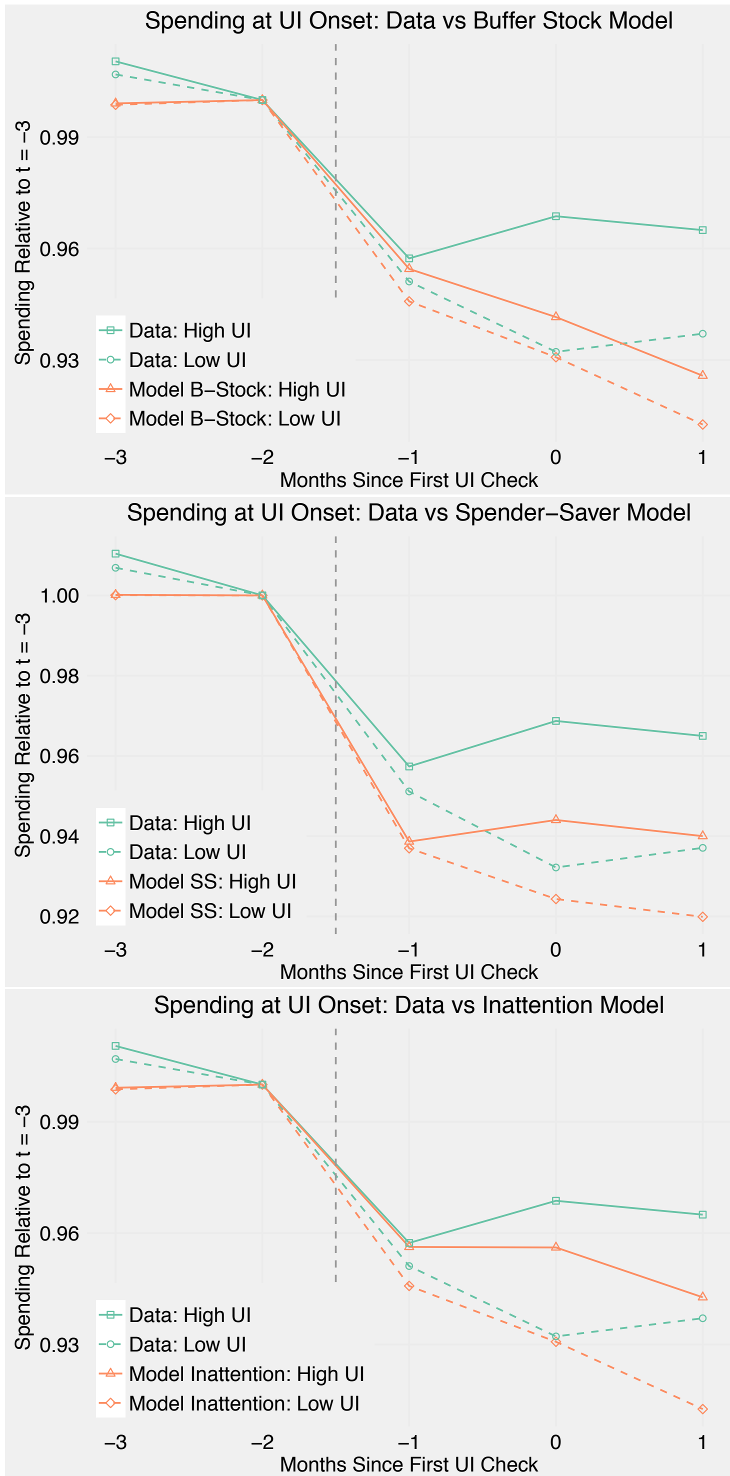
Notes: The top panel plots spending for exhaustees in Florida, which offered up to 4 months of benefits from January 2014 through June 2015, 3.5 months of benefits from July 2015 through December 2015 and 3 months of benefits from January 2016 onward. Two other states in the sample offered less than 6 months of benefits – Michigan and Georgia. The bottom panel plots spending for exhaustees in Michigan, Georgia and Florida, compared to spending in states that offered 6 months of benefits.

Figure A.13: Model: Over-Optimistic Beliefs Spike at Exhaustion



Notes: The top panel plots monthly job-finding expectations under the baseline assumptions (which match the data), and alternative assumptions where agents believe their monthly job-finding probability is 3% in the first five months of unemployment, and jumps to 71% in the final month of benefits. The bottom panel shows the path of spending in the data, the model under baseline job-finding beliefs, and the model under the alternative job-finding beliefs plotted in the previous panel.

Figure A.14: Testing Between Alternative Models: MPC at Onset in Buffer Stock, Spender-Saver and Inattention Models



Notes: This figure compares the path of spending across the high- and low-benefit states in the data (green lines) from Figure 4 to predictions from three models (red lines). For the three models, we alter the economic environment from Section 4.1 so that there is a single income level in the first month of unemployment and then a divergence in income levels thereafter. The top panel shows the predictions from a buffer stock model, the middle panel shows predictions from the spender-saver model, and the bottom panel shows predictions from the inattention model.

Figure A.15: Testing Between Alternative Models: Distribution of Spending Drop at Exhaustion

Note: This figure shows the distribution of the change in three different variables at benefit exhaustion. The top-left panel shows income (defined as the sum of labor income and UI benefits), the top-right panel shows total checking account inflows (which includes paper checks and transfers from other accounts), and the bottom panel shows the change in nondurable spending. The x-axis is the ratio of the change in income, inflows or spending to the household's monthly UI benefit. The "treatment" is UI benefit exhaustion, shown in red. To provide a baseline "control", the green bars show the change three months prior to the onset of unemployment.

Table A.1: Summary Statistics Prior to Unemployment Onset

Category	Detail	Mean (1)	Median (2)	Std Dev (3)	Share > 0 (4)
Total Checking Account Inflows		5,543	4,160	4,256	0.99
Government	Tax Refunds, Social Security (Old Age and Disability), Child Support, Unemployment Insurance, Veterans Benefits, Supplemental Security Income	214	80	721	0.80
Labor	Earnings Paid By Direct Deposit	3,265	2,560	2,898	0.93
Other Income	Cash, Investment Income, Interest, Refunds	148	0	362	0.53
Transfer	Transfers from Checking, Savings, Money Market, and Investment Accounts	224	0	1,179	0.57
Paper Checks		1,045	120	1,812	0.60
Uncategorized[a]		648	0	1,444	0.46
Total Checking Account Outflows		5,545	4,220	4,151	1.00
Work-Related (Chase Card[b])	Examples: Transportation, Food Away From Home.	708	500	657	0.96
Non-Work-Related (Chase Card[b])	Examples: Groceries, Insurance, Utilities	833	660	662	0.97
General Bills	Telecom Bill by ACH, Electric Bill by ACH, or Payment Method Used Primarily for Bills, Uncategorized Chase Card Spend	619	320	776	0.87
Cash	Automated Teller Machine Withdrawal	622	340	741	0.83
Installment Debt	Mortgage, Home Equity, Auto Loan, Student Loan	379	0	737	0.71
Credit Card Bills	Non-Chase Credit Card Bills	383	20	855	0.77
Transfer	Transfers to Checking, Savings, Money Market, and Investment Accounts	354	0	873	0.42
Uncategorized[a]		430	140	5,114	0.70
Paper Checks		986	440	1,279	0.76

Notes: n= 182,269. This table presents summary statistics on the analysis sample three months prior to the onset of UI.

a. This category is constructed as the residual of checking account transactions and includes electronic transfers which cannot be assigned to a category.

b. Spending on Chase debit cards and Chase credit cards. See footnote 12 for details on inclusion of credit cards and Section 3.2 for definition of work-related expenses.

Table A.2: Representativeness: Spending in JPMCI Data Compared to External Benchmarks

Category	JPMCI Mean ($)	External Benchmarks: CEX Mean ($)	Ratio to JPMCI	BEA Mean ($)	Ratio to JPMCI
Total Nondurables[a]	1,797	1,912	0.94	4,130	0.44
Specific Nondurables[b]					
Groceries	475	331	1.44	580	0.82
Food Away From Home[c]	290	219	1.32	471	0.62
Fuel	262	218	1.20	277	0.94
Utilities	371	312	1.19	--	--
Debt Payments[d]		SCF ($)	Ratio		
Mortgage	1,536	1,368	1.12		
Auto Loan	484	465	1.04		
Credit Card	1,010	1,613	0.63		
Student Loan	314	304	1.03		

Notes: All spending estimates are monthly means. For external benchmarks, we use published 2013 Consumer Expenditure Survey (CEX) statistics, Bureau of Economic Analysis Table 2.3.5 for 2013 divided by 125 million consumer units, and 2013 Survey of Consumer Finances (SCF) microdata for employed households. For comparability to public use datasets, estimates from JPMCI data use all households with at least five outflows per month in 2013.

a. Headline: This definition of spending contains the subset of spending which is comparable in the BEA, CEX and JPMCI. This subset excludes health care, which is poorly captured in JPMCI and utilities, which are included in BEA estimates.

b. Specific Nondurables: The JPMCI data categorize expenditures only on Chase debit and credit cards. To adjust for uncategorized spending on the same goods via cash and non-Chase credit cards, we adjust food and fuel spending estimates upward by the ratio of Chase debit card spend + Chase credit card spend to cash + Chase debit card + Chase credit card + non-Chase credit card spend (0.59).

c. Food Away From Home: BEA reports food services together with accomodations, so the BEA estimate overstates true spending on food away from home.

d. Debt Payments: We are only able to identify debt payments made by direct deposit for a small fraction of households. We compare the average payment made by households making any payment in the JPMCI data to comparable estimates in the SCF.

Table A.3: Representativeness: Income in JPMCI Data Compared to External Benchmarks

Dataset	Sample	Share < Age 21 (1)	Household Income (Median) (2)	Household Income (Mean) (3)	Poverty Rate (4)	Household Earnings (Mean) (5)	Person Earn (Mean) (6)	Share Other Earn > 0 (7)	Others' Earnings (Mean) (8)
SIPP	Employed	0.06	6,029	7,405	0.07	6,866	3,739	0.60	3,126
SIPP	Unemployed	0.22	4,374	5,596	0.16	5,064	2,042	0.56	3,023
SIPP	Receive UI	0.02	5,106	6,290	0.08	5,750	3,273	0.54	2,477
JPMCI	Receive UI		5,144	6,334		5,014			
JPMCI	Exhaust UI		5,391	6,557		5,149			

Notes: All income statistics are monthly, for the 12-month period prior to the onset of unemployment.

SIPP The first three rows are from the Survey of Income and Program Participation panel (SIPP) and are inflated to 2014 $ using CPI-U. This survey covered years 2004-2007. "All unemployed" are people with a reported job separation followed by unemployment in the subsequent month. "Get UI" are people who report positive UI income.

JPMCI data are for January 2014 through June 2016. We define income as all inflows which are not explicitly categorized as transfers to external bank accounts and we rescale these inflows into pre-tax dollars. We assume an average tax rate (federal income and payroll) of 12% below $6,671, 13% below $11,048, 14% below $15,316, 15% below $19,484, 17% below $23,588, 18% below $29,592, 20% below $37,428, 23% below $50,798, 25% below $69,933, 28% below $117,368, 36% below $257,355, 47% below $510,789, 52% below $824,902 and 53% above. We calculate in the Survey of Consumer Finances that 15% of labor earnings are paid by paper check or pre-paid debit card. The JPMCI data only show labor income paid by direct deposit and so we adjust the JPMCI estimate upward by 15%.

Table A.4: Representativeness: Assets in JPMCI Data Compared to External Benchmarks

Data	Sample	Asset Balance	p10	p50	p90	Mean
SCF	Employed	All Liquid Assets	270	4,900	54,000	29,952
SCF	Employed	Checking Account	150	1,500	10,000	4,920
JPMCI	UI Recipient, Pre-Onset	Checking Account	60	1,260	9,480	3,109

Notes: This table compares liquid assets in the 2013 Survey of Consumer Finances (SCF) to the JPMCI data. Liquid assets include checking and saving accounts, money market accounts, certificates of deposit, savings bonds, non-retirement mutual funds, stocks and bonds. When households have multiple checking accounts in the SCF, we report statistics for "the checking account you use the most." Employed is defined as at least $15,000 of annual pre-tax labor income in the SCF.

Table A.5: Other Outcomes at Onset, During UI Receipt, and Benefit Exhaustion

	Pre-Onset Mean ($)	Two-Month Change at Onset[a]	Monthly Change During UI Receipt[b]	Two-Month Change at Exhaustion[c]
	(1)	(2)	(3)	(4)
Checking Account: Inflows, Outflows, Food				
Total Inflows ($)	5,543	-164	-169	-505
		(9)	(3)	(20)
Total Outflows ($)	5,545	-198	-97	-377
		(8)	(3)	(17)
Food ($)	522	-33	1	-62
		(1)	(0.2)	(2)
N Checking Account Outcomes		182,269	537,978	35,578
Chase Credit Cards[d]				
New Charges ($)	263	-14	1	1
		(1)	(0.4)	(3)
Revolving Balance ($)	2,445	23	21	45
		(6)	(3)	(15)
Credit Limit ($)	12,897	110	44	42
		(9)	(4)	(19)
N Credit Card Outcomes		77,026	231,614	16,204

Notes: Standard errors are shown in parentheses underneath regression coefficients and are clustered by household.

a. Each observation is a household. Onset is defined as difference from three months before the first UI payment to one month before the first UI payment.

b. Each observation is a household-month.

c. Each observation is a household. Exhaustion is defined as the difference from one month before the last UI payment to one month after the last UI payment for benefit exhaustees. The sample is exhaustees eligible for 26 weeks of benefits.

d. About 40% of the JPMCI UI sample has a Chase credit card. The revolving balance variable captures a stock rather than a flow. For example, a $23 increase in credit card balance at onset corresponds to spending $11.50 extra on the card each month.

Table A.6: Spending Drop Using Alternative Time Horizons

	Pre-Onset Mean ($)	Spending Drop Compared to 3 Months Before UI Onset		
		Onset[a] (t=-1)	While Receiving UI[b]	Annual[c] (t=-1,0,...10)
	(1)	(2)	(3)	(4)
(a) Total Nondurables (i + ii + iii)	2,831	-6.0%	-6.8%	-6.4%
(i) Work-Related	708	-8.5%	-9.7%	-8.0%
(ii) Non-Work-Related	833	-5.5%	-4.5%	-5.7%
(iii) Cash and Bills	1,290	-4.8%	-6.7%	-5.9%
(b) Food[d]	522	-6.2%	-5.3%	-4.3%

Notes: This table computes the spending drop for various time horizons and various spending concepts. In each column, we compute Loss/$Spend_{-3}$. Time subscripts are relative to the first month of UI receipt and T is the last month of UI receipt.

a. Loss = $Spend_{-1}$ - $Spend_{-3}$.

b. Loss = Mean($Spend_{-1}$,$Spend_0$ ... $Spend_T$) - $Spend_{-3}$

c. Loss = Mean($Spend_{-1}$,$Spend_0$ ... $Spend_{10}$) - $Spend_{-3}$.

d. Gruber (1997) estimates a drop in food spending of 6.8%. The reference period in the PSID for food spending is ambiguous. If the reference period is unemployment onset, the comparable estimate is 6.2%, while if the reference period is an annual time horizon then the comparable estimate is 4.3%.

Table A.7: Spending Decomposition at Unemployment Onset

	Pre Onset ($) (1)	Post Onset ($) (2)	Change in $ (2) - (1) (3)	Change in % (2) / (1) (4)
Nondurables: Above-Average Drop				
Department Stores	20.7	17.8	-2.8	-13.8%
Other Retail	156.8	140.3	-16.5	-10.5%
Flights & Hotels	60.5	54.6	-5.9	-9.7%
Food Away From Home	215.5	194.7	-20.8	-9.6%
Transportation	198.8	182.3	-16.5	-8.3%
Cash	622.0	570.7	-51.3	-8.2%
Nondurables: Below-Average Drop				
Online	44.0	41.6	-2.4	-5.4%
Drug Stores	37.0	35.1	-2.0	-5.3%
Entertainment	33.5	31.7	-1.8	-5.3%
Discount Stores	59.6	56.9	-2.7	-4.5%
Home Improvement	47.7	45.8	-1.9	-4.0%
Professional & Personal Services	58.0	55.7	-2.3	-4.0%
Groceries	320.8	308.9	-11.9	-3.7%
Other Consumption	340.4	331.8	-8.6	-2.5%
Telecom	113.3	111.1	-2.2	-1.9%
Utilities	177.5	175.6	-1.9	-1.1%
Insurance	148.4	147.2	-1.3	-0.8%
Medical Copay	35.0	36.6	1.5	4.4%
Other Spending: (Ranked by Size of Drop)				
Uncategorized[a]	429.5	388.7	-40.9	-9.5%
Non-Chase Credit Card Bill	382.9	364.9	-17.9	-4.7%
Durables (Chase Card)	54.8	52.3	-2.5	-4.5%
Installment Debt	379.3	374.4	-4.9	-1.3%
Paper Checks	985.7	987.1	1.4	0.1%
Transfer to External Account	353.9	365.9	12.1	3.4%

Notes: n=182,573 households. This table decomposes the drop in spending during unemployment into twenty-five categories. Column 1 is three months prior to the first UI payment and column 2 is one month prior to the first UI payment.

a. This category is constructed as the residual of checking account outflows and includes electronic transfers which cannot be assigned to a category.

Table A.8: Spending Drop at Exhaustion By Pre-Onset Characteristics

	Spending Change in $ (1)	Ratio of Spending Drop to Income Drop (2)	p-val vs baseline (3)
Baseline	-256	0.285	--
		(0.013)	
<u>Demographics and Economic Characteristics</u>			
Annual Income < Median	-297	0.346	< 0.001
		(0.016)	
Single	-265	0.311	0.061
		(0.016)	
Age < Median	-292	0.365	< 0.001
		(0.02)	
Makes ACH Mortgage Payments	-172	0.183	< 0.001
		(0.034)	
UI Benefits / Income in Bottom Tercile	-173	0.234	0.037
		(0.034)	
UI Benefits / Income in Top Tercile	-338	0.329	0.006
		(0.016)	
<u>Assets and Liabilities</u>			
Total Assets in Bottom Tercile	-319	0.374	< 0.001
		(0.022)	
Total Assets in Top Tercile	-193	0.204	< 0.001
		(0.023)	
Chase Assets in Bottom Tercile	-373	0.43	< 0.001
		(0.03)	
Chase Assets in Top Tercile	-147	0.15	< 0.001
		(0.035)	
<u>Heterogenity in Among Chase Credit Holders</u>			
Has Chase Credit Card	-190	0.204	< 0.001
		(0.024)	
No Revolving CC Balance	-125	0.13	0.11
		(0.052)	
Credit Card Utilization > 50%	-308	0.372	0.004
		(0.06)	

Notes: This table examines heterogeneity in the spending response to exhaustion by pre-onset characteristics. Standard errors are in parentheses. Column 1 reports the drop in spending for the subsample of interest. Column 2 reports the ratio of the spending drop as a fraction of the income loss. Column 3 reports the p-value for the null hypothesis that the MPC in the baseline sample is the same as the MPC subsample.

Table A.9: Welfare Impact of Changes in UI Generosity

Welfare Change as an Equivalent Increase in Lifetime Income

	Gains (JPMCI Data)		Gains (JPMCI Data) + Distortion (Literature)		
	UI Benefits ↑ 1.1% (1)	UI Duration ↑ 1 Month (2)	UI Benefits ↑ 1.1% (3)	UI Duration ↑ 1 Month (4)	Ratio (col 2 / col 1) (5)
Coefficient of Relative Risk Aversion $\gamma = 1$					
Baily-Chetty Approximation					
JPMCI Nondurables	0.008%	0.033%	-0.034%	-0.039%	4.13
Gruber (1997) Food	0.009%		-0.033%		
Structural Model Simulation					
Buffer Stock Model	0.013%	0.042%	-0.029%	-0.029%	3.23
Spender-saver Model	0.011%	0.028%	-0.010%	-0.008%	2.55
Inattention Model	0.013%	0.052%	-0.029%	-0.019%	4.00
Coefficient of Relative Risk Aversion $\gamma = 4$					
Baily-Chetty Approximation					
JPMCI Nondurables	0.038%	0.199%	-0.005%	0.126%	5.24
Gruber (1997) Food	0.040%		-0.003%		
Structural Model Simulation					
Buffer Stock Model	0.037%	0.117%	-0.005%	0.046%	3.16
Spender-saver Model	0.049%	0.177%	0.029%	0.142%	3.61
Inattention Model	0.028%	0.271%	-0.014%	0.199%	9.68

Notes: We evaluate the welfare impact of budget-neutral tax-financed changes in the generosity of UI benefits as a percent of lifetime income. The first two rows show results using the Baily-Chetty approximation. The last three rows show results from three structural models. See Section 5 for details.

Column 1 considers a policy raises monthly benefits by 1.1% and raises taxes during employment by 0.136%; this tax revenue is sufficient to finance this increase in benefits if there is no job search distortion from increased UI benefits.

Column 2 considers a policy which extends potential UI benefit durations by one month and raises taxes during employment by 0.136%; this tax revenue is sufficient to finance this increase in benefits if there is no job search distortion from increased UI benefits.

Column 3 considers a policy which raises monthly benefits by 1.1% and raises taxes during employment by 0.183%; this tax revenue is sufficient to finance this increase in benefits when increased UI levels reduce job search at the median of the estimates reviewed in Schmieder and von Wachter (2016).

Column 4 considers a policy which extends potential UI benefit durations by one month and raises taxes during employment by 0.218%; this tax revenue is sufficient to finance this increase in benefits when extended UI durations reduce job search at the median of the estimates reviewed in Schmieder and von Wachter (2016).

Table A.10: Means by Estimated Liquid Assets at Onset

	Low Asset		Medium Asset		High Asset	
Months	Income	Spending	Income	Spending	Income	Spending
-5	1.000	1.000	1.000	1.000	1.000	1.000
-4	0.996	1.005	0.993	0.999	0.987	0.993
-3	0.995	1.013	0.987	0.997	0.980	0.988
-2	0.970	0.996	0.966	0.985	0.962	0.985
-1	0.871	0.933	0.884	0.933	0.894	0.948
0	0.865	0.927	0.863	0.930	0.859	0.951
1	0.837	0.937	0.831	0.939	0.812	0.965
2	0.856	0.928	0.843	0.930	0.822	0.956
3	0.859	0.920	0.858	0.928	0.842	0.958
4	0.867	0.920	0.866	0.928	0.855	0.960
5	0.869	0.918	0.862	0.920	0.853	0.958
6	0.818	0.893	0.816	0.899	0.813	0.943
7	0.820	0.889	0.810	0.897	0.806	0.937
8	0.837	0.895	0.829	0.899	0.821	0.938
9	0.847	0.898	0.842	0.903	0.836	0.943
10	0.859	0.904	0.851	0.911	0.844	0.946
11	0.873	0.912	0.862	0.916	0.854	0.949
12	0.881	0.919	0.867	0.923	0.861	0.952
13	0.893	0.927	0.882	0.926	0.870	0.959
14	0.903	0.933	0.888	0.929	0.880	0.960
15	0.907	0.928	0.903	0.938	0.895	0.971
16	0.912	0.929	0.909	0.941	0.899	0.975
17	0.924	0.939	0.914	0.942	0.911	0.980
18	0.931	0.942	0.916	0.946	0.909	0.983

Table A.11: Means by Potential UI Duration

Mont	Balance	Debt Pay	Drugstore	Durables	Food	Income	Inflows	Labor	Medical	Outflows	Spending
Florida Exhaustees (Potential Duration 4 Months)											
-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	1.026	1.010	1.002	0.982	0.981	1.020	1.002	1.005	0.964	1.007	1.004
-3	1.038	1.003	0.965	0.910	0.979	1.009	1.017	0.989	1.044	1.018	1.002
-2	1.054	1.002	0.979	0.959	0.966	0.984	0.992	0.947	1.032	1.000	0.982
-1	1.039	0.985	0.892	0.801	0.881	0.851	0.926	0.788	0.961	0.947	0.921
0	1.045	0.932	0.857	0.793	0.827	0.765	0.865	0.411	0.850	0.893	0.868
1	1.000	0.917	0.851	0.773	0.840	0.763	0.827	0.282	0.759	0.857	0.858
2	0.980	0.895	0.845	0.809	0.828	0.767	0.819	0.272	0.805	0.845	0.858
3	0.934	0.883	0.827	0.744	0.829	0.734	0.803	0.292	0.793	0.834	0.839
4	0.898	0.874	0.737	0.644	0.754	0.633	0.756	0.387	0.691	0.786	0.783
5	0.884	0.872	0.727	0.655	0.756	0.652	0.776	0.475	0.677	0.798	0.778
6	0.908	0.889	0.742	0.696	0.790	0.690	0.803	0.511	0.753	0.813	0.807
7	0.903	0.873	0.761	0.737	0.803	0.720	0.812	0.564	0.728	0.831	0.820
8	0.900	0.901	0.754	0.765	0.822	0.742	0.821	0.585	0.810	0.846	0.827
9	0.922	0.902	0.778	0.743	0.844	0.760	0.841	0.610	0.781	0.854	0.844
10	0.952	0.901	0.790	0.796	0.868	0.784	0.853	0.641	0.733	0.866	0.855
11	0.966	0.958	0.780	0.708	0.859	0.788	0.856	0.661	0.812	0.869	0.858
12	1.021	0.927	0.802	0.800	0.885	0.829	0.887	0.677	0.881	0.885	0.875
13	1.018	0.963	0.822	0.752	0.897	0.826	0.882	0.690	0.894	0.890	0.888
14	1.018	0.970	0.798	0.751	0.906	0.833	0.880	0.709	0.869	0.896	0.889
15	1.013	0.997	0.787	0.705	0.896	0.848	0.890	0.717	0.947	0.896	0.875
16	1.004	1.035	0.824	0.689	0.906	0.864	0.895	0.725	0.924	0.902	0.878
17	1.029	0.993	0.837	0.710	0.919	0.882	0.908	0.756	0.945	0.907	0.901
18	1.046	1.015	0.816	0.821	0.932	0.902	0.925	0.777	0.986	0.930	0.912
States with 6 Month Potential UI Duration (and Duration 4 Months)											
-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	1.001	0.994	0.998	1.007	0.999	0.991	0.995	0.988	1.005	0.997	0.998
-3	1.009	0.995	1.006	1.002	1.001	0.986	0.997	0.977	1.003	0.997	0.996
-2	1.038	0.989	0.999	1.012	0.996	0.965	0.994	0.948	1.060	0.993	0.990
-1	1.088	0.979	0.951	0.966	0.943	0.892	0.980	0.841	1.082	0.971	0.947
0	1.137	0.964	0.935	0.997	0.948	0.881	0.970	0.512	0.987	0.975	0.947
1	1.082	0.943	0.945	0.964	0.969	0.820	0.878	0.346	0.948	0.936	0.944
2	1.044	0.928	0.934	0.917	0.954	0.803	0.861	0.325	0.928	0.906	0.921
3	1.018	0.925	0.922	0.897	0.953	0.801	0.862	0.324	0.912	0.895	0.915
4	1.003	0.926	0.921	0.893	0.947	0.806	0.872	0.371	0.886	0.898	0.914
5	0.989	0.921	0.910	0.879	0.932	0.793	0.871	0.447	0.857	0.892	0.903
6	0.962	0.912	0.857	0.818	0.882	0.705	0.835	0.523	0.829	0.867	0.867
7	0.941	0.909	0.839	0.816	0.869	0.691	0.830	0.576	0.818	0.863	0.858
8	0.931	0.901	0.849	0.842	0.878	0.717	0.837	0.609	0.831	0.861	0.861
9	0.935	0.906	0.849	0.838	0.882	0.740	0.848	0.637	0.840	0.868	0.866
10	0.937	0.910	0.874	0.855	0.895	0.753	0.856	0.658	0.874	0.876	0.874
11	0.948	0.922	0.881	0.876	0.908	0.773	0.868	0.683	0.865	0.882	0.883
12	0.956	0.939	0.888	0.863	0.919	0.787	0.876	0.699	0.891	0.892	0.891
13	0.967	0.941	0.881	0.860	0.929	0.802	0.887	0.718	0.938	0.900	0.897
14	0.978	0.938	0.904	0.861	0.938	0.815	0.892	0.732	0.922	0.902	0.901
15	0.977	0.956	0.901	0.860	0.949	0.828	0.902	0.748	0.936	0.915	0.909
16	0.974	0.960	0.893	0.868	0.948	0.835	0.905	0.755	0.933	0.917	0.912
17	0.983	0.966	0.902	0.865	0.961	0.850	0.912	0.770	0.950	0.922	0.919
18	0.986	0.962	0.915	0.863	0.964	0.855	0.921	0.777	0.950	0.929	0.926

Table A.12: Means by Potential UI Duration

Mos	Balance	Non-WR	Debt Pay	WR	Drug	Durables	Food	Income	Inflows	Labor	Medical	Outflows	Spending
Completed UI Duration of 1 Month													
-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	0.992	1.006	1.006	1.006	1.013	1.005	1.002	0.990	0.995	0.988	0.996	0.996	1.001
-3	0.995	1.035	0.995	1.037	1.034	1.026	1.022	0.982	0.995	0.979	1.041	0.994	0.997
-2	1.064	1.001	0.973	1.013	0.990	1.027	1.004	0.958	0.983	0.944	1.029	0.978	0.978
-1	1.024	0.950	0.974	0.931	0.954	0.951	0.929	0.832	0.930	0.775	0.995	0.938	0.910
0	1.056	1.005	0.972	0.994	0.980	1.002	0.978	0.881	0.951	0.497	0.929	0.964	0.964
1	0.965	0.994	0.973	1.031	0.993	0.982	0.993	0.865	0.939	0.801	0.891	0.964	0.972
2	0.948	1.010	0.983	1.037	1.014	0.978	1.011	0.926	0.962	0.883	0.896	0.971	0.975
3	0.947	1.005	0.966	1.033	0.989	0.965	1.009	0.934	0.961	0.899	0.929	0.966	0.973
4	0.945	0.993	0.946	1.018	0.995	0.944	0.996	0.924	0.957	0.897	0.904	0.967	0.967
5	0.960	1.005	0.968	1.029	1.002	1.001	1.010	0.946	0.965	0.922	0.998	0.971	0.978
6	0.965	1.007	0.992	1.018	0.994	0.991	1.017	0.944	0.975	0.924	0.963	0.981	0.976
7	0.976	1.011	0.990	1.019	1.000	0.993	1.014	0.960	0.975	0.933	0.972	0.984	0.978
8	0.982	1.021	0.996	1.030	1.002	0.977	1.022	0.964	0.982	0.945	1.000	0.987	0.982
9	0.992	1.020	1.003	1.018	1.015	0.975	1.027	0.965	0.984	0.951	0.994	0.992	0.986
10	1.007	1.033	1.019	1.030	1.016	1.005	1.043	0.968	0.989	0.952	0.996	0.993	0.990
11	0.999	1.023	1.017	1.029	1.018	1.040	1.027	0.959	0.974	0.939	1.020	0.981	0.979
12	1.023	1.016	1.022	1.029	1.018	0.982	1.033	0.969	0.989	0.947	1.039	1.002	0.985
13	1.041	1.015	1.038	1.041	1.017	0.960	1.040	0.982	1.002	0.962	0.960	1.004	0.988
14	1.049	1.045	1.041	1.054	1.043	0.990	1.054	0.994	1.020	0.973	1.058	1.022	1.007
15	1.036	1.039	1.047	1.056	1.018	1.032	1.057	0.989	1.005	0.972	1.052	1.017	1.003
16	1.031	1.048	1.050	1.031	1.014	0.930	1.063	0.995	1.008	0.973	1.051	1.010	1.004
17	1.051	1.049	1.037	1.054	1.048	0.972	1.066	1.013	1.025	0.993	1.051	1.027	1.018
18	1.051	1.052	1.069	1.035	1.021	0.977	1.062	1.005	1.010	0.990	1.038	1.014	1.011
Completed UI Duration of 2 Months													
-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	0.993	0.976	0.991	0.981	0.956	0.918	0.993	0.991	0.992	0.990	0.979	1.000	1.001
-3	0.999	0.980	0.985	0.983	0.962	0.944	0.989	0.988	0.994	0.981	0.996	0.997	1.001
-2	1.017	0.984	0.993	0.991	0.971	0.953	0.993	0.968	0.986	0.956	1.056	0.989	0.989
-1	1.072	0.929	0.978	0.916	0.897	0.899	0.928	0.883	0.956	0.839	1.014	0.952	0.935
0	1.062	0.946	0.952	0.920	0.901	0.887	0.930	0.831	0.914	0.503	0.953	0.936	0.927
1	1.044	0.973	0.953	0.982	0.944	0.915	0.980	0.857	0.921	0.530	0.927	0.953	0.968
2	0.995	0.968	0.968	0.998	0.943	0.933	0.984	0.910	0.957	0.859	0.931	0.972	0.971
3	0.986	0.969	0.964	1.000	0.943	0.924	0.991	0.939	0.960	0.908	0.923	0.971	0.972
4	0.976	0.964	0.968	0.988	0.925	0.908	0.985	0.941	0.959	0.917	0.926	0.968	0.972
5	0.974	0.969	0.982	0.985	0.929	0.901	0.985	0.947	0.962	0.928	0.961	0.972	0.973
6	0.977	0.965	0.989	0.977	0.928	0.879	0.990	0.953	0.964	0.935	0.955	0.976	0.974
7	0.987	0.972	0.998	0.977	0.936	0.904	0.994	0.960	0.971	0.945	0.960	0.982	0.977
8	1.005	0.983	1.019	0.987	0.949	0.899	0.999	0.972	0.983	0.956	0.996	0.989	0.981
9	1.014	0.988	1.028	0.992	0.945	0.950	1.003	0.981	0.989	0.965	0.979	0.997	0.988
10	1.029	0.994	1.043	0.979	0.941	0.910	1.008	0.981	0.991	0.970	0.996	0.998	0.986
11	1.034	0.992	1.059	0.979	0.948	0.910	1.011	0.987	1.000	0.974	0.999	1.006	0.990
12	1.044	0.999	1.041	0.993	0.954	0.948	1.013	0.981	0.997	0.969	1.055	1.006	0.992
13	1.054	0.993	1.056	0.997	0.954	0.912	1.014	0.990	1.003	0.974	1.048	1.010	0.998
14	1.057	1.000	1.064	0.998	0.951	0.919	1.015	0.992	1.006	0.983	1.089	1.012	0.995
15	1.053	1.003	1.060	1.009	0.954	0.932	1.023	1.004	1.010	0.991	1.079	1.019	1.001
16	1.049	1.003	1.055	1.006	0.952	0.929	1.024	1.007	1.015	0.992	1.059	1.023	1.005
17	1.045	1.004	1.057	0.999	0.956	0.894	1.021	1.005	1.009	0.993	1.068	1.017	0.998

18	1.051	0.999	1.070	0.982	0.944	0.889	1.024	1.004	1.018	0.996	1.055	1.024	1.004
Completed UI Duration of 3 Months													
-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	1.016	1.028	0.991	1.007	1.047	1.012	1.012	0.990	0.997	0.989	1.022	0.996	0.996
-3	1.012	1.002	0.997	0.992	1.010	1.003	1.003	0.981	0.992	0.976	1.039	0.998	0.999
-2	1.034	1.000	0.984	0.987	1.040	0.994	0.994	0.966	0.986	0.953	1.084	0.988	0.987
-1	1.084	0.966	0.980	0.937	0.991	0.948	0.948	0.888	0.965	0.849	1.095	0.957	0.936
0	1.128	0.963	0.963	0.910	0.937	0.931	0.931	0.844	0.929	0.515	1.011	0.944	0.922
1	1.034	0.987	0.950	0.955	0.975	0.972	0.972	0.796	0.860	0.368	0.989	0.923	0.940
2	1.035	0.988	0.943	0.985	0.996	0.984	0.984	0.847	0.920	0.512	0.931	0.938	0.952
3	0.980	0.977	0.949	0.990	0.986	0.981	0.981	0.886	0.942	0.836	0.936	0.958	0.952
4	0.971	0.981	0.958	0.994	0.985	0.990	0.990	0.917	0.955	0.882	0.928	0.967	0.960
5	0.968	0.988	0.961	0.984	0.996	0.986	0.986	0.924	0.954	0.896	0.933	0.962	0.961
6	0.979	0.981	0.964	0.974	0.979	0.986	0.986	0.926	0.950	0.905	0.961	0.959	0.957
7	0.991	0.985	0.979	0.973	1.006	0.989	0.989	0.938	0.960	0.915	0.964	0.971	0.962
8	1.001	1.000	0.994	0.983	0.991	1.001	1.001	0.948	0.967	0.925	1.003	0.975	0.968
9	1.015	1.001	0.991	0.982	0.995	1.004	1.004	0.949	0.971	0.930	1.014	0.980	0.969
10	1.019	1.011	0.992	0.991	0.999	1.013	1.013	0.962	0.973	0.942	1.001	0.986	0.976
11	1.026	1.011	1.001	0.986	1.019	1.011	1.011	0.960	0.976	0.950	1.042	0.985	0.977
12	1.039	1.013	1.008	0.996	0.993	1.021	1.021	0.960	0.981	0.951	1.052	0.991	0.982
13	1.051	1.020	1.026	1.002	0.994	1.026	1.026	0.974	0.986	0.963	1.060	0.997	0.991
14	1.046	1.019	1.038	1.005	1.006	1.028	1.028	0.976	0.985	0.961	1.037	0.999	0.989
15	1.060	1.021	1.026	1.008	1.010	1.030	1.030	0.989	1.003	0.972	1.073	1.006	0.989
16	1.063	1.030	1.027	1.005	1.009	1.036	1.036	0.996	1.004	0.994	1.053	1.014	0.993
17	1.064	1.042	1.035	1.012	1.033	1.039	1.039	0.998	1.015	0.992	1.064	1.027	1.004
18	1.071	1.027	1.049	0.998	0.997	1.034	1.034	0.999	1.011	0.998	1.063	1.021	0.996
Completed UI Duration of 4 Months													
-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	0.971	0.995	0.980	0.986	0.980	1.020	0.995	0.986	0.986	0.981	0.956	0.995	0.998
-3	1.014	1.039	0.971	1.001	1.037	1.111	1.007	0.982	0.993	0.971	0.987	0.993	1.002
-2	1.013	0.991	0.969	0.964	0.995	1.010	0.983	0.953	0.976	0.934	0.976	0.989	0.989
-1	1.043	0.955	0.976	0.901	0.964	0.969	0.924	0.873	0.946	0.822	1.025	0.952	0.935
0	1.100	0.979	0.948	0.897	0.951	0.974	0.926	0.856	0.933	0.506	0.988	0.931	0.923
1	1.053	0.975	0.933	0.918	0.958	0.935	0.945	0.787	0.839	0.334	0.947	0.904	0.924
2	0.991	0.970	0.935	0.926	0.957	0.954	0.944	0.787	0.845	0.339	0.915	0.892	0.915
3	0.999	0.982	0.947	0.956	0.963	0.943	0.959	0.834	0.902	0.478	0.881	0.914	0.940
4	0.942	0.969	0.945	0.967	0.964	0.937	0.965	0.857	0.922	0.789	0.872	0.938	0.943
5	0.941	0.972	0.942	0.973	0.959	0.962	0.967	0.890	0.934	0.839	0.841	0.942	0.950
6	0.938	0.966	0.939	0.960	0.961	0.947	0.961	0.891	0.929	0.848	0.906	0.937	0.944
7	0.941	0.961	0.952	0.948	0.950	0.913	0.954	0.893	0.925	0.854	0.911	0.935	0.941
8	0.961	0.970	0.963	0.953	0.963	0.949	0.970	0.902	0.935	0.871	0.914	0.945	0.949
9	0.974	0.982	0.973	0.944	0.970	0.943	0.974	0.905	0.931	0.878	0.952	0.941	0.946
10	0.974	0.994	0.997	0.966	0.979	0.970	0.984	0.919	0.944	0.887	0.963	0.960	0.959
11	0.985	1.013	0.983	0.979	0.996	1.043	0.999	0.933	0.960	0.908	0.964	0.963	0.969
12	1.002	1.008	1.009	0.980	0.999	1.003	1.000	0.937	0.955	0.911	1.011	0.962	0.971
13	1.013	1.009	1.018	0.987	0.998	0.992	1.009	0.936	0.963	0.914	1.007	0.973	0.976
14	1.030	1.015	1.026	0.995	1.007	1.001	1.018	0.953	0.970	0.926	1.040	0.978	0.977
15	1.040	1.026	1.028	1.018	1.012	1.029	1.027	0.965	0.986	0.933	1.014	0.992	0.990
16	1.038	1.033	1.030	1.005	1.008	1.024	1.025	0.968	0.987	0.945	1.019	1.000	0.991
17	1.051	1.039	1.042	1.004	1.016	0.961	1.034	0.981	0.996	0.954	1.032	1.002	0.996
18	1.053	1.042	1.069	1.007	1.013	1.017	1.041	0.978	0.993	0.957	1.023	1.005	1.000

Completed UI Duration of 5 Months

-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	1.009	1.008	0.972	1.003	1.018	1.029	1.006	0.992	0.991	0.995	0.993	0.995	1.002
-3	1.003	1.000	0.995	0.986	1.005	0.990	0.992	0.982	0.992	0.967	0.966	0.994	0.996
-2	1.024	1.008	0.975	0.977	1.008	1.038	0.992	0.944	0.976	0.921	1.042	0.988	0.979
-1	1.056	0.962	0.939	0.898	0.951	0.992	0.929	0.856	0.952	0.800	1.001	0.953	0.931
0	1.109	0.990	0.946	0.888	0.966	0.988	0.934	0.856	0.937	0.488	0.944	0.943	0.927
1	1.032	0.992	0.921	0.900	0.948	0.949	0.956	0.804	0.852	0.343	0.915	0.914	0.925
2	1.006	0.980	0.926	0.891	0.963	0.966	0.938	0.795	0.851	0.327	0.937	0.895	0.912
3	0.980	0.991	0.918	0.911	0.963	0.963	0.954	0.796	0.846	0.336	0.933	0.883	0.912
4	1.001	0.979	0.930	0.941	0.989	0.968	0.958	0.831	0.917	0.588	0.842	0.923	0.926
5	0.989	0.969	0.928	0.936	0.960	0.945	0.955	0.863	0.921	0.801	0.876	0.929	0.926
6	0.993	0.972	0.936	0.929	0.940	0.900	0.957	0.891	0.938	0.838	0.923	0.944	0.939
7	1.002	0.971	0.943	0.934	0.946	0.916	0.965	0.895	0.939	0.844	0.945	0.954	0.937
8	0.997	0.978	0.952	0.920	0.940	0.965	0.963	0.890	0.926	0.850	0.928	0.934	0.930
9	1.010	0.980	0.946	0.927	0.972	0.921	0.977	0.915	0.944	0.872	0.960	0.958	0.941
10	1.016	0.990	0.960	0.939	0.995	0.951	0.980	0.918	0.946	0.890	1.050	0.963	0.944
11	1.025	0.997	0.981	0.937	0.970	0.989	0.988	0.925	0.954	0.904	1.014	0.966	0.948
12	1.043	0.999	0.951	0.944	1.007	0.911	0.990	0.933	0.958	0.912	0.978	0.964	0.950
13	1.042	0.998	0.974	0.943	0.972	0.914	0.992	0.928	0.957	0.910	1.023	0.974	0.951
14	1.038	1.002	0.974	0.942	1.005	0.896	0.987	0.931	0.951	0.916	1.038	0.961	0.940
15	1.042	1.001	0.972	0.944	0.975	0.885	0.993	0.951	0.967	0.929	1.052	0.966	0.948
16	1.039	0.992	1.009	0.970	0.995	0.935	0.984	0.953	0.965	0.932	0.970	0.982	0.954
17	1.057	1.024	0.986	0.964	0.974	0.896	1.018	0.976	0.989	0.953	1.017	0.995	0.974
18	1.047	1.015	1.001	0.970	1.017	0.945	1.005	0.978	0.988	0.951	1.015	0.993	0.967

Completed UI Duration of 6 Months

-5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
-4	0.995	0.993	0.991	0.994	0.984	0.973	0.989	0.988	0.992	0.988	1.045	0.995	0.998
-3	1.030	0.998	0.990	0.987	0.998	0.945	0.992	0.983	0.994	0.975	1.010	0.993	0.993
-2	1.041	1.006	0.980	0.979	0.991	0.986	0.987	0.964	0.993	0.952	1.095	0.990	0.988
-1	1.113	0.980	0.966	0.907	0.952	0.942	0.936	0.891	0.985	0.843	1.111	0.972	0.947
0	1.150	0.996	0.949	0.902	0.921	0.955	0.949	0.873	0.965	0.468	0.973	0.977	0.947
1	1.081	0.997	0.931	0.913	0.940	0.931	0.961	0.809	0.869	0.340	0.936	0.928	0.940
2	1.047	0.986	0.905	0.903	0.942	0.852	0.949	0.805	0.861	0.316	0.938	0.903	0.921
3	1.028	0.973	0.902	0.885	0.902	0.821	0.941	0.781	0.848	0.300	0.895	0.881	0.902
4	0.999	0.960	0.896	0.875	0.910	0.853	0.937	0.799	0.856	0.314	0.885	0.878	0.898
5	1.013	0.952	0.900	0.873	0.891	0.836	0.921	0.796	0.869	0.318	0.848	0.880	0.897
6	0.947	0.843	0.874	0.778	0.792	0.725	0.814	0.578	0.764	0.435	0.752	0.815	0.811
7	0.917	0.868	0.879	0.810	0.798	0.771	0.830	0.633	0.795	0.498	0.812	0.830	0.830
8	0.910	0.872	0.863	0.813	0.808	0.765	0.846	0.666	0.806	0.539	0.788	0.827	0.832
9	0.910	0.868	0.872	0.794	0.799	0.765	0.842	0.680	0.806	0.567	0.796	0.830	0.829
10	0.920	0.884	0.882	0.835	0.822	0.819	0.865	0.707	0.824	0.597	0.846	0.839	0.846
11	0.934	0.895	0.883	0.837	0.833	0.795	0.873	0.723	0.836	0.618	0.825	0.851	0.857
12	0.934	0.908	0.923	0.859	0.851	0.842	0.897	0.739	0.843	0.640	0.847	0.862	0.866
13	0.948	0.919	0.911	0.862	0.845	0.825	0.912	0.757	0.858	0.665	0.920	0.868	0.877
14	0.970	0.912	0.899	0.865	0.867	0.773	0.906	0.779	0.866	0.684	0.904	0.870	0.876
15	0.957	0.929	0.892	0.877	0.877	0.800	0.925	0.778	0.863	0.694	0.894	0.883	0.884
16	0.959	0.928	0.930	0.875	0.853	0.837	0.930	0.792	0.870	0.697	0.877	0.882	0.884
17	0.968	0.938	0.908	0.886	0.851	0.828	0.945	0.806	0.882	0.713	0.904	0.890	0.890
18	0.960	0.943	0.923	0.877	0.895	0.837	0.933	0.814	0.886	0.731	0.943	0.892	0.905