Unemployment benefits and consumption smoothing: Cross-state study from the U.S. *

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Abstract

Unemployment insurance programs have three common parameters: weekly benefit amount, potential benefit duration, and payment frequency. Exploiting variations in these dimensions across American states over time as well as deterministic kinks in the policy schedule, I study their effects on the ability of unemployed workers to smooth their consumption relative to that in employment periods. Using quarterly micro data, I find that weekly benefit amount plays the most important role in helping unemployed workers smooth consumption, namely in food and nondurables. Payment frequency also has a modest smoothing effect, while potential benefit duration rarely plays a significant role.

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1 Introduction

Unemployment is perhaps one of the most negative and prevalent income shocks that workers might face. Consequently, unemployment insurance (UI) is a major integral part of labor market institutions in most countries. UI provides the much-needed temporary liquidity to help workers smooth consumption during unemployment spells (Gruber 1997), but also gives rise to moral hazard costs as unemployed workers are disincentivized to look for a new job. While the welfare costs of UI programs' generosity have attracted great interest, less is known about their consumption smoothing benefits. In this paper I ask the question: how do different dimensions of UI programs affect unemployed workers' consumption smoothing ability?

In specific, state-administered UI programs in the U.S. share three common features. First, the benefit level that unemployed workers are entitled to is a function of their past labor earnings. Second, UI compensation is limited to a certain potential duration threshold, above which workers no longer receive their benefits. Third, benefit payments are made at deterministic frequency, namely weekly or biweekly. While benefit level and duration enhance consumption smoothing during unemployment by guaranteeing the compensation of lost income over a certain time period, frequency of benefit payments matters for workers facing borrowing constraints by providing more regular liquidity. The focus of this paper is on quantifying these effects in parallel.

My contributions are twofold. First, this paper is the first, to the best of my knowledge, to study consumption smoothing effects of different dimensions of UI programs *simultaneously*. As to be discussed in the literature review, most studies have so far focused on one dimension in isolation, namely benefit amount, while ignoring others. This approach omits other potentially relevant channels of UI benefits can help smooth consumption during unemployment. Second, earlier work on the smoothing effects of UI programs employ *annual* panel data with limited scope of consumption. Instead, for my analysis I use rich panel data from the Consumer Expenditure Survey (CEX) which contains detailed information on different expenditure categories at household level. The data is collected every quarter, thus able to also capture responses to unemployment spells lasting less than one year.[1]

For identification I exploit institutional variations along the three aforementioned features of UI programs across American states and over time, which I show to be substantial. From the CEX I also know each households' state of residence as well as its primary earner's labor earnings and number of non-working weeks within twelve months before the interview. I consider only the primary earners, or heads, as their earnings are of first order importance to the households' income and consumption (Browning & Crossley 2001). As a result, I can assign each household head to a particular *eligible* UI schedule, should they experience any job displacement between interview rounds, and then evaluate the smoothing effect of the three features on different consumption categories.

One challenge is the possibly endogenous relation between UI benefit amounts, which directly depend on previous earnings, and households' ability to smooth consumption. I circumvent this issue by exploiting exogenous state-specific, time-varying maximum unemployment benefit thresholds in an ideal *regression kink design* (Card et al. 2015). These ad hoc ceilings create sharp kinks in the assigning rule from earnings to ben-

[1]According to OECD labor statistics, about 75% of unemployment spells in the U.S. between 2000 and 2020 last less than 6 months.

efit amounts, facilitating meaningful comparison of workers slightly below and above the cut-off level in the same fashion as in standard regression discontinuity design framework.

Overall, I find that weekly benefit amount significantly smooths unemployed workers' expenditures in most consumption categories, with the largest magnitude in food. A one-hundred-dollar increase in weekly benefit amount helps smooth consumption fluctuations over a year by between 0.3% and 0.5% on average. The effects are also strong for semi-nondurable items (healthcare, education, reading), while not affecting durables. Meanwhile, potential benefit duration does not have significant effects on consumption smoothing in general. The frequency in which UI benefits are paid matters for food consumption smoothing, conditional on liquidity at hand. Moreover, the smoothing effects of benefit amount are cyclical, while those of payment frequency are counter-cyclical.

Two upfront caveats are in order. First, I ignore the moral hazard aspect of UI programs in my analysis. Thus, my results should be interpreted as the upper bound when labor supply incentives are not distorted. Second, I calculate *eligible* UI benefit amounts and *potential* duration instead of the *actual* amount and duration. Consequently, my results are intention-to-treat effects instead of treatment-on-the-treated. Nevertheless, mine are free from endogeneity in the decision of workers to take up benefits and more policy relevant, as explained in Gruber (1997) and East & Kuka (2015).[2]

Related Literature: The operation of UI programs inherently entails a trade-off

[2]Policymakers are generally interested in setting the parameters of UI programs for the average worker who *might* lose her job and then *might* claim benefits.

between moral hazard costs and consumption smoothing gains. Due to the size and the importance of UI programs within the welfare system, economists have long been interested in the consequent optimal design of UI. Notable papers in this literature strand are Chetty (2008), Schmieder & Von Wachter (2016), Kolsrud et al. (2018), Ganong & Noel (2019).

Several papers have examined the "cost" side of UI programs, namely the effects on unemployment duration and labor supply behaviors (see **?**, **?**, and **?**, among others). For example, Landais (2015) studies UI benefit schedules across a few American states and finds the negative effects of higher benefit level and longer potential duration on unemployed workers' search effort. Card et al. (2015) also reach the same conclusion for the behavioral cost of benefit level in the context of Austria. Meanwhile, abrupt cuts in the potential duration of UI benefit significantly push unemployed workers back to employment, as documented by Hagedorn et al. (2016) and Johnston & Mas (2018). More recently, Zhang (2021) explores the frequency dimension of UI payments, finding that workers have higher reservation wage and exert less search effort for new jobs when their states switch from biweekly to weekly UI payment schedule. My paper examines all three features of UI programs discussed by this literature strand, but focuses solely on their effects on consumption smoothing instead of their moral hazard aspect.

Much less has been done on the "benefit" side of UI programs. Gruber (1997) finds evidence supporting the substantial smoothing role of UI benefit amount in the U.S. context. Later East & Kuka (2015) also show that the smoothing effect varies over time, being stronger in the 1970s than in the 1990s due to the relative low unemployment rate and less generosity in UI during the latter. Both studies use the Panel Study of Income Dynamics (PSID) and therefore are restricted to observing food consumption only. Meanwhile, using recent CEX data, I can evaluate multiple categories of expenditures at the same time. Browning & Crossley (2001) study the smoothing effects of multiple statutory changes in UI rules in Canada between 1993 and 1995 on a wider range of expenditures. However, they can only observe workers who had been continuously separated from the prior jobs for 26 weeks or more at the first interview. In contrast, my sample includes also shorter-term displacement spells, which make up the majority of unemployed cases.

The rest of the paper has the following structure. Section 2 introduces the institutional background about UI programs in the U.S. and variations along the three dimensions of interest across states and time. Section 3 decribes the data source and the sample for empirical analysis. Section 4 discusses the methodological approach. Section 5 presents the main results and robustness checks. Section 6 concludes.

2 Institutional Background

Although UI regulations vary across states, they often share common eligibility requirements for claimants. First, workers must have earned a sufficient amount from their jobs during a *base period* spanning from two to four quarters before the unemployment spell. The qualifying amount typically ranges from a few hundreds to a few thousands dollars across states. Next, they must have been laid off from their previous job instead of quitting *and* by reasons other than their own faults. Finally, they must demonstrate that they have been actively searching for a new job every time they file a new claim. Not every unemployed worker who is eligible for UI benefits decides to file a claim, however, leading to an average take-up rate of less than 60% (Anderson & Meyer 1997 and Kuka & Stuart 2021).

In the remaining part of this section I discuss the institutional background and demonstrate the variations of UI programs in the three dimensions of interest across states and time.[3] For regulations on benefit levels and benefit duration, I use archived semiannual state law publications consolidated by the Employment & Training Administration (ETA), U.S. Department of Labor. The data is published every January and July, covering every state in the U.S. and containing information about how, within each state, the weekly benefit amount as well as the potential benefit duration is calculated. For benefit claiming frequency, I use data from Zhang (2021) who summarizes historical audit information from the Benefit Accuracy Measurement program. Also recorded by the ETA, the program randomly samples UI benefit claimants every week from each state and checks if they have been incorrectly denied, underpaid, or overpaid. Relevant to my purpose, the data has information about the most prevalent frequency of claims filing in the state, which is then designated as the statewide benefit payment frequency.

2.1 Weekly benefit amount

The amount of UI benefit that a worker can claim for each week of unemployment ("weekly benefit amount," or WBA) depends on her labor earnings prior to the

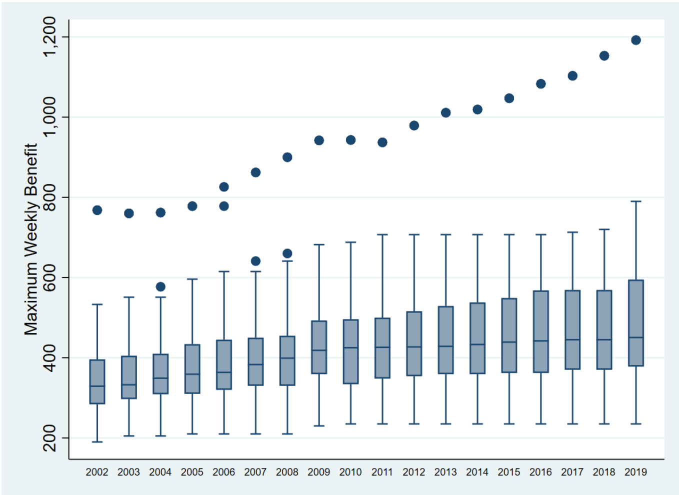
[3]State-level data fully covers the period that I focus on in this paper, namely from 2002 to 2019.

job loss. Specifically, this amount equals a fixed fraction of the total wage received within the calendar quarter with the highest earnings during the base period (so-called "highest quarter wage"). The fraction varies across states, but typically falls within the range from 1/29 to 1/21. In case the worker earns the same earning every quarter before the unemployment spell, the weekly benefit translates to roughly 50% of the pre-unemployment weekly earnings. On top of that some states provide allowance per payment based on the number of dependents.

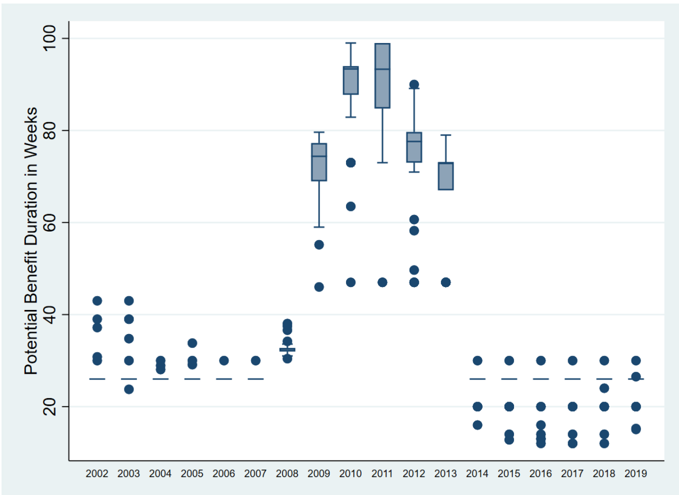
Nevertheless, higher pre-unemployment earnings do not always imply higher benefit amounts, as every state also has a specific weekly UI benefit cap stipulated in absolute dollar value. The actual amount that an unemployed worker can receive is the lesser between this cap and the fraction of her base period earnings. Figure 1a depicts the variation of benefit level caps across states over time. For each year the shaded rectangle box represents the 25th-to-75th-percentile span, the line within it expresses the median, while dots are outliers. We can see that since 2002 there is not only an overall upward trend in the median benefit ceilings, which is due to rising costs of living, but also a widening difference in these ceilings among states. These features are attributable to the rising generosity in the upper tail of the distribution while the lower tail is generally stable.

2.2 Potential benefit duration

In general there are two ways in which the potential benefit duration (PBD) can be determined for a claimant. On one hand, there are ad hoc hard ceilings, typically 26 weeks, stipulated by the state law that the benefit duration cannot exceed. Some



(a) Weekly Benefit Caps (current $)



(b) Maximum Potential Benefit Duration (weeks)

Figure 1: UI dimensions distribution between 2002 and 2019
Source: Employment & Training Administration.
Note: Boxplots illustrate distribution across states over time. Boxes' lower (upper) bounds denote the 25th (75th) percentile. Horizontal line within each box is the median. Whiskers span 1.5 times the interquartile range from each bound. Dots are outliers.

states allow uniform PBD at these levels for every eligible worker. On the other hand, some states also regulate the maximum benefit amount payable during the whole unemployment spell to not be higher than a certain fraction, normally ranging from 1/2 to 1/4, of total earnings in the base period. This results in technical ceilings of potential benefit weeks which are restricted to the quotient of total benefit amount divided by the eligible WBA. If these technical ceilings are larger than the ad hoc ones, the latter prevail.[4]

Figure 1b illustrates the variations of maximum PBD (hard ceilings) over state and time. Before 2008 duration caps among states are quite uniform at 26 weeks, with only a few exceptions expressed as dots. To ameliorate the fallout of the Great Recession, the Obama administration passed the Emergency Unemployment Compensation Act in June 2008 (EUC08) to extend the UI benefit duration in all states by federal funds. The Act was re-authorized multiple times (in "Tiers"), each with some extra weeks of benefit entitlement, by the Congress until it was terminated abruptly in December 2013. The historical data of EUC08 extensions comes from the Department of Labor.

In conjunction with the EUC08, during episodes of high unemployment within a state, the Federal-State Extended Benefits (EB) also automatically came into effect with additional duration provision of either 13 weeks or 20 weeks after exhaustion of both regular UI and EUC08.[5] Within my sample period, EB program was triggered on in some states before 2006 and then in many states between 2009 and 2012, resulting in the colloquial "99ers" cohort - unemployed workers with up to 99 weeks of UI

[4]Technical ceilings can be lower and prevail if, for example, workers earn most of their qualifying base period wage in one or two quarters, thus are entitled to a relatively large WBA compared to their total earnings.

[5]In particular, the extension is based on the moving average of either insured unemployment rate (IUR) or total unemployment rate (TUR). States have the choice between these two options.

benefits altogether. I hand-collect the specific length of multiple extensions at state level between 2002 and 2019 using the Trigger Notices on the Department of Labor's website.[6] Table 1 summarizes the details of these extension programs. After 2014 benefit duration caps became generally less generous but still diverged, ranging from 12 weeks in Florida to 30 weeks in Massachusetts as in January 2019.

Program	**Date in Effect**	**Weeks**	**Trigger Condition at State**
EUC08 Tier 1	June 30th 2008	13	
EUC08 Tier 1 Upgrade	November 21st 2008	7	
EUC08 Tier 2	November 21st 2008	13	Unemployment rate > 6%
EUC08 Tier 2 Upgrade	November 6th 2009	1	
EUC08 Tier 3	November 6th 2009	13	Unemployment rate > 6%
EUC08 Tier 4	November 6th 2009	6	Unemployment rate > 8.5%
EB	2009-2012	13 (20)	State-specific rules

Table 1: UI benefit duration extension from 2008 to 2013
Source: Employment & Training Administration.

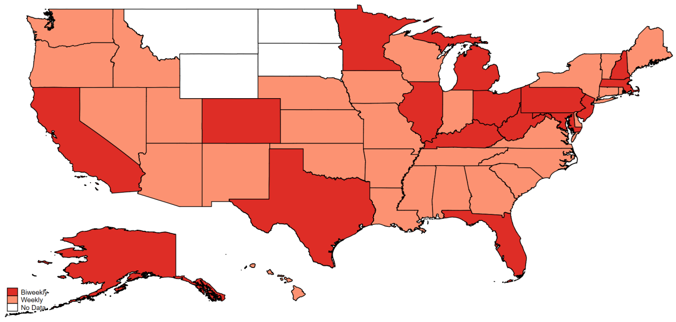
2.3 Payment frequency

The frequency of UI benefit payments is indeed the rate at which unemployed workers can file their claims with the state labor authority. As one condition of continuous eligibility for UI benefits is the active search for a new job, workers must "re-certify" their claims every one or two weeks, depending on the state, in order to document their searching efforts. Payments often follow a few days after each re-certification. If workers file their claims every two weeks, each payout sum would be their entitled weekly benefit amount doubled.

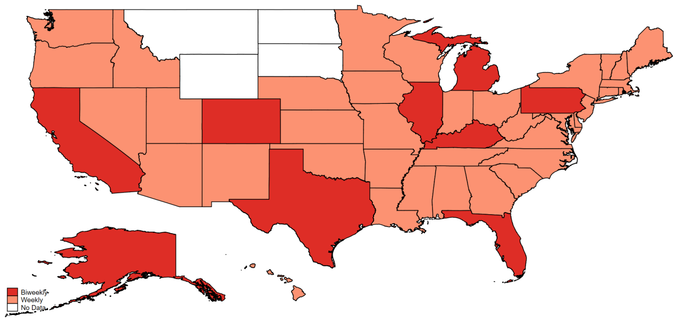
Figure 2 demonstrates the change in UI claim filing frequency across states between January 2002 and July 2019. At the begin of 2002, the majority of American states

[6] The data is archived online at `https://oui.doleta.gov/unemploy/claims_arch.asp` .

have already allowed eligible unemployed workers to file their claims every week. By the later half of 2019, several states in the North Eastern region have also switched from biweekly to weekly UI payouts. Nevertheless, there are still 9 states adhering to the biweekly frequency, among them some with the largest labor forces in the nation such as California, Texas, and Florida. Notably, Ohio allows both weekly and biweekly filing, but most claimants opt for the latter, making it a weekly-UI-paying state in practice (Zhang 2021).



(a) January 2002



(b) July 2019

Figure 2: UI benefit payment frequency distribution across states
Source: Employment & Training Administration. Dark color denotes biweekly frequency, light color denotes weekly frequency. No consistent data available for Montana, North Dakota, South Dakota, and Wyoming.

3 Micro Data

For my analysis I use the CEX Interviews data from 2002 to 2019. I focus on this period for the practical reasons of data availability as well as avoidance of COVID-19 related restrictions on consumption. The American-representative CEX Interviews have a panel structure and are conducted every quarter for around 5,000 households. After a maximum of four such consecutive interviews, households are rotated out of the sample and replaced by new ones. The information is collected on a recall basis, i.e. households provide details about their various categories of expenditures in the last three months.

Compared to other widely used public micro datasets, CEX's strength lies in the comprehensiveness of expenditure items, while its main weakness is the coarse coverage of income and finance. Only at the first and last rounds of interview are household members asked about their worked weeks and earnings during the last twelve months. No further information is given about their exact employment history or status at the moment. Additionally, the interviewer inquires about the households' financial assets and debts at the time of the last interview and twelve months before that.

3.1 Sample Selection

To connect the expenditures data at the household level to the earnings and employment data at individual level, I focus on the primary earner in each household, defined as the one making more than half of that household's labor earnings throughout the year. If primary earners declare themselves non-earners in subsequent interviews, I only keep those still actively looking for jobs. If there is a change of the primary earner between interviews, I drop the households entirely for consistency. Moreover, I also drop those with incomplete consumption or employment profile, with self-employment income or with non-positive before-tax income or food consumption. For better comparability within the sample I keep only workers who are in their prime age (from 25 to 55 years old) and at the time of their first interview report having worked 52 weeks and earned at least $4,000 in current-dollar wage during the past twelve months.[7] These filters make sure that those workers have been in continuous employment, earned adequate income, and thus are in theory entitled to UI benefits if they lose their job at a later point. Since most states require a waiting-time of one week between the termination of the last job and first filing of UI claim, I exclude people reporting only one week of unemployment. Additionally, I drop observations with missing or top-coded salary and wealth data.[8] Finally, I drop employees in armed forces, farming, forestry or fishing industry.

3.2 Variables Construction

3.2.1 Dependent Variables

While we are interested in consumption, the CEX contains only expenditures data which can approximate consumption only to a limited extend. As a result, I follow

[7]Among over 10,000 heads having worked 52 weeks before the first interview, only 84 have earned less than $4,000.

[8]Between 2004 and 2006 the CEX did not collect information on salary earned in the prior twelve months. Therefore, I impute this figure for this period from the last paycheck earned and the paycheck frequency (weekly, biweekly, or monthly). The underlying assumption is that workers earns a similar amount every working week.

the standard literature (Krueger & Perri 2006, Fernández-Villaverde & Krueger 2007) and consider four categories of observable expenditures, each one a subset of the one before it: food, strictly nondurable, nondurable, and total. Food expenditures are self-explanatory, containing both food at home and away. Strictly nondurable goods and services include, besides food, alcohol beverages, tobacco, utilities, personal care, household operations, public transportation, gas and motor oil, entertainment and miscellaneous expenditures. Nondurable goods and services further extend the scope to health care without insurance, education, and reading. Finally, total expenditures encompasses every expenses of the households over the referred period. Each expenditure item is discounted to the 2000 U.S. dollars using the appropriate series of the Consumer Price Index.[9]

For each of the four expenditure categories above, I construct the measure of log consumption changes, which is the antithesis of smoothing effects and thus the main focus of my subsequent analysis, as:

$$\Delta C = \sum_{j=2}^{4} |\log C_j - \log C_{j-1}| \tag{1}$$

where C denotes expenditures in interview round j. The formula 1 calculates the sum of absolute oscillation in the expenditure category between consecutive quarters. A smooth consumption profile throughout the year, after controlling for observable characteristics and fixed effects, implies a relatively small value of ΔC. This choice of measurement is helpful in tackling the main weakness of the data: lack of detailed employment history. For my purpose, formula 1 can catch any inter-quarter changes

[9] I use separate CPI series for each respective category in order to take into account also the contemporary price effects which might cause consumption fluctuations.

in consumption without the need to identify the contemporary employment status.[10]

3.2.2 Independent Variables

In order to construct variables for earnings and employment from the CEX data, I need to make two further assumptions: (1) people are paid the same amount every week during the periods in which they are employed and (2) those observing positive weeks of non-work in the data were all fired instead of quitting. Let hqw_i be the quarterly earning of worker i as implied by the salary reported in the first round and τ_{st} being the UI benefit fraction in her state s at time t as reported by the ETA. The *eligible* WBA is then calculated for every worker in the sample *without* taking benefit caps into account:

$$WBA_{ist} = hqw_i \times \tau_{st}. \tag{2}$$

This amount is theoretically expected by everyone at the time of the first interview in case they are to lose their jobs in the next twelve months. The reason for momentarily disregarding the benefit caps is the application of the regression kink design framework, which I clarify in the next section.

Last, I extract individual unemployment information from the number of weeks that the person works, including paid vacation and sick leave. The exposure to unemployment UD in the 12 months prior to the last interview is then the number of *non-working* weeks. Among workers exposed to at least an unemployment spell in

[10]For instance, if I use the largest quarterly consumption change to measure smoothing I would need to know the quarters in which unemployment spells occur for identification. Similarly, if I use the gap between consumption in first round and the average across the other rounds, I would need to know the duration of each specific spells.

my sample, the majority of these workers are left without a job for less than 13 weeks, while more than 75% are unemployed for less than 24 weeks within the year, and only a small fraction face long-term or recurrent unemployment (40 weeks or more).

3.3 Descriptive Statistics

I summarize the main variables for the "employed" and "unemployed" group within the sample in Panel A of Table 2. The former have zero exposure to unemployment between the first and fourth round, while the latter have at least two weeks of non-work. Within the unemployed group, I further split them by total number of non-working weeks into short (less than 12 weeks), medium (between 12 and 26 weeks), and long exposure (more than 26 weeks). We can notice that despite similarities in age and family size, the group exposed to unemployment are more likely to be female and less likely to be college graduates. These factors might play a role, among others, to explain their lower average salary and hourly wage compared to the fully employed group.

Among those exposed to unemployment, three noticeable patterns emerge. First, workers with medium unemployment exposure (between 12 and 26 weeks of non-work) are more likely to be female and college-educated than those with either small or large exposure. Second, the number of non-work weeks does not correlate with any indicator of labor earnings, but slightly increases in household income from other sources. Last, people who maintain full employment following the first interview are more likely to be male, college-educated, and have higher income, both in salary and wage, than those exposed to unemployment. This discrepancy suggests considerable

Panel A: Demographic Summary of Sample

Characteristics	Exposed to Unemployment (in weeks)				Fully employed	Total
	< 12	12 - 26	≥ 27	*Total*		
Demographics						
Age	40.47	39.77	40.74	40.31	40.94	40.88
Male share (%)	57.86	47.10	59.42	54.94	62.13	61.41
Family Size (persons)	2.98	2.85	3.09	2.97	2.98	2.98
College Degree (%)	44.27	52.58	44.44	46.80	52.19	51.65
Income						
Pre-unemployment salary	39,595	40,144	39,070	39,655	47,294	46,524
Pre-unemp. hourly wage	17.39	18.77	17.43	17.81	20.86	20.55
Other income sources	32,133	32,907	34,922	32,925	34,391	34,243
N	515	310	207	1,032	9,211	10,243

Panel B: Consumption Smoothing Measurements ΔC

Classification	N	Food	Strict nondur.	Nondur.	Total Exp.
Full Sample	10,243	0.998***	0.831***	0.890***	0.838***
Fully Employed (1)	9,211	0.988***	0.827***	0.885***	0.832***
Exposed to Unemployment (2)	1,032	1.092***	0.872***	0.936***	0.892***
Difference (1)-(2)		-0.104***	-0.046***	-0.051***	-0.061***
Among the Exposed					
$WBA < \overline{WBA}$ (3)	489	1.127***	0.859***	0.933***	0.876***
$WBA \geq \overline{WBA}$ (4)	543	1.062***	0.884***	0.939***	0.907***
Difference (3)-(4)		0.065	-0.025	-0.006	-0.032
$UD < PBD$ (5)	886	1.094***	0.864***	0.931***	0.885***
$UD \geq PBD$ (6)	146	1.081***	0.922***	0.965***	0.936***
Difference (5)-(6)		0.014	-0.058	-0.034	-0.050
Weekly filing (7)	498	1.086***	0.846***	0.926***	0.899***
Biweekly filing (8)	534	1.098***	0.897***	0.945***	0.886***
Difference (7)-(8)		-0.012	-0.051	-0.019	0.013

Statistical significance:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Descriptive Statistics

Note: CEX first-round Interview Data 2002-2019. Observations conditional on working fully 52 weeks during 12 months before the first interview. Average salary, hourly wage, and other income are also reported for this period. *Panel A:* Monetary values are in 2000 US$. *Panel B:* WBA is weekly benefit amount, $\overline{WBA}$ is benefit cap. UD is number of non-working weeks, PBD is the potential benefit duration. Differences report the t-test results.

heterogeneity in employment stability across observable characteristics.

Finally, I summarize in Panel B of Table 2 consumption smoothing by different categories of log consumption change ΔC among the two groups by employment status and, among those exposed to unemployment, along the three dimensions of UI programs. The changes are all statistically significant for the whole sample and for every sub-samples that I look at. The implication is that expenditures, especially for food, tends to vary over time. This variation holds even for the fully employed group, although to a significantly lesser extent than for the unemployment-exposed group. Among the latter, there is little evidence of differences in consumption changes around the caps on eligible benefit amount, between different degrees of exposure to unemployment, or between a weekly and a biweekly payment schedule.

4 Empirical Strategy

Out of the three dimensions that we are interested in, unemployment benefits are known to be haunted by the problem of endogeneity when used for assessing consumption smoothing (East & Kuka 2015).[11] The reason is that the benefit amount is calculated by a function of pre-unemployment labor earnings, so any unobservable factors determining wage can also potentially affect consumption decicions. To circumvent this issue, I follow Card et al. (2015) and Landais (2015) and exploit the exogenous nature of state-wide benefit caps. Those deterministic ceilings impose a kink in the slope between previous wages, or the running variable, and the benefit

[11] While unemployment duration might also be endogeneous to consumption smoothing, the maximum potential benefit duration, which I focus in this paper, is not.

amount, or the policy variable. The appropriate method for causal inference in this situation is a *sharp* Regression Kink Design (RKD).[12]

4.1 Regression Kink Design

The main idea behind RKD is similar to that of standard regression discontinuity design (RDD): workers around an exogenous threshold are likely to be comparable but randomly assigned to different policies, which are unemployment benefits in this case. Different from RDD, in which there is a discontinuous jump in level of the treatment at the threshold, RKD focuses on the abrupt change in the treatment's *first derivative*, or a kink, at the cutoff (Card et al. 2015). Estimation also involves a local polynomial regression around the cutoff level as in the case of RDD except that the "shifting" intercept indicating exposure to treatment would be absent as we do not expect discontinuity. Formally, let Y be the outcome, V the observable running variable, and $X = x(V)$ the regressor of interest that is a deterministic function of V and has a kink at $V = 0$. Card et al. (2015) show that the weighted average marginal effect of X on Y is then

$$E[Y|V=0, X=x(0)] = \frac{\lim_{v_0 \to 0^+} \frac{dE[Y|V=v]}{dv}|_{v=v_0} - \lim_{v_0 \to 0^-} \frac{dE[Y|V=v]}{dv}|_{v=v_0}}{\lim_{v_0 \to 0^+} x'(v_0) - \lim_{v_0 \to 0^-} x'(v_0)}. \quad (3)$$

The identification strategy for RKD works under two assumptions. First, all covariates other than the running variable must have twice differentiable conditional expectation around the kink point. I validate this assumption for the regression con-

[12] I assume that everyone is a complier with respect to the assignment rule. This setting is also used previously by Landais (2015).

trols by providing graphical evidence in Figure A1 (see Appendix). Specifically, I plot the equally-sized bin-averages of age, education levels, other household income, post-unemployment earnings, weeks of non-working, and pre-unemployment net liquidity against the eligible weekly benefits normalized by the respective caps.[13] There are no visible significant changes in slope, i.e. from negative to positive or vice versa, of any these variables at the kinks.

Second, the assignment variable must have a smooth density around the kink point. In our context, people should not manipulate their labor earnings in order to affect their expected unemployment benefits and sort themselves relative to the kink point. There are practical reasons to believe in the validity of this assumption. Since the cutoff level in UI benefits might be adjusted every year, it is impossible to manipulate one's earnings *one year* prior to the supposedly unexpected laid-off date.

Still, for concrete evidence, I implement a manipulation test in the spirit of McCrary (2008) and Cattaneo et al. (2020) for the log ratio of eligible weekly benefits to the benefit cap. The result of the test shows no evidence supporting the possibility of self-selection, validating the assumption. Graphically, there is no bunching of observations at either sides of the kink, as can be seen in Figure 3.

4.2 Specification

Within the region $[-h, h]$ around the kinks in weekly benefit amount, h being the bandwidth, I run the following regression for household head i in state s at time t

[13] In all graphs depicting the cutoff, I use the log of weekly benefit-to-cap ratio for scaling.

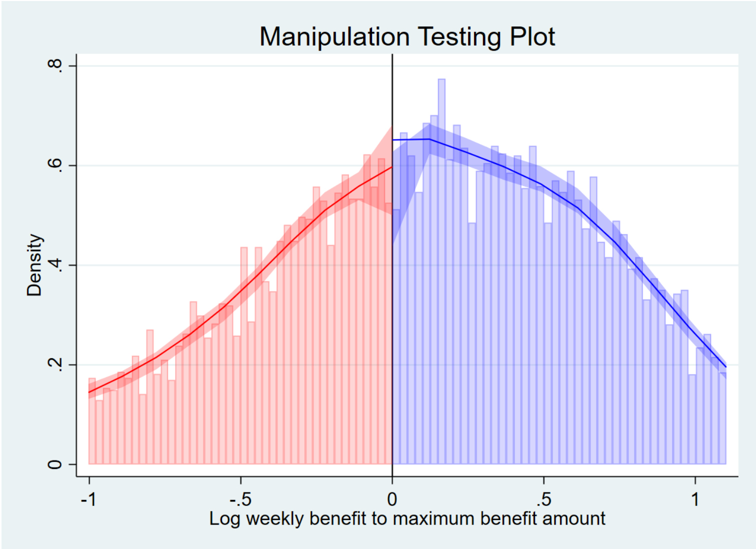


Figure 3: Graphical evidence for smooth density of running variable
Kink at 0. Eligible weekly benefit amount lie below the cap in the red region and above the cap in the blue region. The curves represent the kernel density. Shaded areas denote the 95% confidence interval. McCrary-type Test Statistics: 1.5343 (p-$value$ = 0.1250)

with standard error clustered at state level:

$$\Delta C_{ist} = \alpha + U_{ist} * \left(\sum_d \beta_{d,0} \widetilde{WBA}^d_{ist} + \sum_d \beta_{d,1} D\widetilde{WBA}^d_{ist} + \beta_2 PBD_{st} + \beta_3 Weekly_{st} Liq_{ist} \right) + \Theta_1 X_{ist} + \Theta_2 Z_{st} + \phi_t + \mu_s + \xi_{ist} \tag{4}$$

where

$$\widetilde{WBA}_{ist} = WBA_{ist} - \overline{WBA}_{st}$$

and

$$|\widetilde{WBA}_{ist}| < h.$$

Variable $\widetilde{WBA}_{ist}$ denotes the weekly benefit WBA in relation to the respective state-specific cap $\overline{WBA}$. The kink in benefit amount is therefore transformed to zero.

The RK specification for weekly benefit amount contains local polynomials of order d around the benefit caps. The dummy D_1 indicates whether WBA exceeding the benefit cap $\overline{WBA}$. U is the dummy variable which equals 1 if workers are exposed to unemployment between interviews. PBD is the maximum potential benefit duration, and $Weekly$ is the binary indicator of UI payment frequency (1 if weekly, 0 otherwise). The effect of payment frequency on consumption smoothing is expected to be conditional on liquidity constraint.[14] Therefore, I interact $Weekly$ with variable Liq, which is the ratio of net liquidity to earnings at the first interview. A smaller value of Liq thus implies a more constrained household.

Vector X contains workers' relevant controls: quadratic polynomials in age, gender, educational attainment, living in urban or rural dummy, marital status, changes in family size, number of children, income from other sources, post-unemployment salary, and pre-unemployment net liquidity.[15] Meanwhile, vector Z controls for state-specific time-varying economic characteristics, namely unemployment rate and per-capita expenditures on public welfare programs *other than* UI benefits.[16] Finally, ϕ and μ correspondingly denote time and state fixed effects.[17]

The variables representing three UI dimensions all appear in interaction with the unemployment dummy U. This specification explicitly imposes that the treatment

[14]Workers with adequate buffer wealth/ borrowing capacity can tap on their resources for consumption irrespective of UI payment frequency. In contrast, those facing constraints are better off in terms of consumption smoothing with more frequent liquidity streams, i.e. weekly benefits.

[15]Net liquidity is defined as the total liquid wealth such as checking deposits and money market instruments minus total liquid borrowing in the form of credit card debts, both dated one year before the fourth interview. For readability of estimates, I monotonically transform net liquidity a, which might be negative, into the log scale using the formula $\log(a + \sqrt{a^2 + 1})$.

[16]State-level unemployment rate is collected from the Bureau of Labor Statistics. Detailed data on personal current transfer receipts and unemployment insurance compensation by state is available on the website of the Bureau of Economic Analysis, while state population data is from the Census.

[17]Time fixed effects have two separate components, year and quarter, to capture also seasonality.

of interest is conditional on workers experiencing at least one unemployment spell. If worker i is fully employed during the 12 months prior to the last interview, i.e. $U_i = 0$, she belongs to the control group as UI programs' dimensions are not relevant to her. The inclusion of this control group is to address concerns about unobserved factors, e.g. local macroeconomic outlook, that affect both state-level UI policies and household consumption volatility.

The coefficients corresponding to the three UI dimensions denote their estimated smoothing effects on an unemployed worker's consumption compared to that of a fully employed worker. In specific, coefficients $\beta_{d,1}$ are the polynomial approximation of the change in slope of benefit amount above the kink. Within the RK framework, these are the one relevant for our interpretation. The other coefficients of interest are $\{\beta_2, \beta_3\}$, which respectively measure the effects of potential benefit duration and benefit payment frequency, the latter conditional on liquidity constraint, on consumption change. If a dimension helps smooth consumption during unemployment, we expect the associated coefficients to be negative.

Theoretically speaking, I could also implement the RKD procedure in a similar manner when evaluating the effect of potential benefit duration on consumption smoothing. While unemployment duration can be endogenous to the ad hoc hard ceilings, the technical caps imposed by the total benefit payment during unemployment, as discussed in Section 2, can serve as exogenous thresholds as shown by Landais (2015). However, I abstain from this analysis because the latter type of cap rarely binds in the sample. Keep in mind that I retain only workers who are fully employed for the whole year before the first interview, so these people have a relatively high labor earnings in the base period compared to the weekly benefit amount they are entitled to. As a result, their technical duration caps are generally higher than the state-wide hard ceilings and thus not relevant.[18]

5 Results

5.1 Benchmark Results

I run the regression 4 with four different measures of consumption change outlined before. For robustness checks, I alter the order of RK local polynomials between linear and quadratic, as well as the bandwidth h between \$300, \$500, and full sample in my specifications.[19] I report in Table 3 only the coefficients corresponding to variables of interest in this study, namely $\beta_{1,1}$, β_2, and β_3. I do not report $\beta_{2,1}$ for the quadratic specification which are statistically insignificant in all cases considered and informative only about the curvature rather than the level of the effect of interest. Note that the RK estimates, reported here as the coefficients of "Weekly amount" and their respective standard errors have been normalized by the deterministic change in slope of weekly benefit amount per Equation 3 to recover the treatment effects. This value equals $-\tau$, the UI fraction in Equation 2, as the slope before the kink is τ and after the kink is 0 due to the benefit cap.

[18]For example, denote hqw the highest quarter wage and assume the worker earns the same amount every working quarter. The base period wage is $4hqw$, and, with a typical fraction of one-third, the total benefit payment is $\frac{4hqw}{3}$. Dividing this amount by the typical weekly benefit of $hqw/26$ yields a duration cap of nearly 35 weeks.

[19]In general RK estimators require a wider bandwidth and a larger sample size than in the case of RDD (Card et al. 2015, Landais 2015).

	Linear			Quadratic		
	$h = \$300$	$h = \$500$	$h = \infty$	$h = \$300$	$h = \$500$	$h = \infty$
			Food			
Weekly amount	- 0.067***	-0.054***	-0.026**	-0.091*	-0.125***	-0.049
	(0.016)	(0.014)	(0.011)	(0.051)	(0.036)	(0.030)
Potential duration	-0.075	-0.043	-0.001	-0.076	-0.071	-0.015
	(0.076)	(0.076)	(0.069)	(0.075)	(0.081)	(0.069)
Weekly frequency	-0.044*	-0.070***	-0.067**	-0.043*	-0.074***	-0.068***
	(0.024)	(0.024)	(0.023)	(0.024)	(0.025)	(0.023)
AIC	15,773	18,768	20,888	15,769	18,764	20,881
			Strict Nondurables			
Weekly amount	-0.026*	-0.027***	-0.018**	-0.009	-0.044	-0.027
	(0.017)	(0.008)	(0.009)	(0.037)	(0.027)	(0.022)
Potential duration	0.048	0.049	0.041	0.059	0.046	0.033
	(0.069)	(0.081)	(0.074)	(0.068)	(0.080)	(0.074)
Weekly frequency	0.006	-0.016	-0.015	0.006	-0.017	-0.015
	(0.026)	(0.019)	(0.021)	(0.026)	(0.019)	(0.021)
AIC	12,298	15,210	17,373	12,297	15,209	17,360
			Nondurables			
Weekly amount	-0.036**	-0.038***	-0.031***	-0.040	-0.036	-0.038
	(0.016)	(0.010)	(0.008)	(0.048)	(0.046)	(0.029)
Potential duration	0.011	0.003	-0.013	0.016	0.004	-0.026
	(0.085)	(0.089)	(0.088)	(0.081)	(0.088)	(0.086)
Weekly frequency	-0.027	-0.011	-0.014	-0.028	-0.011	-0.013
	(0.025)	(0.021)	(0.022)	(0.025)	(0.021)	(0.021)
AIC	13,259	16,351	18,816	13,257	16,347	18,796
			Total Expenditures			
Weekly amount	-0.033	-0.020	0.049	-0.067	-0.010	0.002
	(0.024)	(0.012)	(0.006)	(0.087)	(0.044)	(0.024)
Potential duration	-0.022	-0.017	-0.061	0.007	-0.006	-0.061
	(0.080)	(0.086)	(0.084)	(0.083)	(0.089)	(0.085)
Weekly frequency	-0.058***	-0.008	-0.010	-0.057***	-0.006	-0.008
	(0.021)	(0.021)	(0.020)	(0.021)	(0.023)	(0.021)
AIC	15,904	19,110	21,327	15,900	19,106	21,323
Observations	7,658	9,151	10,243	7,658	9,151	10,243

Robust standard errors in parentheses, clustered at state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Baseline Regressions

Note: Coefficient estimates for WBA adjusted by slope change in UI schedule. h denotes the bandwidth around the kinks. AIC is the Akaike information criterion. Weekly amount in \$1,000. Potential duration in weeks over 52. See text for the full description of covariates.

Overall the negative coefficients of weekly amount and weekly frequency in most specifications suggest that these two dimensions help smooth consumption in all categories. Meanwhile, those of potential duration, all statistically insignificant, are negative for food but positive for strict nondurables and nondurables, while indeterminate for total expenditures. This result suggests that potential duration does not affect consumption smoothing of unemployed workers in general. Alternating between linear and quadratic formations of RK polynomials does not change the direction of treatment effects, but greatly decreases statistical significance of estimates in most cases. Nevertheless, the gaps in Akaike information criteria between the two choices of polynomials are not large. Moreover, the assigning rule from earnings to WBA is linear in nature below the kinks. Therefore, I choose the linear formation as the preferred specification for the rest of my analysis for simplicity.

Figure 4 provides further graphical evidence for my RK estimators. I plot the average changes in all four expenditures groups within bins against the log of weekly benefit amount normalized by benefit caps for those exposed to unemployment. The general pattern is clear: the negative slope to the left side of the kink indicates that UI benefits reduce compounded changes in expenditures, thus help smooth consumption up to the cap. The discontinuity in the benefit schedule's first derivative, triggered at the kink point, leads to sharp, significant reverses in slopes of all outcomes but total expenditures changes.

Weekly benefit amount help workers smooth their consumption in all categories except total expenditures. The economic significance is also substantial, as a *one-hundred-dollar* increase in eligible WBA decreases fluctuations in expenditures for

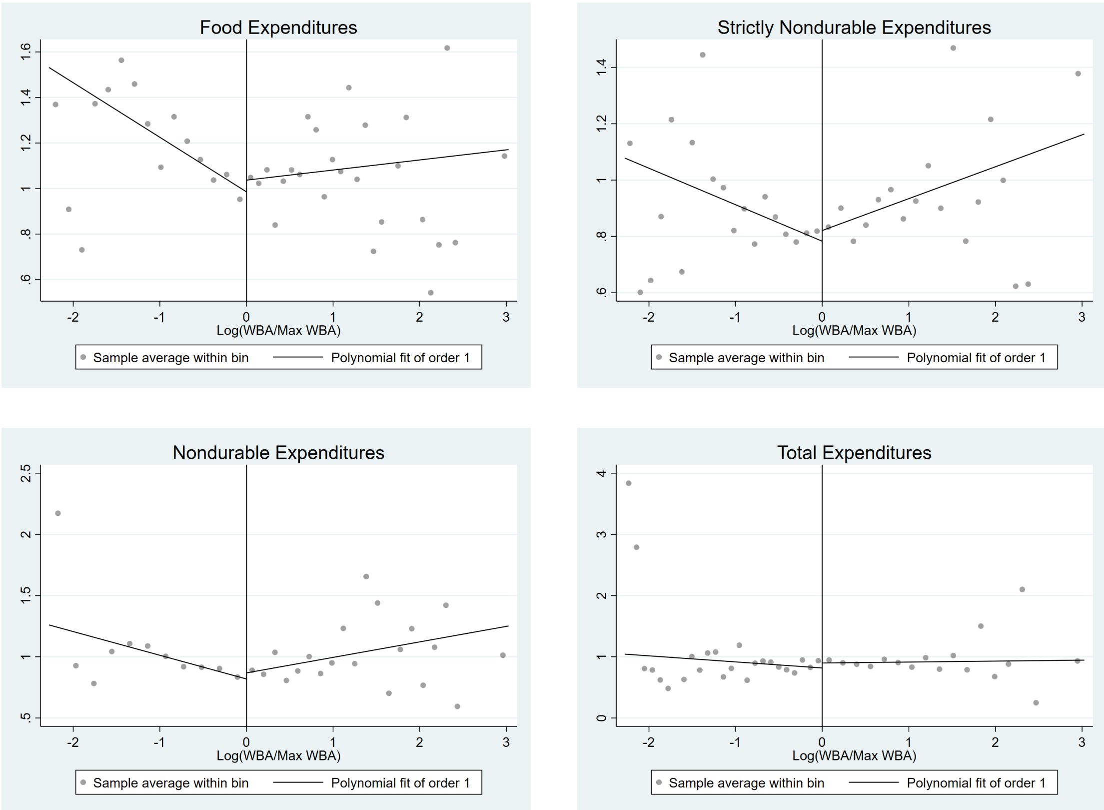


Figure 4: RKD Plots for log consumption changes against weekly benefit amount

Note: Kink of running variable at 0. Linear polynomial regression, full bandwidth. Each dot denotes the average consumption change of a bin on the horizontal axis. Only including workers at least once exposed to unemployment in past 12 months. Bins are selected by the mimicking variance evenly-spaced method using spacings methods.

food at the $500 bandwidth by 0.54% (strongest), for strict nondurables by 0.27%, and for nondurables by 0.38% on average. These effects become smaller in magnitude for the full sample, albeit still statistically significant, ranging from 0.18% to 0.31%. When we move to the specifications with $300 bandwidth, the effect of WBA becomes larger for food but slightly smaller for the two categories of nondurables.

These results have smaller magnitude than those of East & Kuka (2015), who look at PSID data from 1968 to 2011 and find that a 10-percentage point increase in replacement rate reduces year-to-year food consumption change during unemployment by 1% on average.[20] Their estimate is nevertheless driven by a high, significant smoothing component between 1968 and 1987 of nearly 3% per 10-percentage more generous replacement rates are, as in Gruber (1997), which dies out after the 1990s. My estimates are smaller yet still statistically significant, as I control also for the other two dimensions of UI, which are ignored in both of these two studies.

The frequency of UI benefits receipt also plays an important role, with weekly payments significantly smoothing food and, at the $300 bandwidth, total expenditures. The effects on food consumption are also strongest at the $500 bandwidth. The estimates can be interpreted in two ways. Evaluated at the average level of net liquidity, weekly UI benefits can reduce food consumption fluctuations by 0.43% to 0.74% compared to a biweekly payment pattern. Conditional on weekly frequency, these estimates inform us about the degree of consumption smoothing if net liquidity increases relative to earnings. Either way, the results illustrate the mechanism between liquidity constraint and smoothness in consumption.

[20] Back-of-envelope calculation indicates that, with average yearly earnings of over $46,000 as in my sample, a 10-percentage point increase in replacement rate translates into a $90 hike in WBA.

Since food expenditure is also a component of the other three categories, it is necessary to look at the responses of non-food items to variations in UI dimensions on their own. I run the regressions with linear RK specifications and the following categories as dependent variables: strict nondurables excluding food, nondurables excluding food, and semi-nondurables, i.e. items such as healthcare (excluding health insurance), education, and reading. The latter group is essentially the difference between strict nondurables and nondurables. The results are shown in Table 4. There are no statistically significant effects of WBA on the first category across all considered bandwidth lengths, implying that the smoothing responses of strict nondurables to WBA in Table 3 are mostly driven by food. As we move to the wider category of nondurables excluding food, the effects become negative and significant at the $500 bandwidth and above with around 0.40% less compounded fluctuations per $100 more of weekly benefit. This contrast implies that besides food, semi-nondurable items are also smoothed thanks to WBA. I confirm this impression by looking at the last category, whose estimates effects of WBA stand at 0.75 to 1%. Meanwhile, the absence of significant effects of UI benefit frequency across all categories shows that food is the main component of expenditures smoothed by a more frequent payment pattern, as shown in Table 3.

In summary, the baseline results indicate that benefit amount is by far the most important feature of UI programs in smoothing consumption, followed by benefit payment frequency, conditional on liquidity, with modest effects, and potential duration with no effect at all. The absence of the latter's effects can be attributed to the lack of granular variations in the data, where many states stipulate their hard ceilings at 26 weeks, except during the time of intensive extended benefits. Meanwhile, the fact that the three UI dimensions do not have significant smoothing effects on total expenditures agrees with the story of consumption commitment suggested by Chetty & Szeidl (2007). Expenditures on multiple goods and services, such as housing or insurance, are costly to adjust and thus resistant to changes in income.

	$h = \$300$	$h = \$500$	$h = \infty$
	Strict Nondurables excluding Food		
Weekly amount	-0.033	-0.021	-0.026
	(0.027)	(0.016)	(0.017)
Potential duration	0.160*	0.155	0.108
	(0.093)	(0.106)	(0.097)
Weekly frequency	0.082	0.054	0.050
	(0.090)	(0.060)	(0.062)
	Nondurables excluding Food		
Weekly amount	-0.050	-0.039**	-0.041**
	(0.031)	(0.018)	(0.015)
Potential duration	0.099	0.082	0.038
	(0.107)	(0.117)	(0.108)
Weekly frequency	0.022	0.045	0.038
	(0.096)	(0.071)	(0.072)
	Semi-nondurables only		
Weekly amount	-0.054	-0.103*	-0.075*
	(0.097)	(0.060)	(0.043)
Potential duration	0.226	-0.115	0.005
	(0.449)	(0.416)	(0.394)
Weekly frequency	-0.128	0.249	-0.276
	(0.150)	(0.313)	(0.305)
Observations	7,658	9,151	10,243

Standard errors in parentheses, clustered at state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regressions with Non-Food Categories

Note: Coefficient estimates for WBA adjusted by slope change in UI schedule. h denotes the bandwidth around the kinks. Linear RK polynomials. Weekly amount in \$1,000. Potential duration in weeks over 52. See text for the full description of covariates.

5.2 Heterogeneous Effects

I am interested in the heterogeneity of UI benefits' effects on workers of different exposure to unemployment by following two strategies. First, I re-run the regression for all unemployment-exposed workers ($UD > 0$), which gives me the smoothing effects of UI dimensions exclusively on this sub-sample. Due to the small sample size, I do not restrict the bandwidth in this case ($h = \infty$).[21] The results are shown in the first column of Table A1. Conditional on being exposed at least once to unemployment between the first and last interview, UI dimensions all have considerable and significant effects. A $100 increase in WBA significantly improves smoothing in all three considered categories by around 0.4%. A weekly pattern of benefit payments reduces fluctuations in food and strict nondurable expenditures by 0.22% and 0.13%, respectively, compared to a biweekly frequency. Potential duration also slightly helps smooth consumption in strict nondurables and nondurables. The effects are significant statistically but not economically at around 0.003% per one more week of UI.

Second, I also want to quantify the treatment effects on the worker with the *average* exposure to unemployment. Therefore, I replace the dummy U_{ist} in Equation 4 by the fraction of non-work weeks UD to 52 weeks. The next three columns of Table A1 show the results. Similar to the baseline, WBA has significant smoothing effects in all three categories at larger RK bandwidths, while potential duration does not. Weekly frequency dummy has significant estimates in the case of food and strict nondurables. It is noteworthy that the magnitude of the effects are larger for both WBA and payment frequency in all categories compared to the baseline in Table

[21] At this stage I omit the regression of total expenditures for brevity. All estimates of that analysis are statistically insignificant however.

3. For example, the worker with average exposure to unemployment in my sample (around 1.5 weeks of non-work in 12 months) can smooth food by 0.37-0.77% per $100 additional WBA or by 0.16-0.17% if UI payment is paid every week rather than biweekly.

Next, I also want to check if UI programs' effects change along the business cycle. I divide my sample into two sub-periods: one between 2008Q3 and 2013Q4 during the aftermath of the Great Recession when unemployment rate spiked up throughout the U.S. and many states extended the benefit duration, and one outside of this time interval. The regression results for these two sub-periods are reported in the last two columns in Table A1. Two interesting patterns stand out. For food and strict nondurables, the smoothing effects of weekly benefit amount are only statistically significant during episodes outside the Recession, except a positive, i.e. exacerbating, effect on nondurables. Meanwhile, during the Recession period fluctuations in food and nondurable expenditures are responsive to the payment pattern of UI. Overall the consumption smoothing effect of WBA seems to be cyclical, while those of frequency are counter-cyclical. This result stands in contrast to that of Kroft & Notowidigdo (2016), who find pro-cyclical moral hazard but non-cyclical consumption smoothing benefit of benefit amount. The explanation for this difference might lie in the fact that they use average benefit level for each state instead of individual, cap-subject amount as I do.

5.3 Further Robustness

Though quite comprehensive, the CEX data that I have used so far only records expenditures if there exist actual transactions for those during the interview period. That design essentially leaves out a sizable component of consumption: rental expenses for homeowners. Since these households do not pay rents, their presence, totaling 70% in my sample, might potentially dampen the true effects of UI on consumption smoothing. Therefore, as the first robustness check, I add imputed rents for these workers, collected directly in the CEX interviews, to strict nondurables, nondurables, and total expenditures.[22] The results are fundamentally similar to those of the baseline.

Next, I also change the way I measure consumption smoothing with my dependent variables. Instead of the compounded quarterly changes in expenditures as in Equation 1, I use the *maximal* absolute change in the last three interviews compared to consumption reported in the first interview, when workers are fully employed. The new consumption change $\Delta\tilde{C}$ has the form

$$\Delta\tilde{C} = \max(|\log C_j - \log C_1|)$$

with interview rounds $j = 2, 3, 4$. The results however remain the same as in the baseline regressions for all four categories.

The last robustness check targets the inherent endogeneity problem of unemployment exposure measure. I follow the two-stage strategy of Chetty (2008) and East & Kuka

[22] Households owning the dwelling in which they are living are asked how much, in their opinion, the place would have cost if rented out.

(2015) for the number of non-working weeks. In the first stage, I want to isolate the components in UD that are not explained by observables and potentially correlate with workers' ability to smooth consumption. To do this, I regress UD of the subsample exposed to unemployment on their individual characteristics vector X, the state-specific vector Z, and state and time fixed effects, i.e. variables included in the baseline regression other than UI programs' three dimensions. I then use the estimated coefficients from this regression to predict exposure $\hat{UD}$ for these workers which are free of unobservable variations. In the second stage, I use this predicted exposure measure in place of U_{ist} in Equation 4. In general, the patterns in the baseline regressions still persist here.

6 Conclusion

In this paper I study the simultaneous consumption smoothing effects of three fundamental features of UI programs across American states: the eligible benefit amount per week, the potential benefit duration, and the benefit payment frequency. The regulation regarding these three dimensions varies exogenously across states and time, creating the chance for clear identification. Moreover, I exploit kinks in the UI benefit schedule originated from state-specific ceilings in order to address the endogeneity concern about benefit amount. Using quarterly consumption data, I find clear evidence that more generous weekly benefit amount decreases fluctuations in workers' different expenditures categories during spells of unemployment. The effects are most notable for food and semi-nondurables such as healthcare, education, and reading, while absent for durable consumption. The benefit payment frequency in conjunction with liquidity level also has modest smoothing effects on certain categories, while potential benefit duration does not play a significant role. These findings shed light on a so far under-studied aspect of UI programs.

One limitation of this study is the exclusion of the moral hazard aspect of UI programs. If, for example, more generous UI both in benefit amount is granted, workers might actively extend their unemployment spells in length, possibly leading to a deeper drop in consumption before benefits eventually expire. Moreover, such generosity must also be viewed in conjunction with governments' budget constraints. Future work that aims to study consumption smoothing alongside endogenous unemployment duration, taking moral hazard into account either with better data or with an appropriate identification strategy, is promising from both academic and policy-making perspectives.

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A Appendix

	Only Exposed	**Interact with UD**			**Recession? ($h = \infty$)**	
	$h = \infty$	$h = \$300$	$h = \$500$	$h = \infty$	Yes	No
			Food			
Weekly amount	-0.041**	-0.076*	-0.077**	-0.037**	0.002	-0.027*
	(0.017)	(0.038)	(0.031)	(0.016)	(0.014)	(0.015)
Potential duration	-0.136	-0.124	-0.093	-0.012	-0.019	0.120
	(0.102)	(0.081)	(0.079)	(0.070)	(0.089)	(0.189)
Weekly frequency	-0.224***	-0.204	-0.169***	-0.162***	-0.088***	-0.018
	(0.031)	(0.279)	(0.032)	(0.028)	(0.000)	(0.058)
			Strict Nondurables			
Weekly amount	-0.039**	-0.028	-0.038*	-0.042**	0.020	-0.029*
	(0.017)	(0.033)	(0.021)	(0.016)	(0.013)	(0.014)
Potential duration	-0.150**	-0.035	-0.044	0.044	0.068	0.074
	(0.066)	(0.066)	(0.062)	(0.053)	(0.081)	(0.128)
Weekly frequency	-0.128***	-0.056	-0.072***	-0.068***	-0.056	0.060
	(0.029)	(0.241)	(0.020)	(0.020)	(0.034)	(0.056)
			Nondurables			
Weekly amount	-0.043**	-0.052	-0.058***	-0.057***	0.023*	-0.050***
	(0.019)	(0.038)	(0.021)	(0.015)	(0.012)	(0.015)
Potential duration	-0.180***	-0.078	-0.085	-0.069	0.009	-0.091
	(0.065)	(0.073)	(0.064)	(0.053)	(0.093)	(0.168)
Weekly frequency	-0.056	-0.191	-0.006	-0.006	-0.066***	0.072
	(0.040)	(0.216)	(0.024)	(0.025)	(0.014)	(0.048)
Observations	1,032	7,658	9,151	10,243	3,225	7,018

Standard errors in parentheses, clustered at state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Regressions with Non-Food Categories
Note: Coefficient estimates for WBA adjusted by slope change in UI schedule. h denotes the bandwidth around the kinks. Linear RK polynomials. Weekly amount in $1,000. Potential duration in weeks over 52. UD is non-work weeks over 52. Only Exposed contains people with $UD > 0$. Recession period between 2008Q3 and 2013Q4. See text for the full description of covariates.

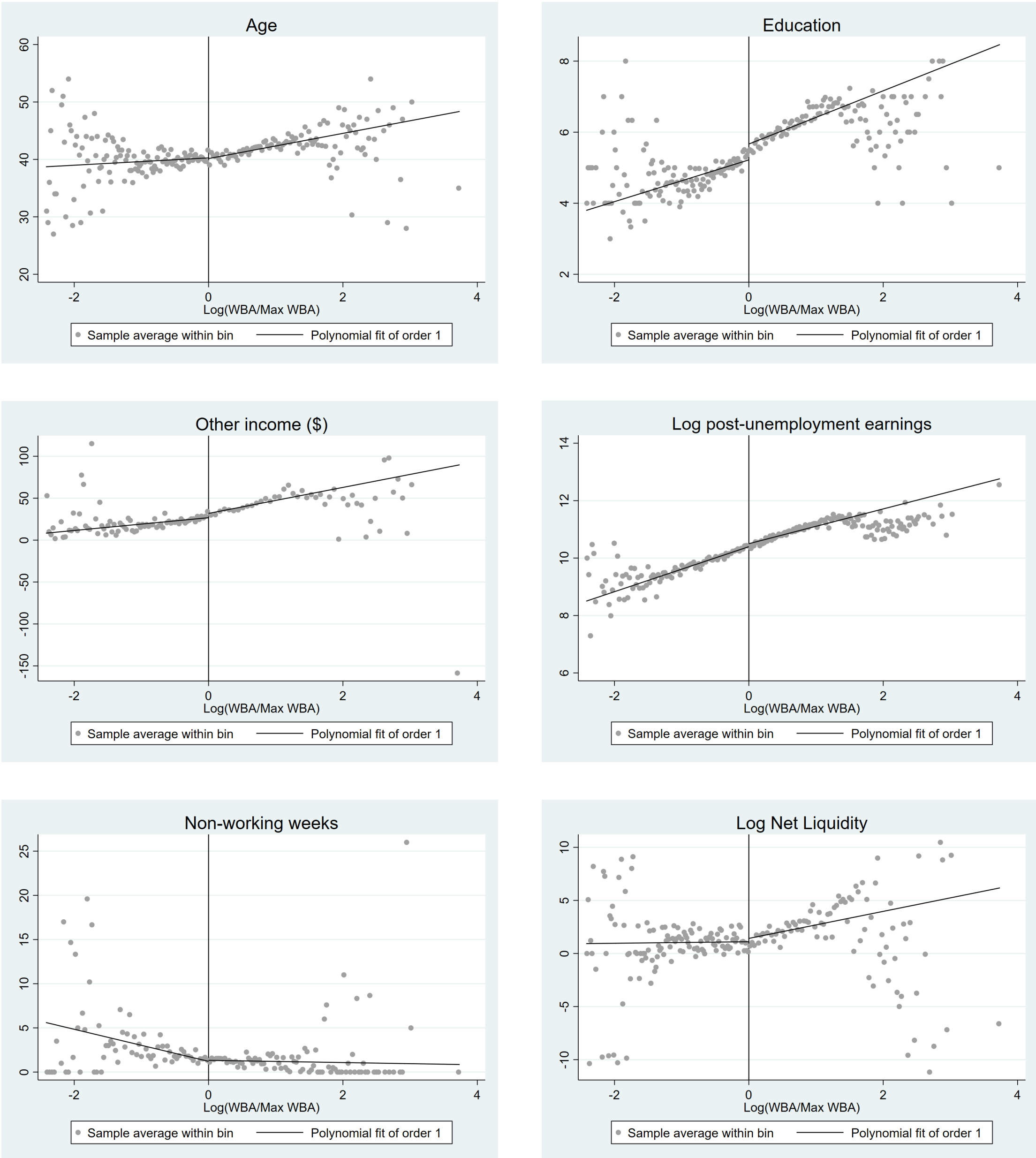

Figure A1: RKD Plots for Covariates

Note: Kink of running variable at 0. Education levels are categorical: (1) no schooling, (2) 8th grade, (3) 12th grade but no diploma, (4) high school diploma, (5) Some college, (6) Associate's degree, (7) Bachelor's degree, (8) Postgraduate. Bins are selected by the mimicking variance evenly-spaced method using spacings methods.