

Consumer Spending During Unemployment: Positive and Normative Implications – Online Appendix

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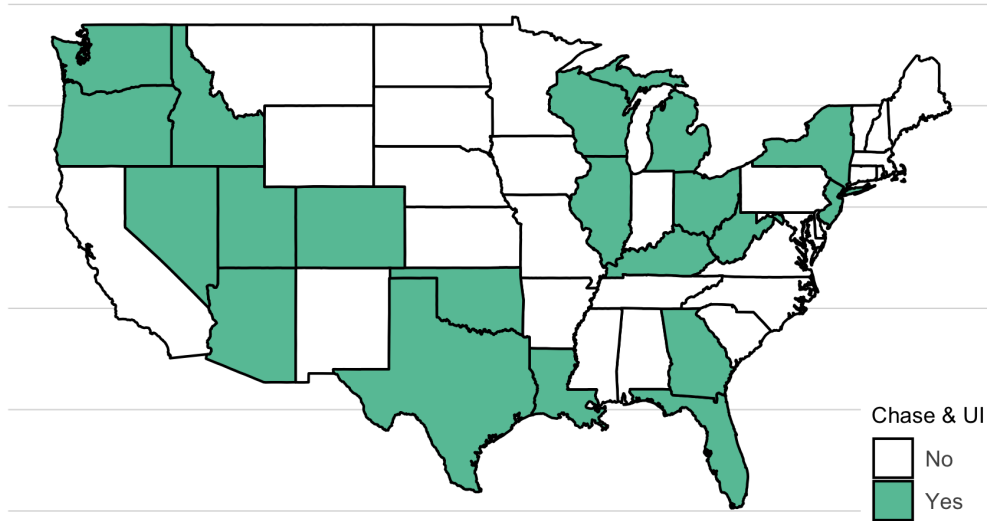
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A Figures and Tables

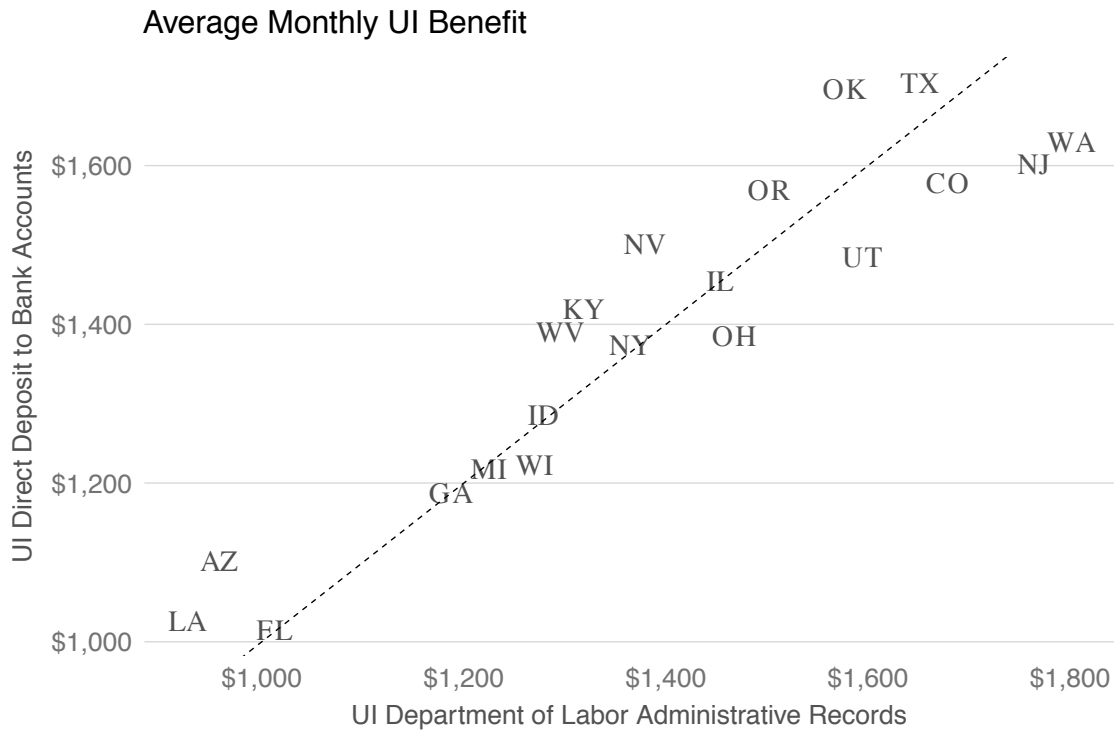
Figure 1: Representativeness: Geographic Distribution

States with Chase Branches and Direct Deposit of UI Benefits



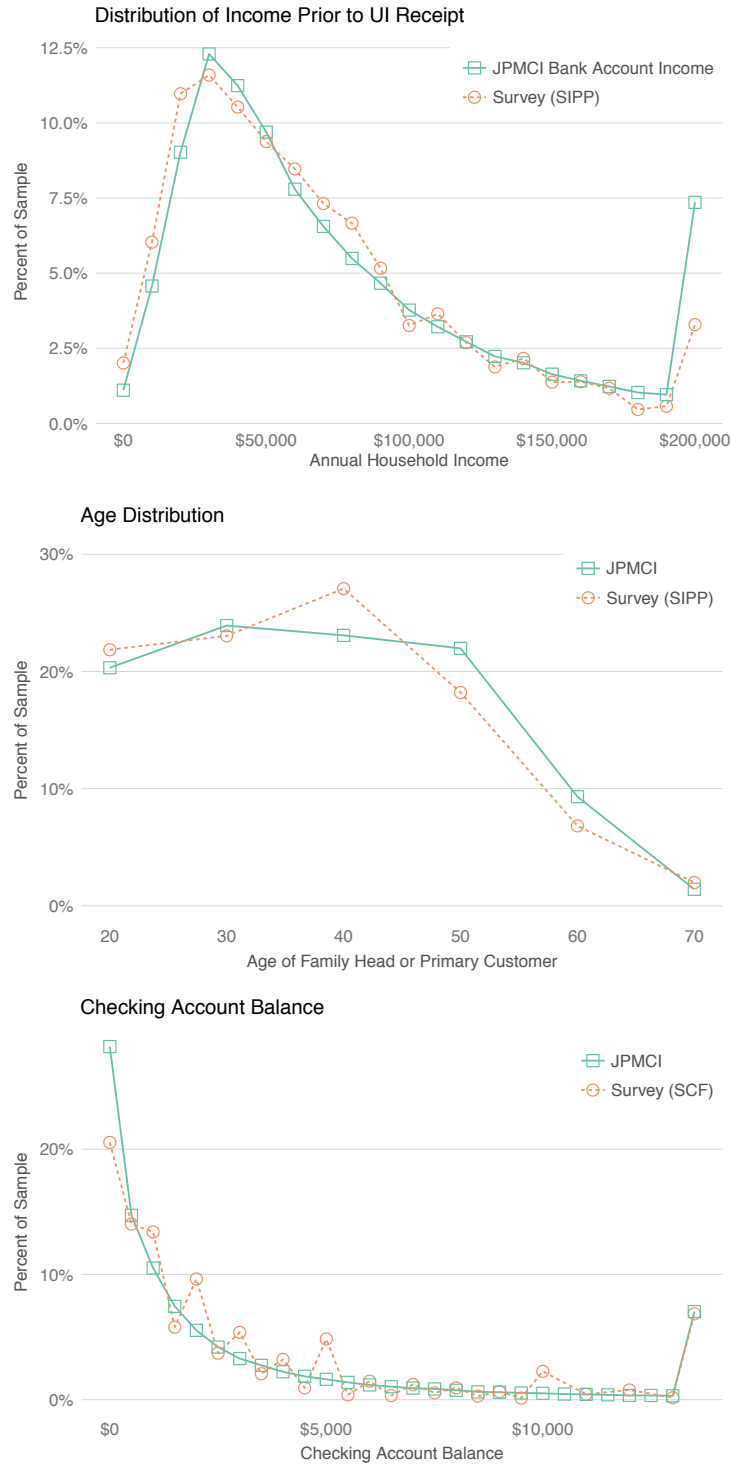
Notes: This figure shows the states in which the bank has branches and UI recipients may elect to receive benefits by direct deposit.

Figure 2: Representativeness



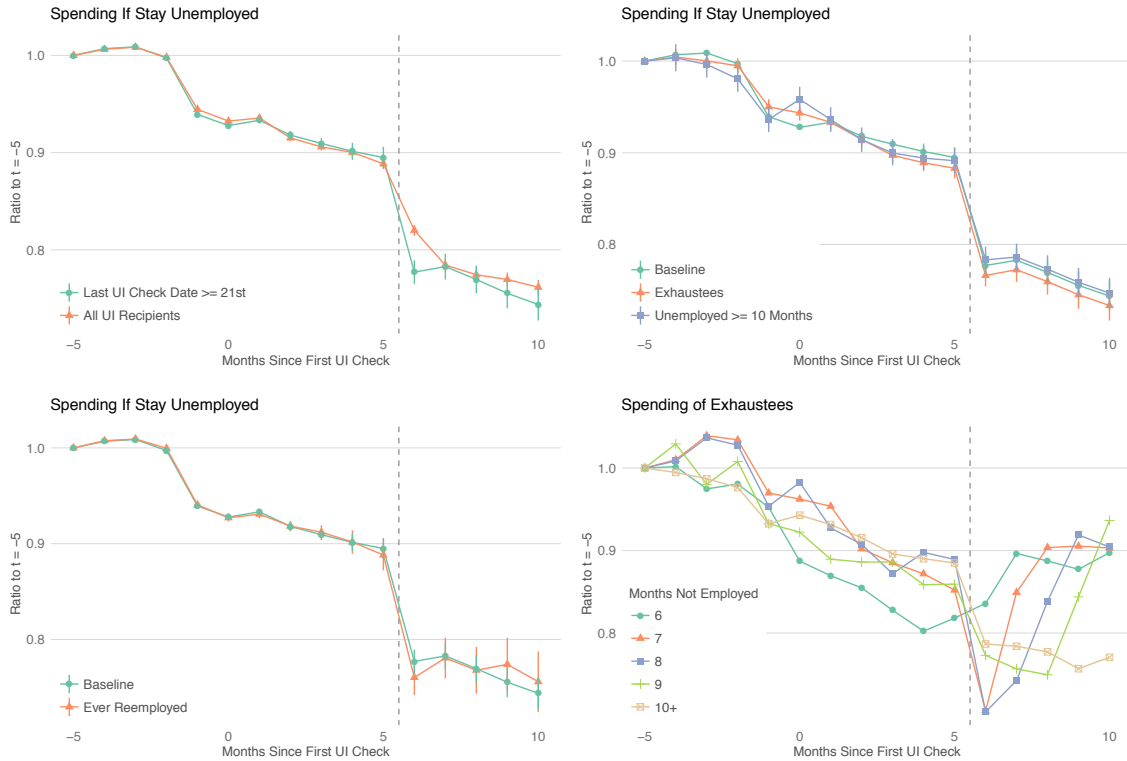
Notes: This figure plots average UI benefits in Department of Labor administrative records and in the JPMCI data. The diagonal dashed line is at a 45 degree angle. Because UI benefits are determined by pre-separation earnings, this figure shows that pre-separation earnings of UI recipients in the JPMCI data are similar to average pre-separation earnings of all UI recipients. The JPMCI sample is households that receive UI benefits and meet the sampling criteria described in Section 2.1.

Figure 3: Representativeness: Income, Assets, and Age



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 (SIPP) and in the JPMCI data. The middle panel plots age of household head in the SIPP and in JPMCI. The bottom panel plots the distribution of checking account balances in the 2013 Survey of Consumer Finances (SCF), and in the JPMCI data three months prior to UI receipt. See Section 2.3 for details. The JPMCI sample is households that receive UI benefits and meet the sampling criteria described in Section 2.1.

Figure 4: Empirics Robustness: Spending If Stay Unemployed



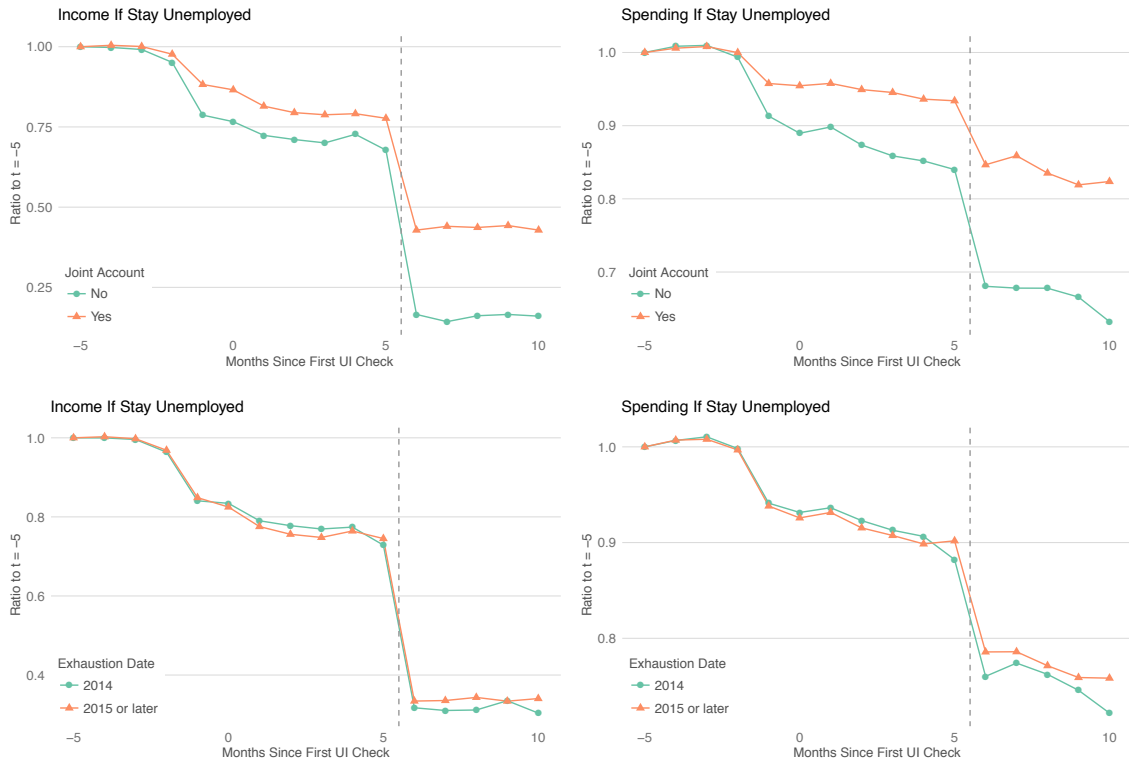
Notes: The top-left panel shows the path of spending for people receiving their last UI check on the 21st of the month or later (this sample is used for all spending figures in the main text), such that the drop in income occurs from one calendar month to the next, and for all UI recipients for whom the drop in average income occurs over two calendar months.

The top-right panel compares spending for the baseline stay-unemployed sample to the path of spending for UI benefit exhaustees.

The bottom-left panel plots spending for the subsample of exhaustees who are ever reemployed according to paycheck data. The sample for these three panels is households that receive UI and stay unemployed, as described in the note to Figure 2. Vertical lines indicate 95 percent confidence intervals.

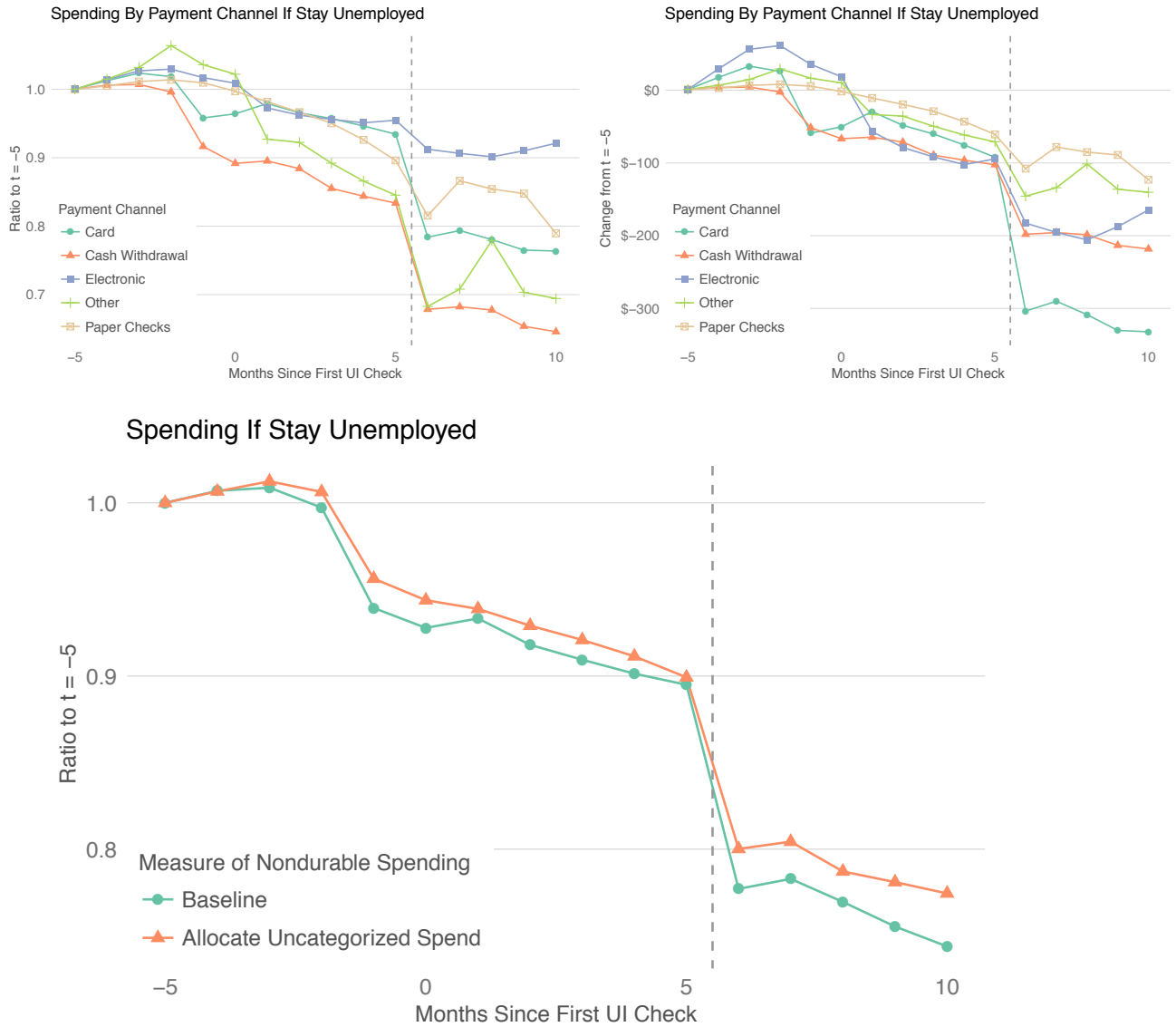
The bottom-right panel shows spending by nonemployment duration among UI exhaustees that meet the sampling criteria described in Section 2.1.

Figure 5: Empirics Robustness: Heterogeneity in Income and Spending If Stay Unemployed



Notes: This figure shows heterogeneity in income and spending by whether the household has a joint checking account (a coarse proxy for marriage), and the year in which UI benefits were exhausted. The sample is households that receive UI and stay unemployed, as described in the note to Figure 2.

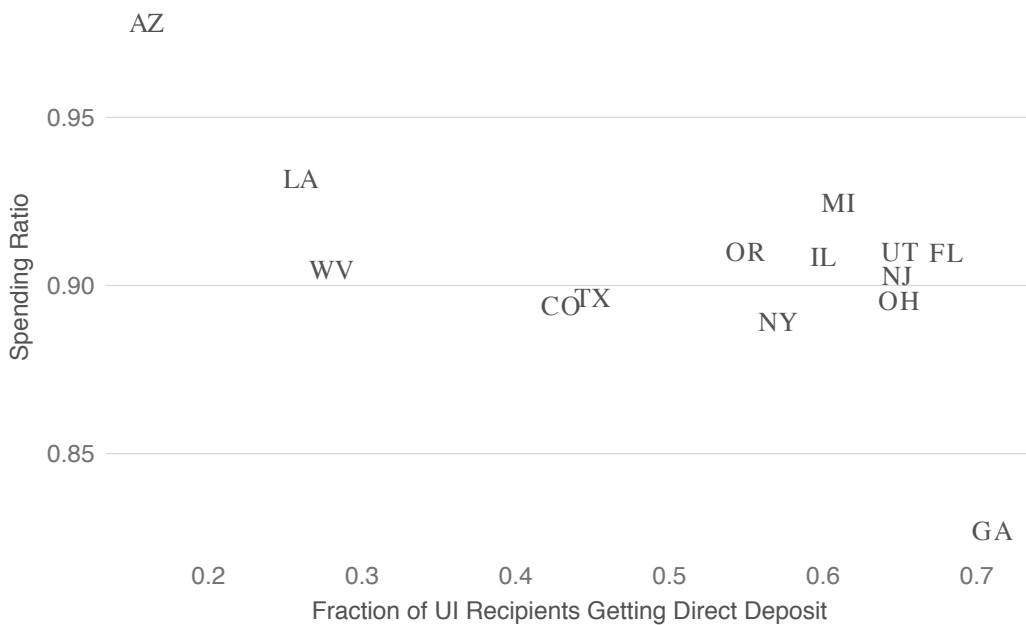
Figure 6: Empirics Robustness: Spending Method If Stay Unemployed



Notes: The top-left panel decomposes the change in checking account outflows into five components and shows the change as a ratio to their pre-unemployment level. The top-right panel shows the same five measures, but using the change in dollars from their pre-unemployment level. The bottom panel plots the baseline measure of nondurable spending and an alternative measure which assumes that 75 percent of cash, 83 percent of credit card bills, 34 percent of uncategorized electronic transfers and 32 percent of paper checks (which are always uncategorized) are spent on nondurables. See online Appendix E.1 for details. The sample is households that receive UI and stay unemployed, as described in the note to Figure 2.

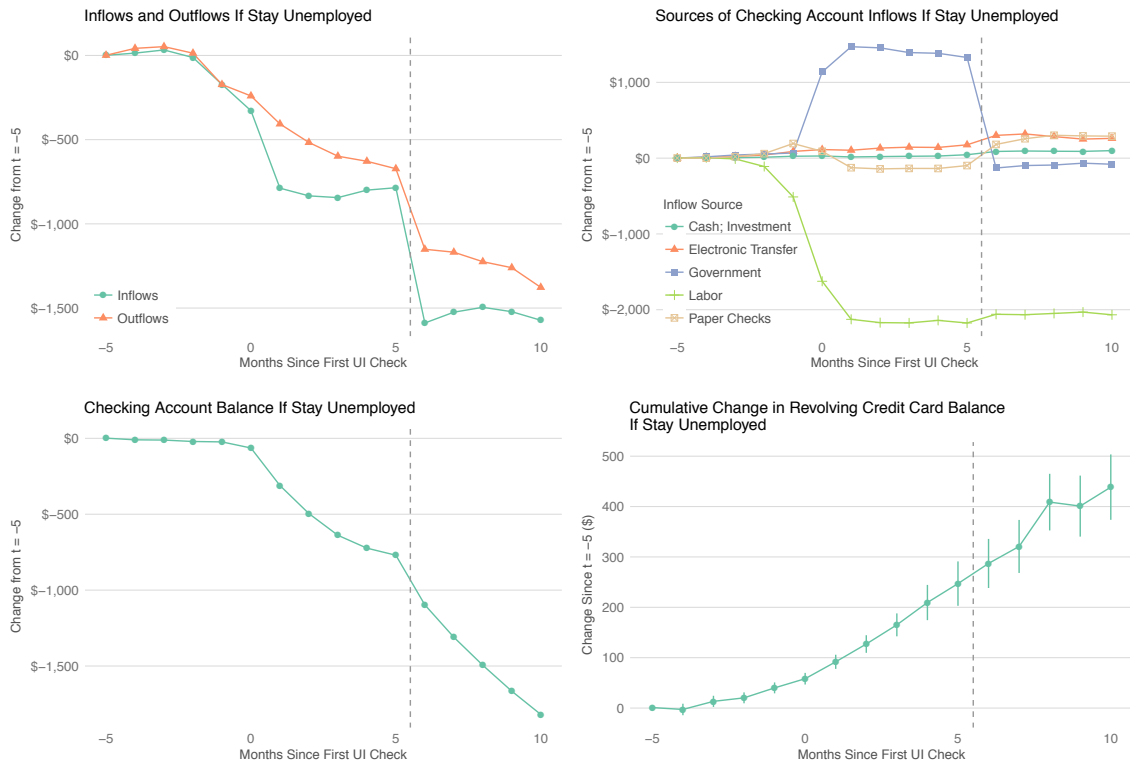
Figure 7: Empirics Robustness: Direct Deposit of UI Benefits

Usage of Direct Deposit and Spending Change at Exhaustion



Notes: This figure plots on the x-axis the share of UI beneficiaries paid by direct deposit (rather than a pre-paid debit card) on the x-axis from Saunders and McLaughlin (2013). The y-axis is the ratio of spending in the month after exhaustion to the month before exhaustion used in the bottom panel of Figure 5. The two states that are outliers—Arizona and Georgia—account for 0.6 percent and 1.3 percent of the sample of exhaustees, respectively. See online Appendix E.1 for details.

Figure 8: Empirics Robustness: Inflows, Outflows, Liquid Assets, and Credit Card Borrowing If Stay Unemployed



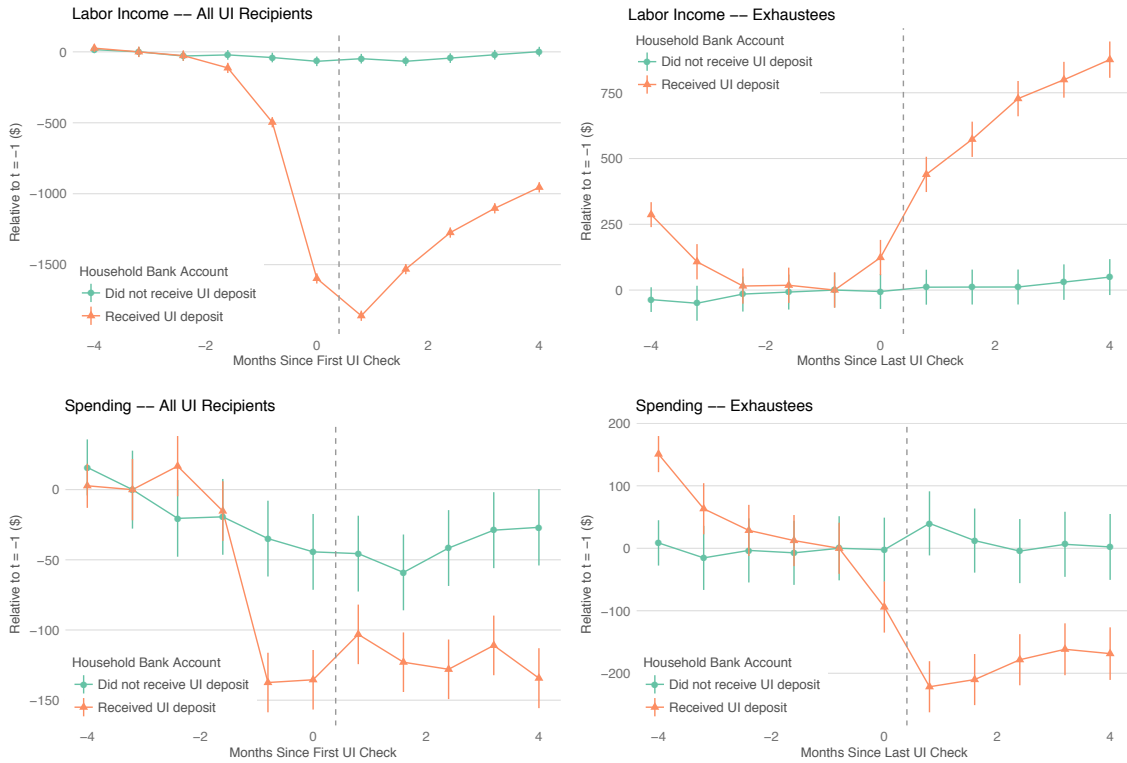
Notes: The sample is households that receive UI and stay unemployed, as described in the note to Figure 2. The top-left panel plots checking account inflows and checking account outflows for the stay-unemployed sample.

The top-right panel decomposes the change in inflows into five components.

The bottom-left panel plots the cumulative change in Chase checking account balances.

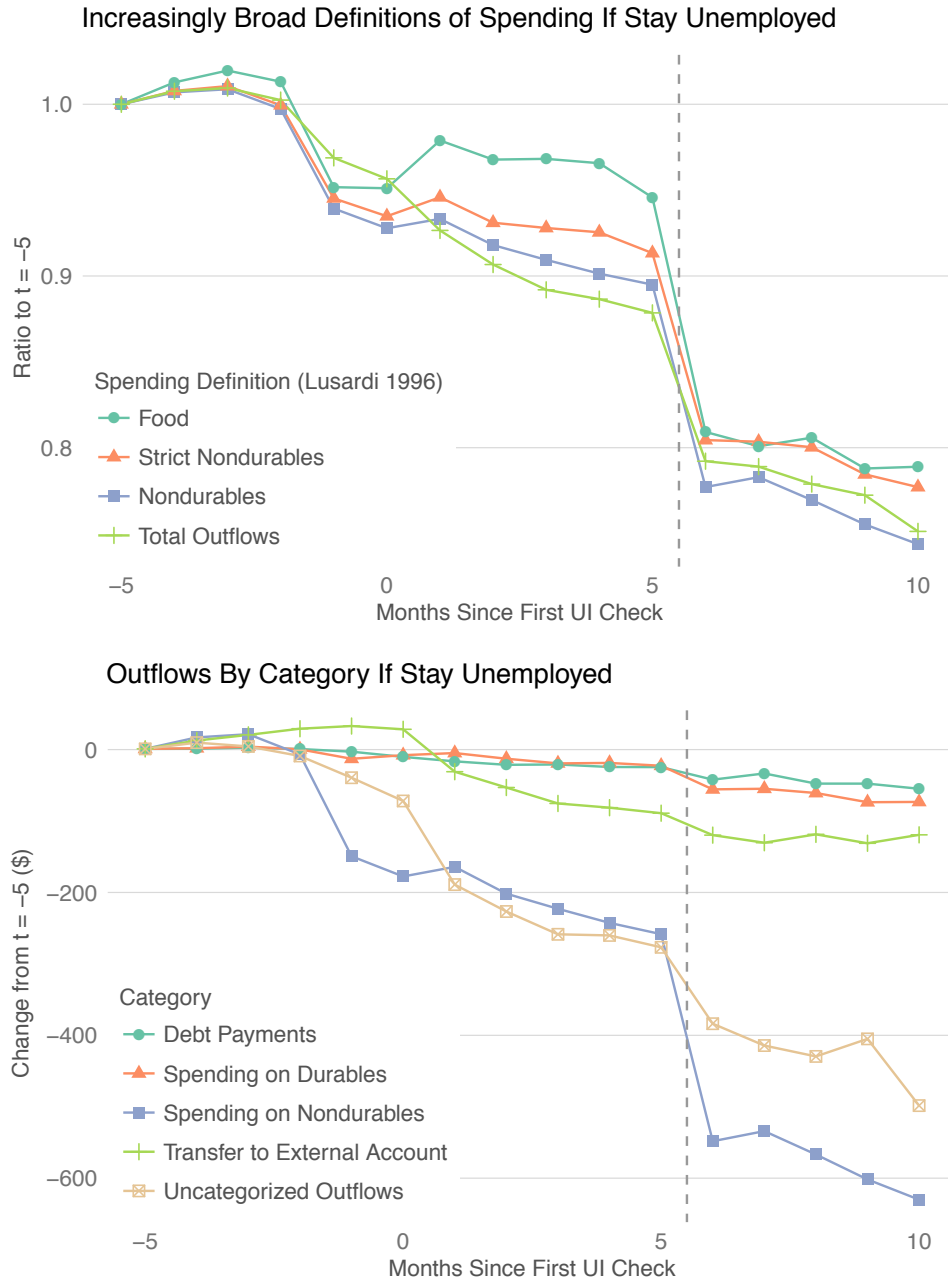
The bottom-right panel is the cumulative change in Chase revolving credit card balances. Vertical lines indicate 95 percent confidence intervals.

Figure 9: Empirics Robustness: Other Household Accounts



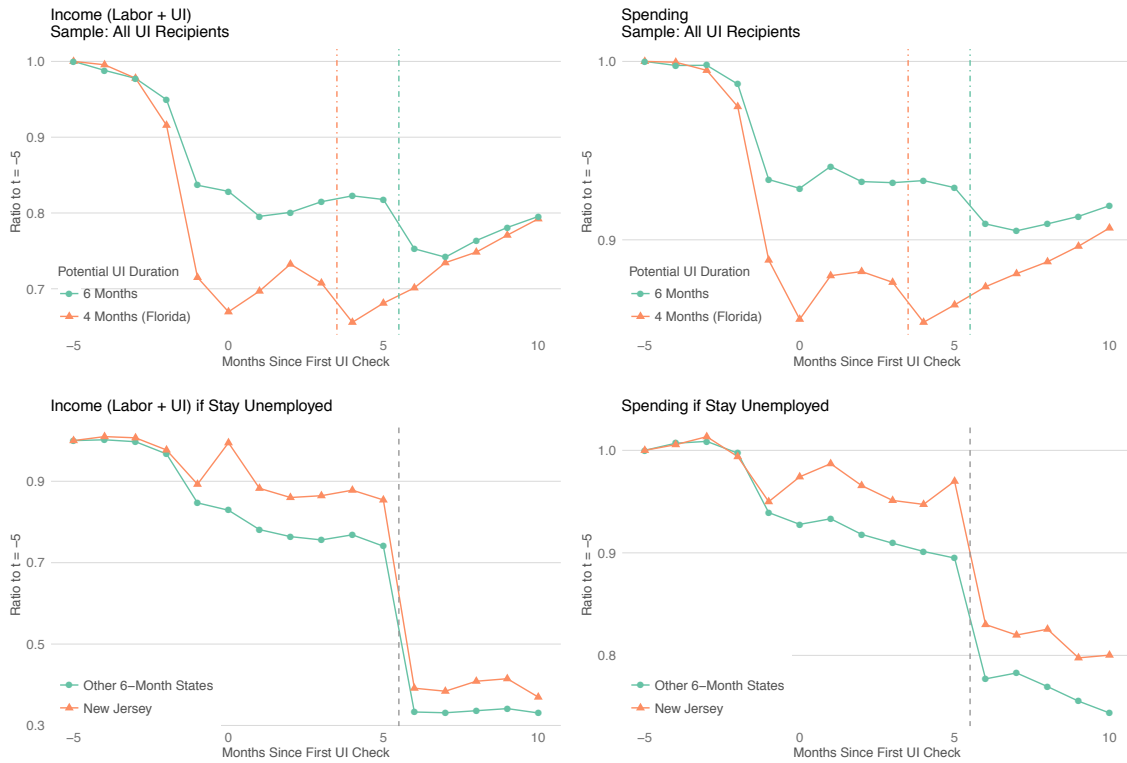
Notes: About one-quarter of households have checking accounts at multiple banks. In some cases, JPMCI observes spending for an account belonging to a household member who is not receiving UI, which is a useful proxy for spending out of non-Chase bank accounts. See Section 2.1 for details on how JPMCI finds other household accounts. The top panels show that income is stable around benefit onset (top-left panel) and benefit exhaustion (top-right panel) in the other household account. The bottom panels show that spending falls slightly at UI benefit onset (bottom-left panel) and is stable around benefit exhaustion in the other account (bottom-right panel), indicating that UI recipients do not substitute between accounts at benefit exhaustion. The sample is households that have two unlinked bank accounts, and receive UI payments into one account. We also require that households meet the sampling criteria described in Section 2.1.

Figure 10: Empirics Robustness: Spending Definition If Stay Unemployed



Notes: The top panel shows the evolution of spending using the methodology from Figure 2 for four increasingly broad definitions of spending used in Lusardi (1996). From most narrow to broadest, they are spending on groceries and food away from home; strict nondurables, which adds transportation, utilities, personal & professional services; all nondurables (same as Figure 2); and total checking account outflows. The bottom panel shows a decomposition of changes in checking account outflows during unemployment into five mutually exclusive and comprehensively exhaustive categories described in Section 2.2. The sample is households that receive UI and stay unemployed, as described in the note to Figure 2.

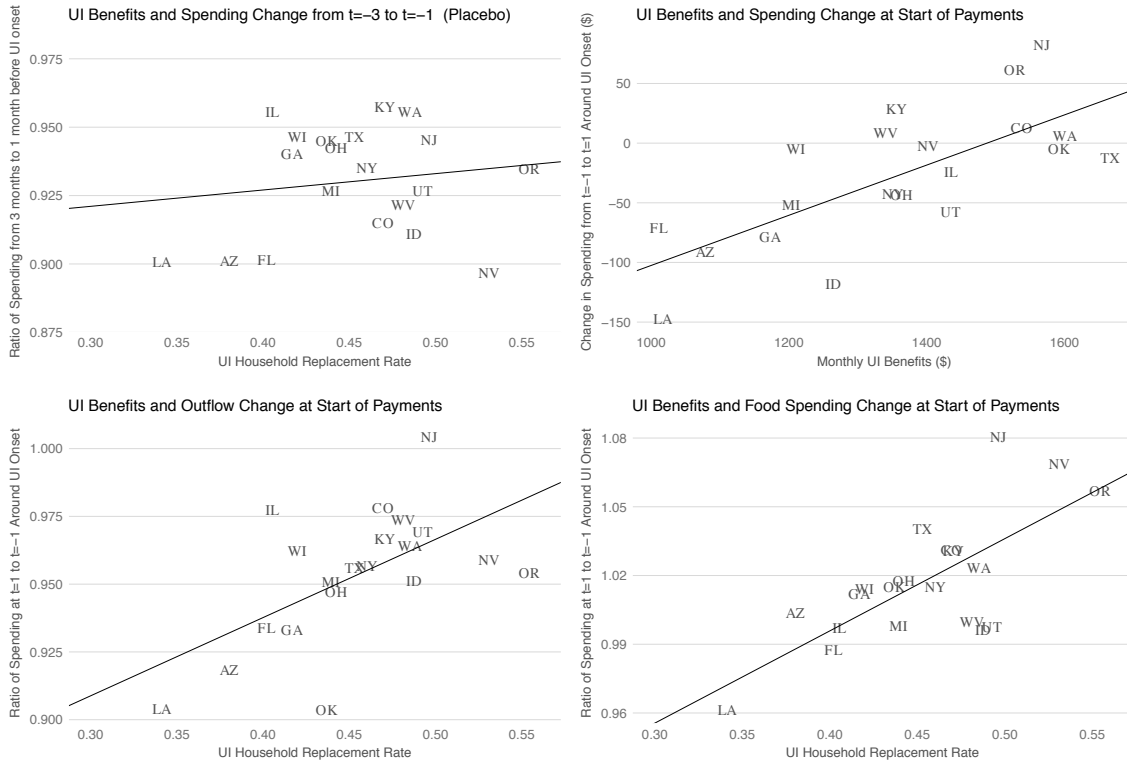
Figure 11: Empirics Robustness: Spending in New Jersey and Florida



Notes: The top panels compare income and spending in Florida to states where benefits last six months for the sample of all UI recipients using the sample criteria described in Section 2.1. This is a robustness check on Figure 4, which shows the same variables for the stay-unemployed sample.

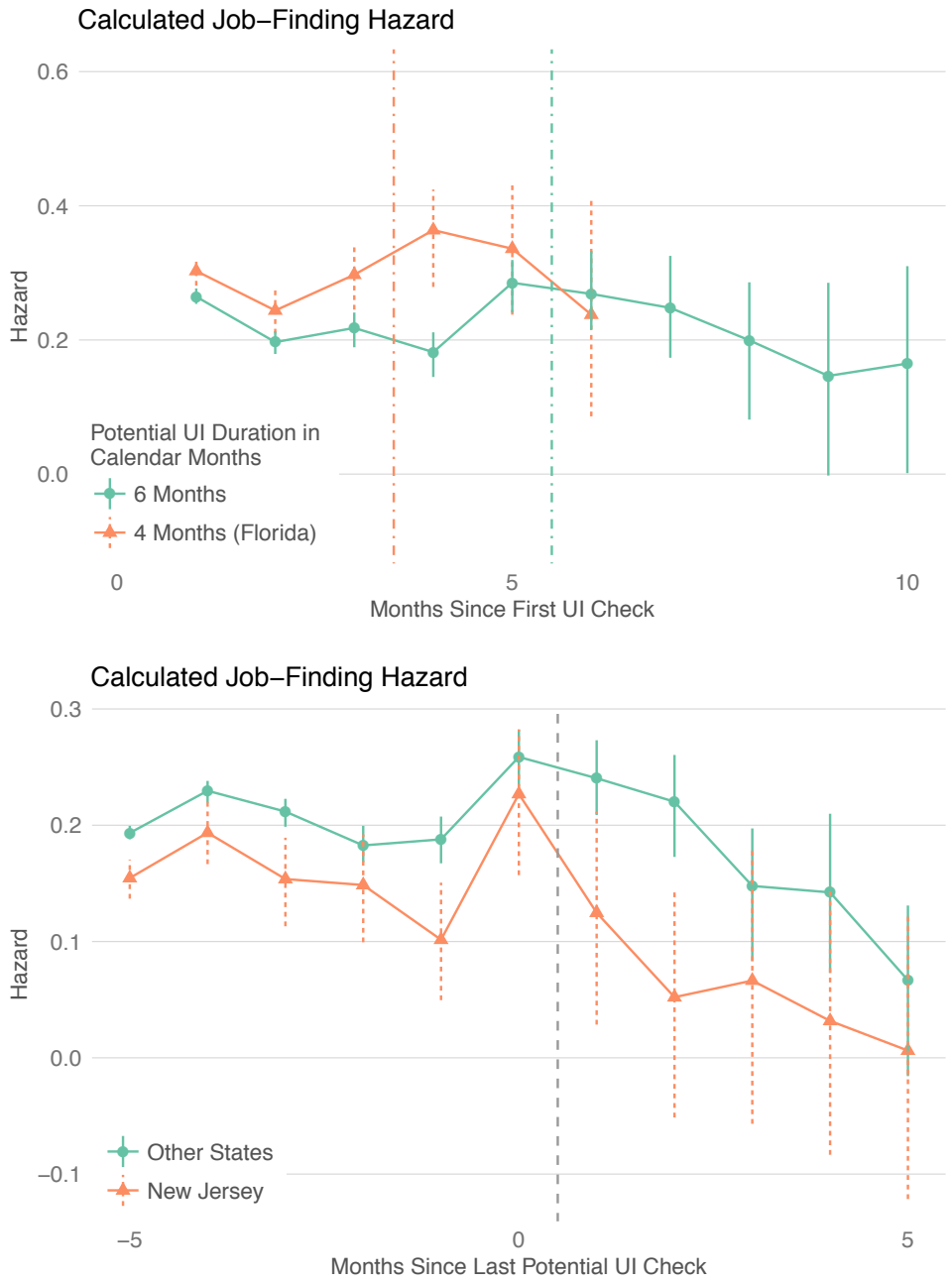
The bottom panels compare income and spending in New Jersey to other states where UI benefits last six months for the stay unemployed sample, as described in the note to Figure 2. This is a robustness check on Figure 4, which shows the same variables for all UI recipients.

Figure 12: Empirics Robustness: Spending Drop by UI Replacement Rate



Notes: This figure reports robustness checks on Figure 5. We analyze households that receive a full calendar month of UI benefits at $t = 1$ and meet the sampling criteria described in Section 2.1. The top-left panel reports results from a placebo test by regressing the change in spending from three months before the first UI check ($t = -3$) to one month before the first UI check ($t = -1$). The top-right panel compares the spending drop at onset in dollars to the level of monthly UI benefits in dollars. The bottom-left panel compares the state-level UI household replacement rate and the change in total checking account outflows around UI onset. The bottom-right panel compares the state-level UI household replacement rate and the change in food spending around UI onset.

Figure 13: Empirics Robustness: Hazards in Florida and New Jersey

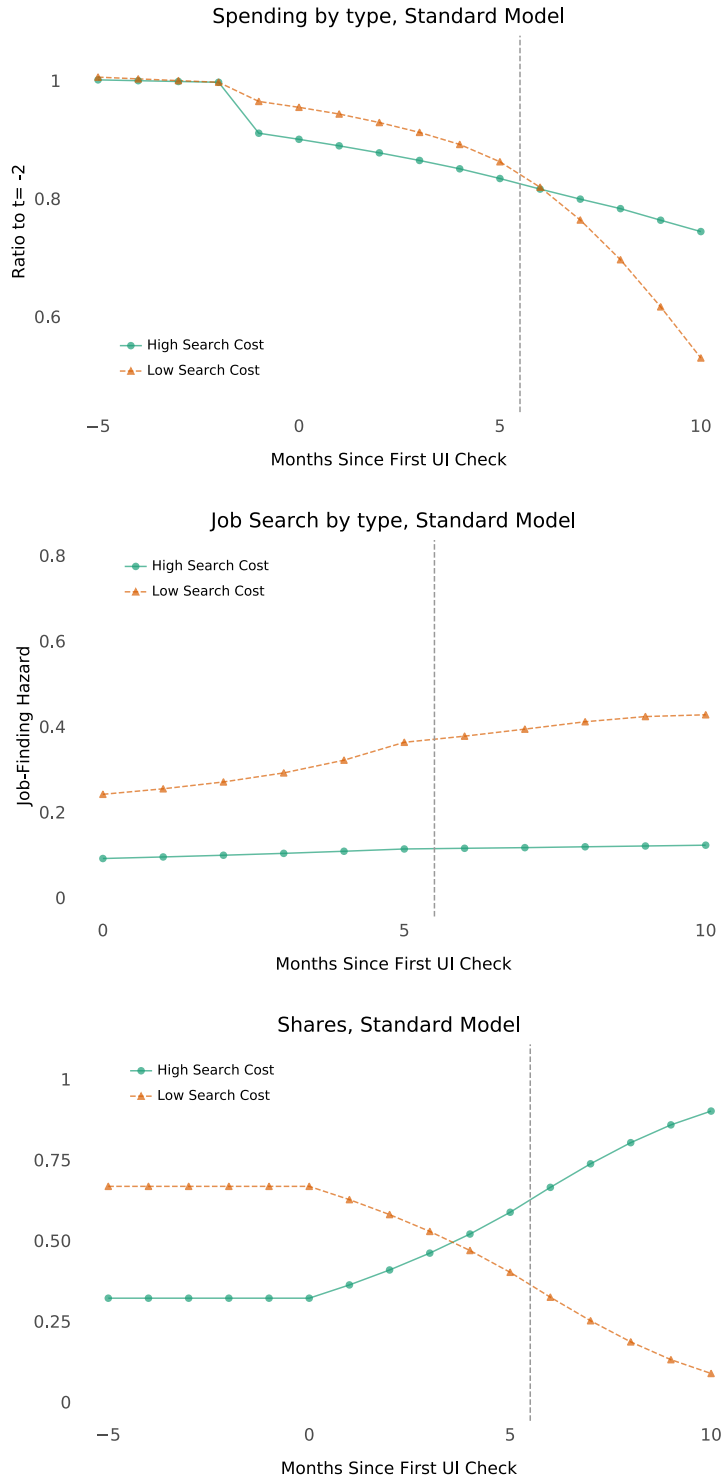


Notes: This figure compares job-finding hazards across states using the methodology described in Section 3.4. Vertical lines indicate 95 percent confidence intervals constructed by bootstrap.

The top panel compares the path of job-finding in Florida to the path for UI recipients in other states who are likely to receive their 26 weeks of UI benefits in six calendar months. (This series, along with the companion series for UI benefits who are likely to receive their 26 weeks of benefits in seven calendar months, is shown in the top-right panel of online Appendix Figure 26.) We omit estimates of the job-finding hazard in month 0 because a significant share of the sample is still employed at the start of this month and estimates for durations longer than six months in Florida because the estimates are very imprecise.

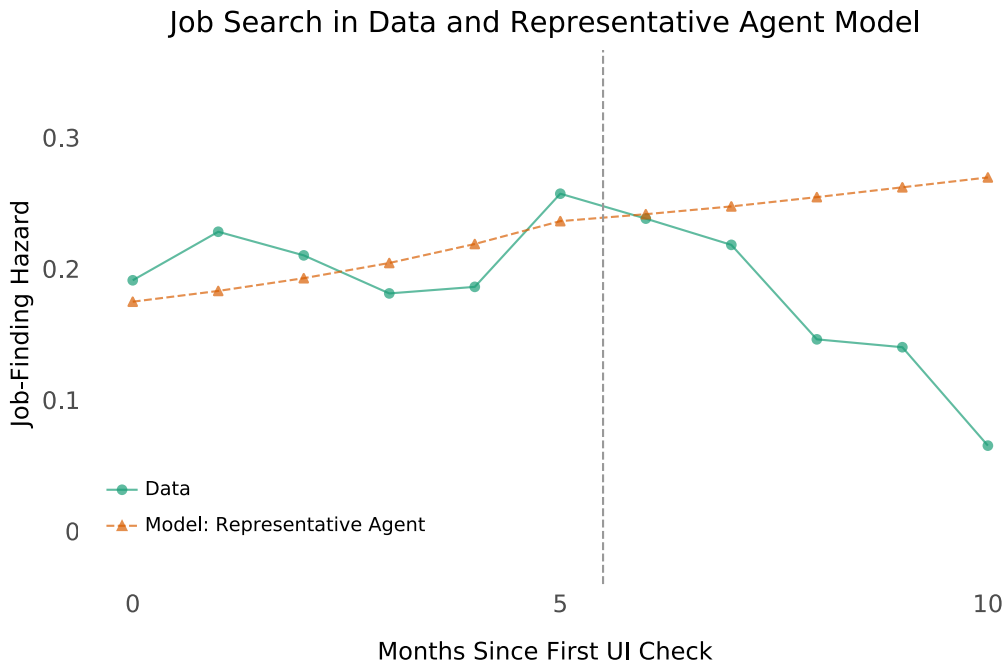
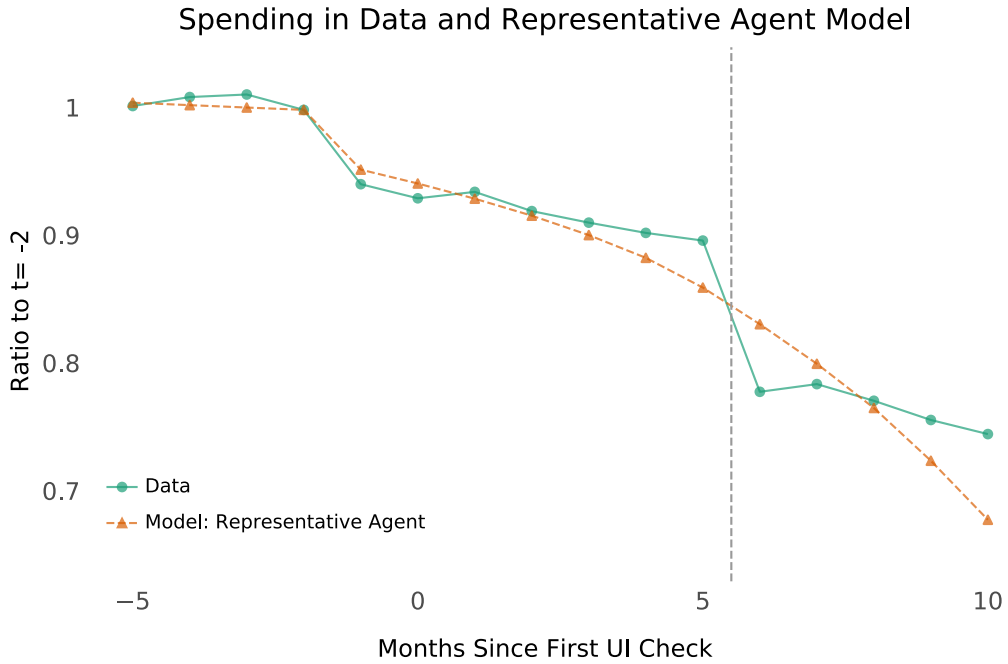
The bottom panel compares New Jersey to the series from Figure 6 (all states where benefits last six months).

Figure 14: Standard Model – Behavior by Type



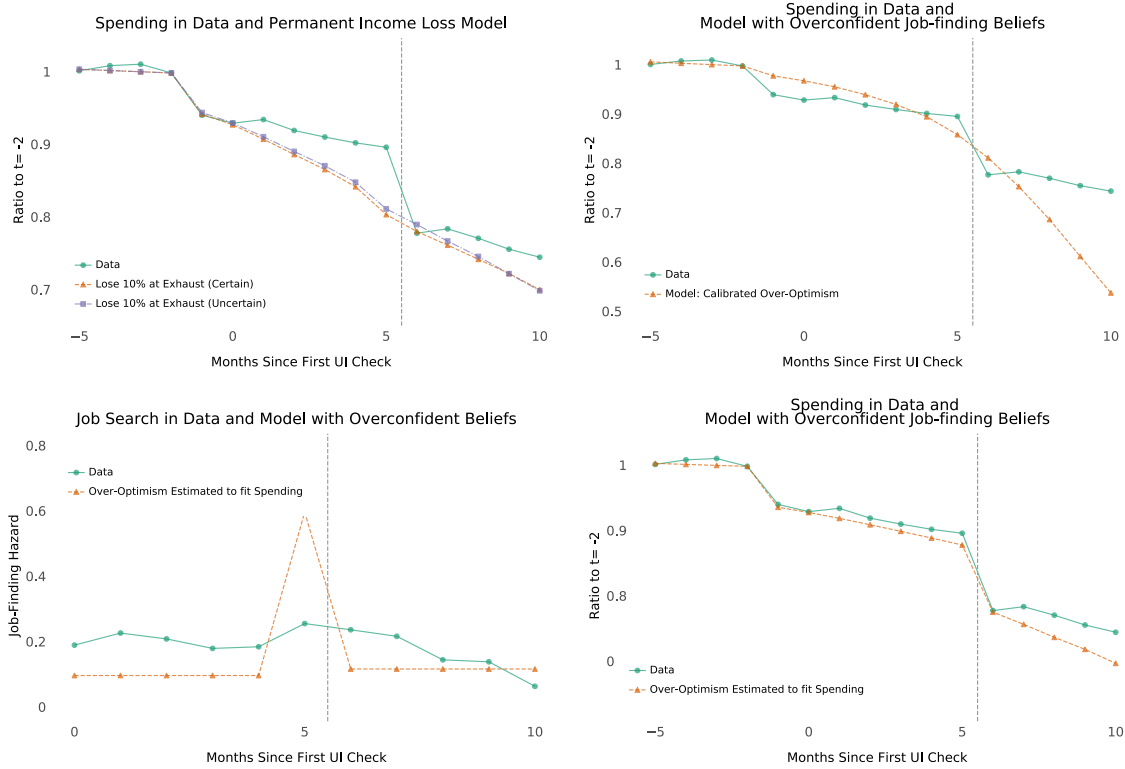
Notes: This figure reports additional moments of the “standard model” depicted in Figure 7 and described in Section 4.1. The model features heterogeneity in the job search cost parameter k . The top panel shows predicted spending by type, the middle panel shows predicted search by type, and the bottom panel shows the share of each type among the remaining pool of unemployed households.

Figure 15: Model Robustness: Representative Agent Model



Notes: This figure plots the predictions of a representative agent model alongside data on spending and job search during an unemployment spell from Figures 2 and 6, respectively. By representative agent, we mean that this model does not allow for unobserved heterogeneity in job search costs or time preferences. Predictions and data are for an environment where UI benefits last six months and the UI recipient stays unemployed for 10 months. Parameter estimates are shown in Appendix Table 18, column 1.

Figure 16: Model Robustness: Productivity Loss and Optimistic Beliefs



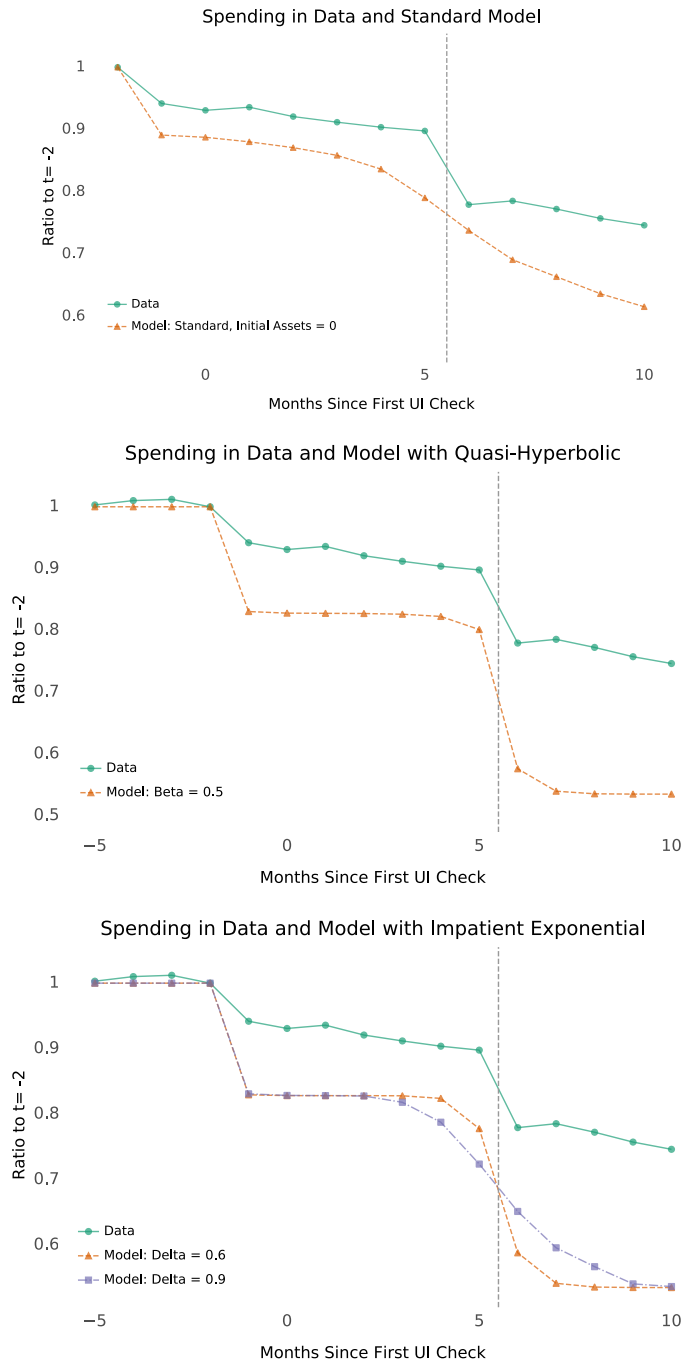
Notes: This figure examines how productivity loss and optimism about job search prospects affect consumption. The details of these calculations are described in online Appendix F.1. The top-left panel plots spending under the assumption that permanent income is 10 percent lower for any job found after benefit exhaustion, either with certainty or with a 50 percent probability.

The top-right panel plots a behavioral model where job seekers have optimistic beliefs of the job-finding hazard parameterized to match Spinnewijn (2015).

The bottom-left 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 7 percent in the first five months of unemployment, and jumps to 60 percent in the final month of benefits.

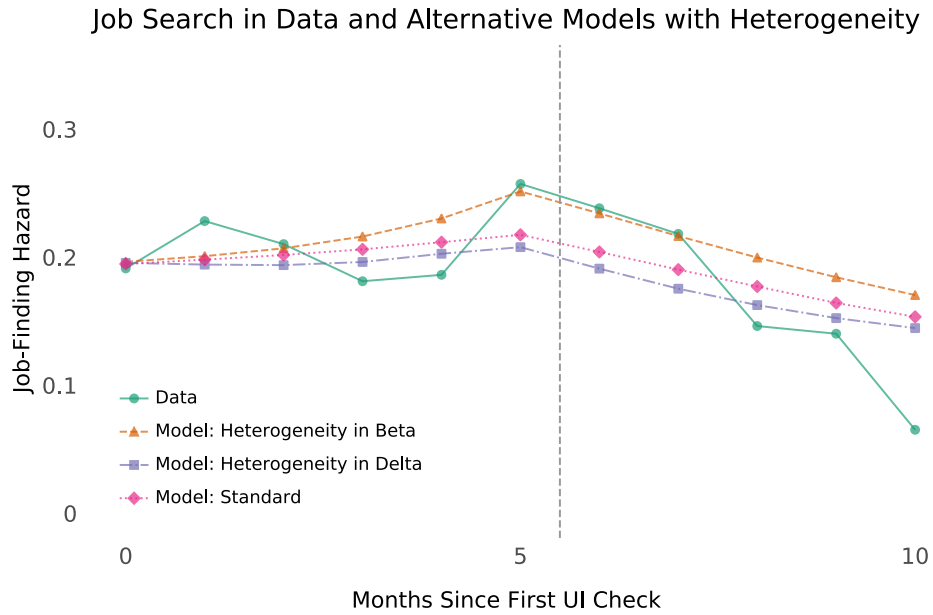
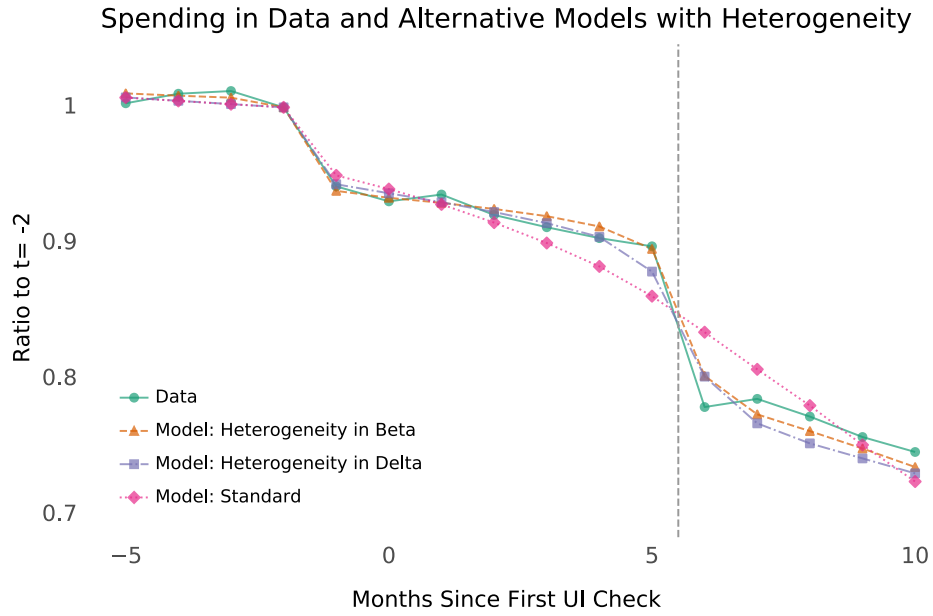
The bottom-right panel shows the path of spending in the data and in the model under the alternative job-finding beliefs plotted in the bottom-left panel.

Figure 17: Model Robustness: Corner Cases



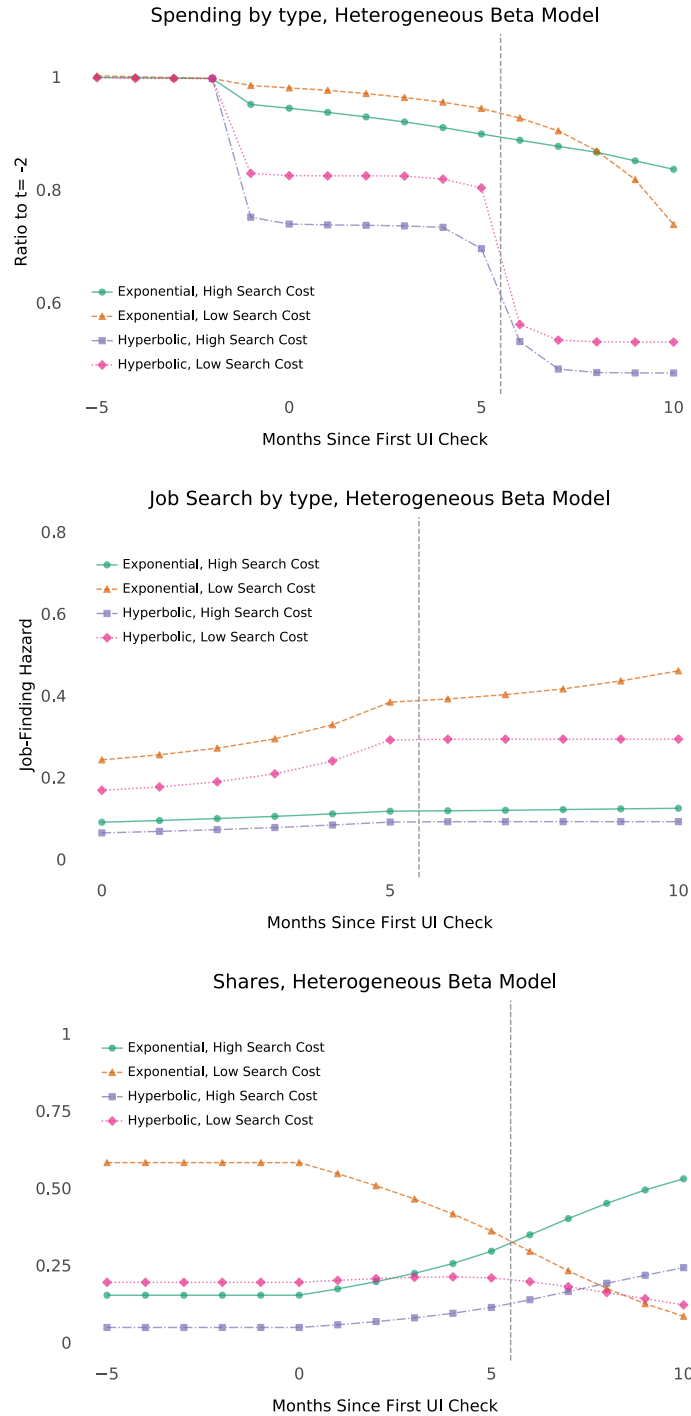
Notes: All three panels show spending in the data compared to a model with the preference parameters from Section 4.1, subject to one change in each panel. The top panel examines a model where agents have no assets at the start of unemployment and no ability to borrow. Because agents are assumed to exogenously have zero assets the month before unemployment begins, it is not possible to plot history for months $t = \{-5, -4, -3\}$. The middle panel assumes quasi-hyperbolic discounting with $\beta = 0.5$. The bottom panel assumes a monthly exponential discount rate of either 10 percent or 40 percent.

Figure 18: Model Robustness: Delta Heterogeneity



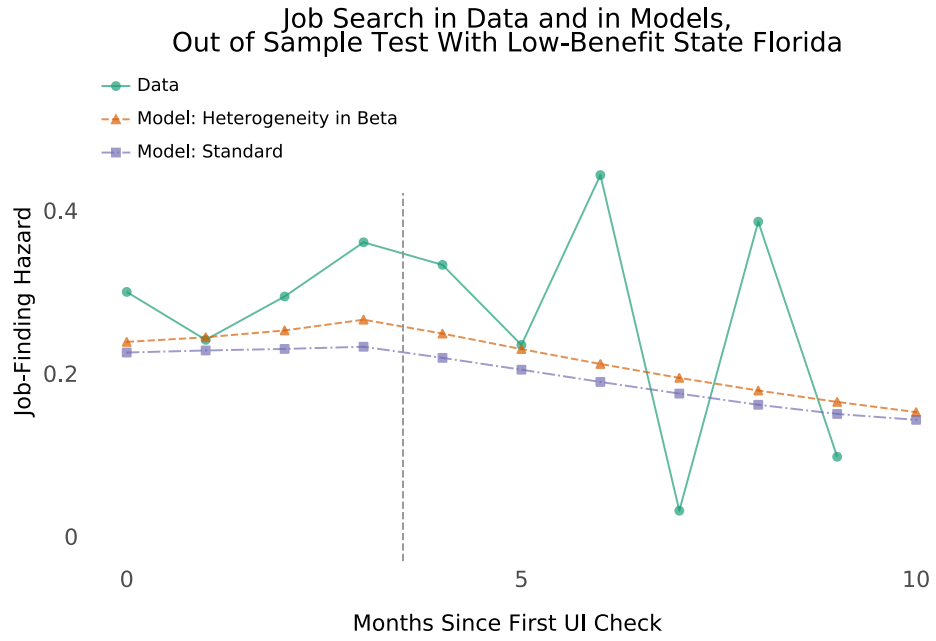
Notes: This figure compares average consumption and job search predicted by the β -heterogeneity model depicted in Figure 8 to an alternative model which has heterogeneity in the exponential patience parameter δ (and no heterogeneity in the present-bias parameter β). The estimates for this alternative model are shown in Table 3 column (4).

Figure 19: Heterogeneity in Search Cost and β – Behavior by Type



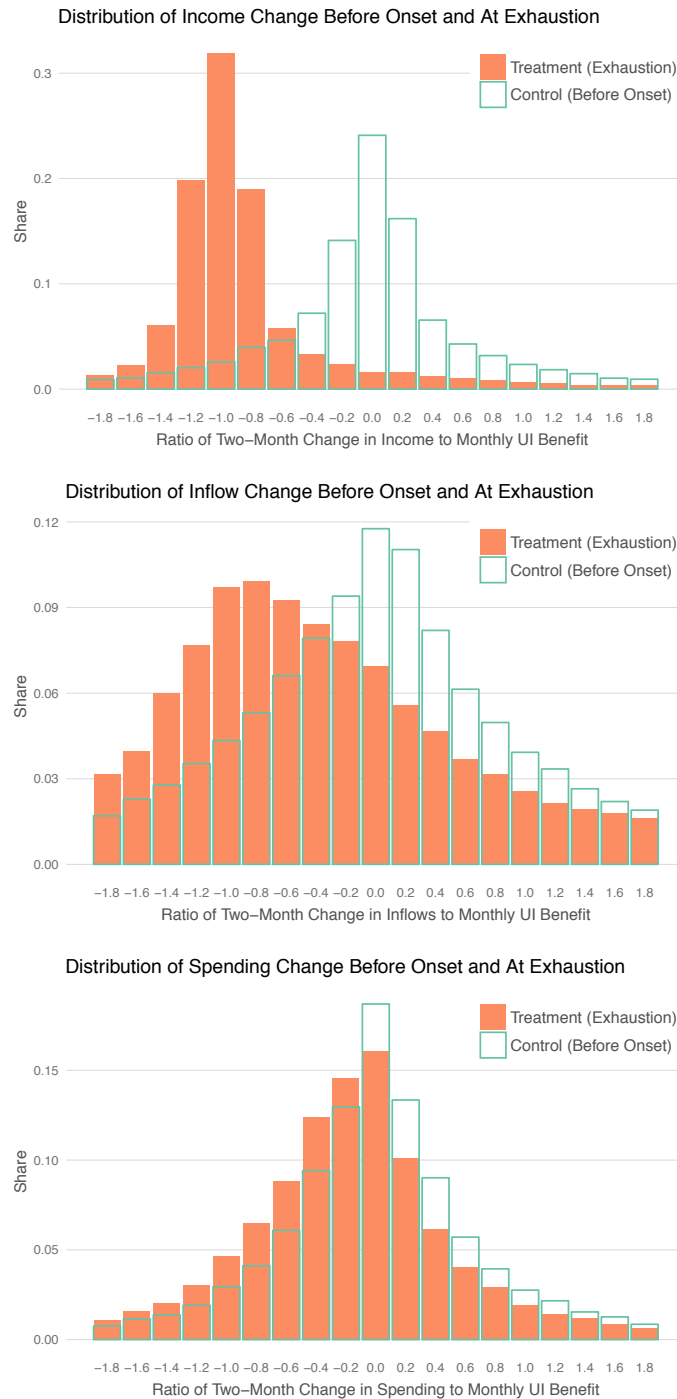
Notes: This figure reports additional moments of the model depicted in Figure 8 and described in Section 4.2. The model has a total of four types arising from the Cartesian product of two types with low or high job search cost k and two consumption types with low or high β in a $\beta\delta$ model. The top panel shows predicted spending by type, the middle panel shows predicted search by type, and the bottom panel shows the share of each type among the remaining pool of unemployed households.

Figure 20: Model Robustness: Florida Out-of-Sample Search Prediction



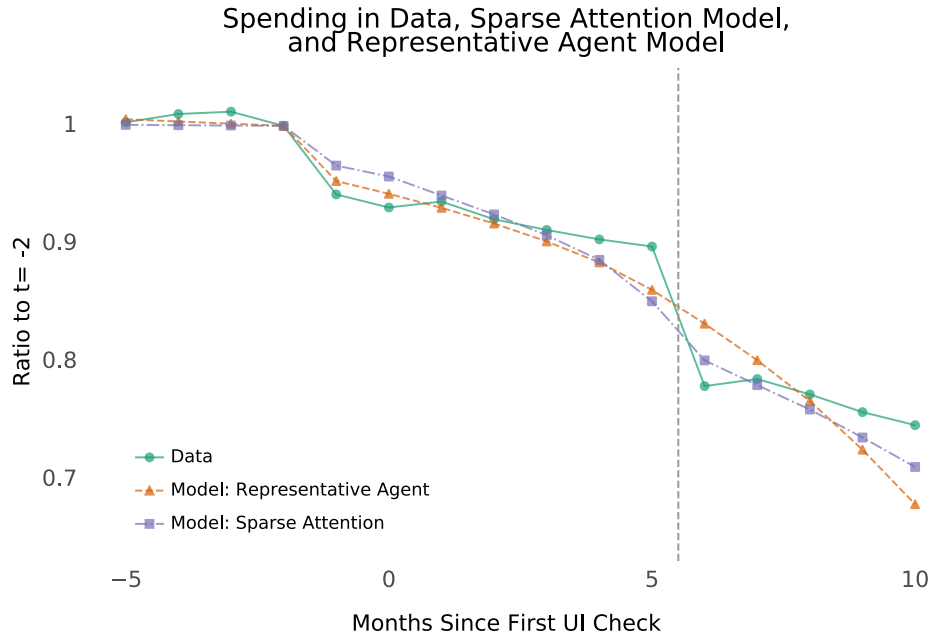
Note: This figure shows job search in Florida compared to the predictions from the standard model and predictions from the heterogeneous β model.

Figure 21: Model Robustness: Distribution of Spending Drop at Exhaustion Does Not Distinguish Between Alternative Models



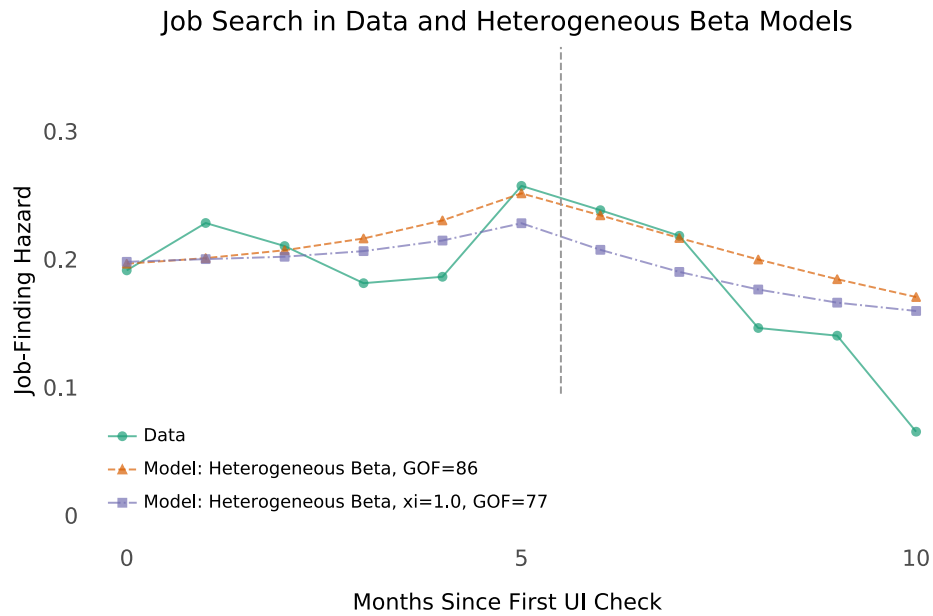
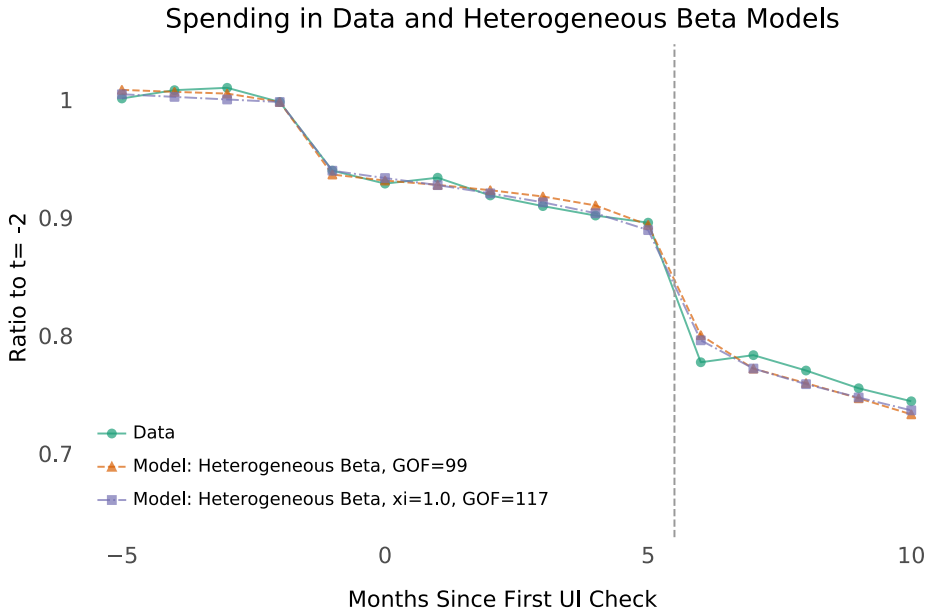
Note: This figure shows the distribution of the change in three different variables at UI benefit exhaustion for households that meet the sampling criteria described in Section 2.1. The top panel shows income (defined as the sum of labor income and UI benefits), the middle panel shows total checking account inflows (which include 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.

Figure 22: Sparse Attention Model



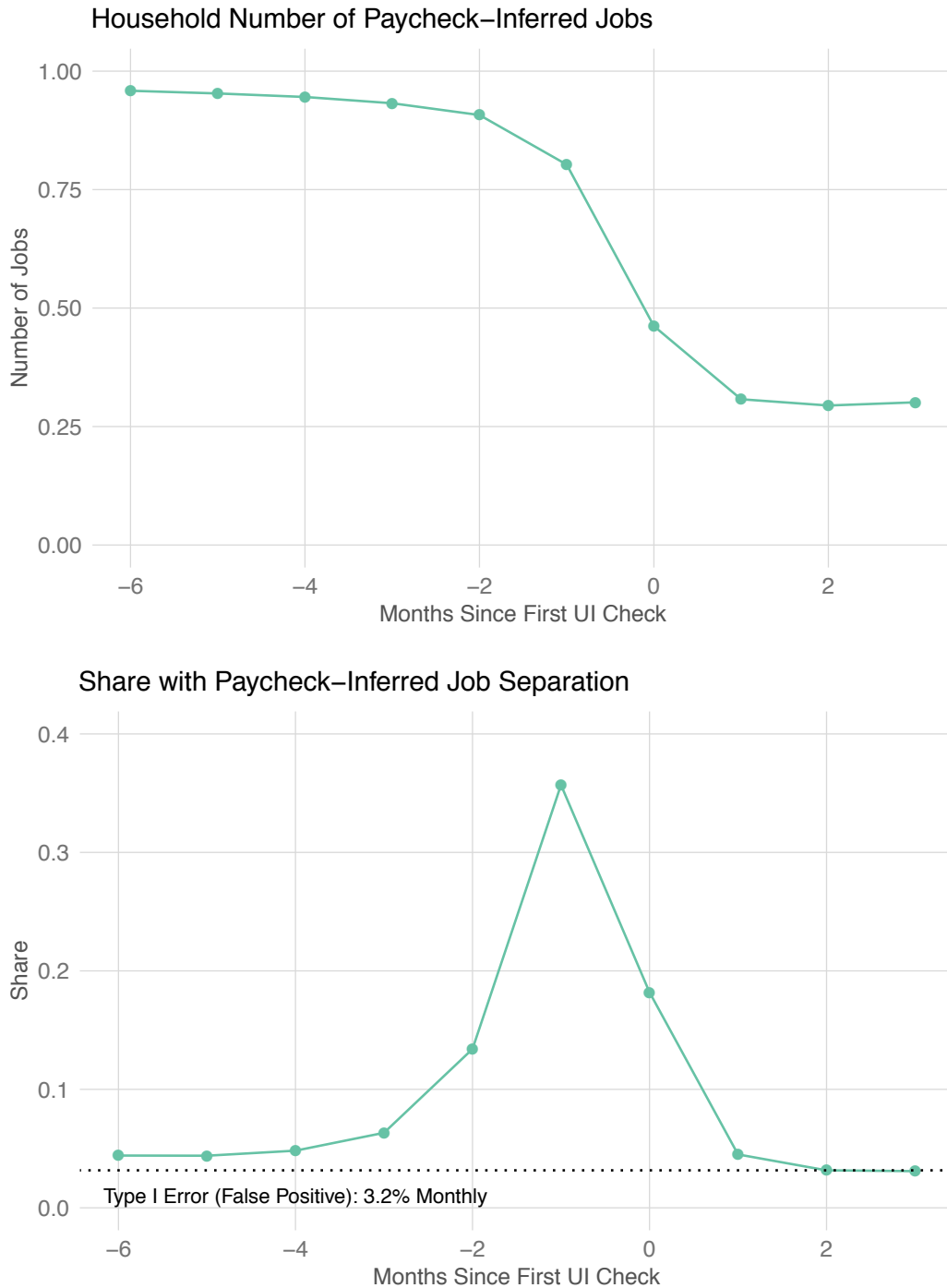
Note: The figure shows the data alongside predicted spending from the representative agent model from Table 18 column 1 and a sparse attention model by Gabaix (2016). See online Appendix F.2 for details.

Figure 23: Model Robustness to Changes in Job Search Cost Convexity



Notes: This figure reproduces Figure 8, which shows the predictions of the model described in Section 4.2 alongside data on spending and job search during an unemployment spell from Figures 2 and 6 respectively. In that model, we estimate a job search cost convexity parameter of 1.1 with a standard error of 0.1. The plots above include an additional series where we re-estimate the model fixing the job search cost convexity parameter ξ at 1.0. These parameter estimates are shown in online Appendix Table 18.

Figure 24: Job-Finding: Labor Market Transitions Around UI Onset

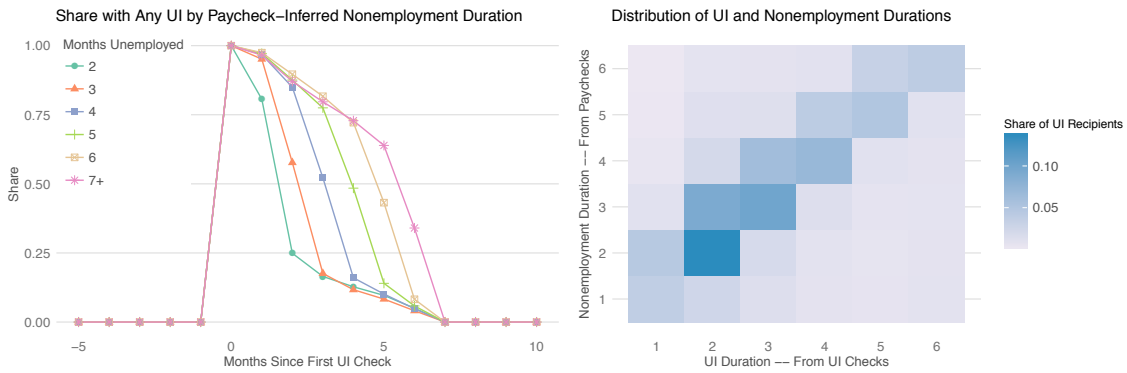
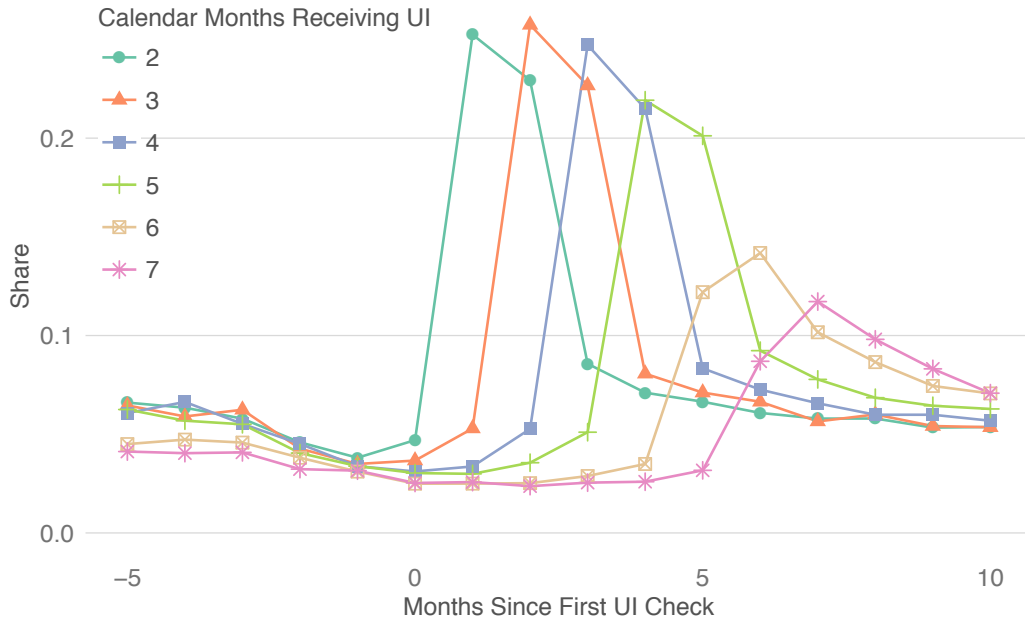


Notes: The top panel shows the number of paycheck-inferred jobs around UI onset using paychecks paid by direct deposit. It is less than one before the onset of UI because some employees are not paid by direct deposit and some paychecks are not categorized as labor income. It is greater than zero during UI receipt because other household members may be employed.

The bottom panel shows the monthly separation rate. See online Appendix D for details. The sample is households that receive UI benefits for at least four months and meet the sampling criteria described in Section 2.1.

Figure 25: Job-Finding: UI Durations and Nonemployment Durations

Share with Paycheck-Inferred Job Start by UI Duration

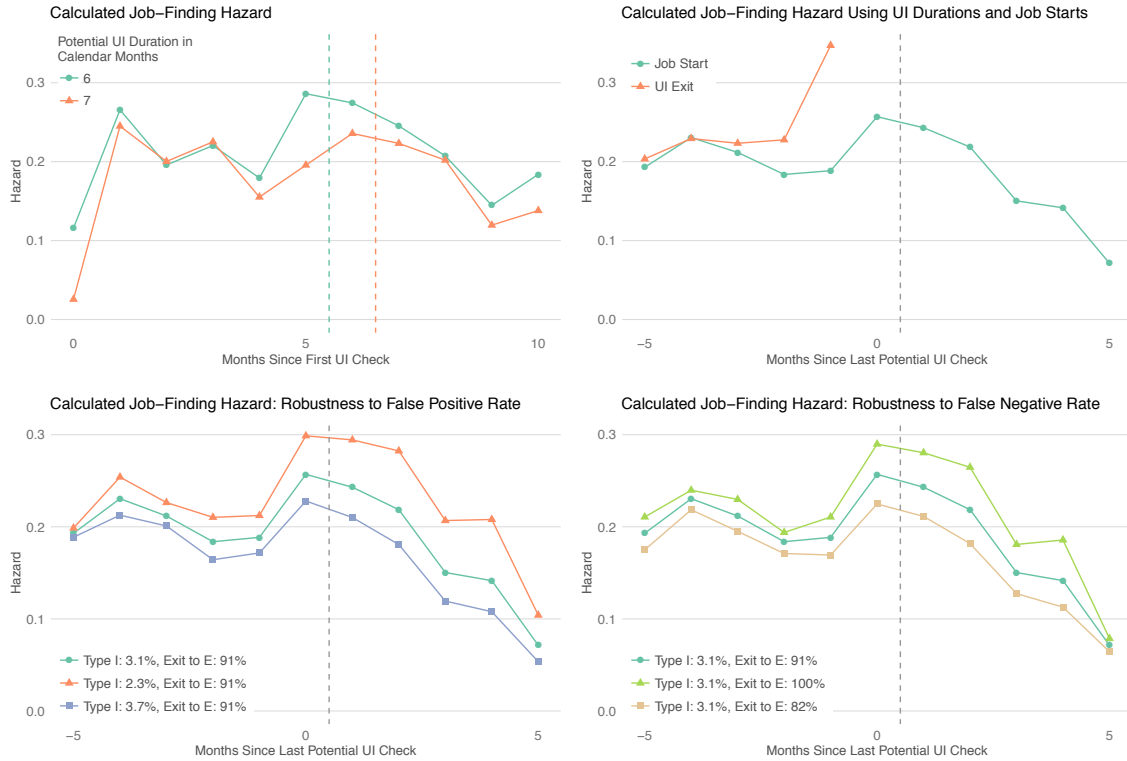


Notes: The top panel shows share of UI recipients with a paycheck-inferred job start, stratified by the number of calendar months in which UI benefits are received.

The bottom-left panel shows, among the sample of households that ever receive UI payments, the monthly share receiving any UI, stratified by the number of months of non-employment in the paycheck data.

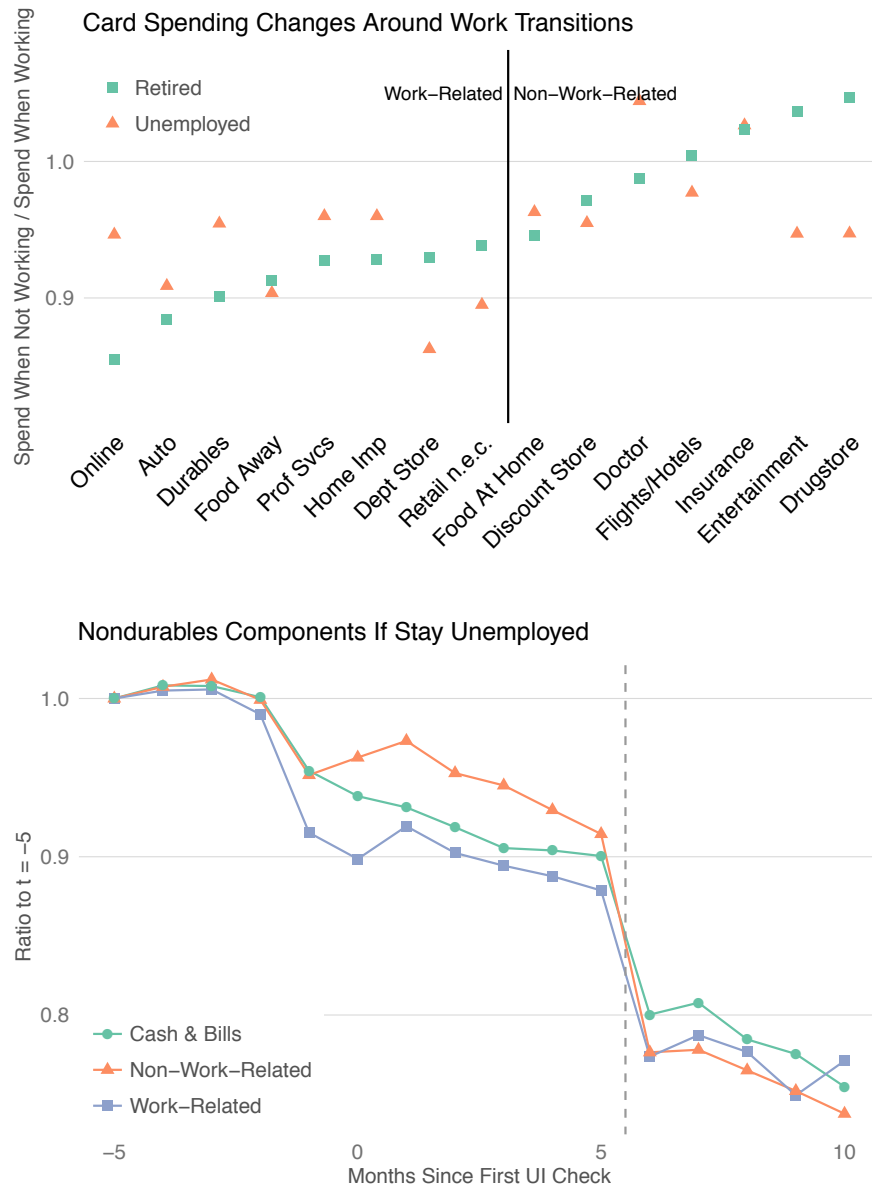
The bottom-right panel shows the bivariate distribution of UI duration and nonemployment duration among people with durations between one and six months. See online Appendix D for details. Sample is households that receive UI benefits and meet the sampling criteria described in Section 2.1.

Figure 26: Job-Finding: Robustness Checks on Hazard Rate



Notes: The top-left panel shows the job-finding hazard for people who are likely to receive their 26 weeks of UI benefits in six calendar months and people who are likely to receive their 26 weeks of UI benefits in seven calendar months. The vertical lines denote the last month of UI benefits for each group. The top-right panel shows UI exit hazards, compared to the job-finding hazard from Figure 6. The bottom panels show hazard rates under alternative assumptions about the type I error rate (bottom-left panel) and the share of UI recipients exiting to employment (bottom-right panel). See online Appendix D for details. Sample is households that receive UI benefits and meet the sampling criteria described in Section 2.1.

Figure 27: Work-Related Expenses



Notes: 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. “Home imp” reflects “Home Improvement” expenditures and “Retail n.e.c” reflects retail spending that is not elsewhere classified. 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 percent of pre-onset nondurable spending), non-work-related expenditures on debit and credit card (30 percent) and cash withdrawals and bills (44 percent). In online Appendix E.3, we estimate that two-thirds of the drop in spending on work-related expenses at the onset of unemployment is attributable to the drop in income.

Table 1: Summary Statistics Prior to Unemployment Onset

Category	Detail	Mean (\$) (1)	Median (\$) (2)	Std Dev (\$) (3)	Share > 0 (4)
Total Checking Account Inflows		5,544	4,160	4,257	0.99
Government	Tax Refunds, Social Security (Old Age and Disability), Child Support, Unemployment Insurance, Veterans Benefits, Supplemental Security Income	214	80	722	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 from External Account	Transfers from Checking, Savings, Money Market, and Investment Accounts	648	0	1,444	0.46
Paper Checks		1,045	120	1,812	0.60
Uncategorized ^a		224	0	1,179	0.57
Total Checking Account Outflows		5,546	4,220	4,152	1.00
Nondurable Spending		2,459	2,060	1,613	1.00
Durable Spending		396	220	460	0.93
Transfer to External Account	Transfers to Checking, Savings, Money Market, and Investment Accounts	354	0	873	0.42
Debt	Mortgage, Home Equity, Auto Loan, Student Loan, Non-Chase Credit Card Bills	762	160	1,265	0.80
Uncategorized ^a + Paper Checks		1,415	780	5,239	0.87

Notes: n= 182,361. This table presents summary statistics three months prior to the onset of UI for households that meet the sampling criteria described in Section 2.1.

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

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

	External Benchmarks				
	JPMCI Mean (\$) (1)	CE Survey Mean (\$) (2)	Ratio to CE Survey (3)	PCE Mean (\$) (4)	Ratio to PCE (5)
<u>Nondurable Expenditures</u>					
Drug Stores	13	13	1.01	14	0.93
Flights	32	35	0.92	38	0.86
Food Away From Home	216	251	0.86	460	0.47
Groceries	267	314	0.85	531	0.50
Ground Transportation	170	194	0.87	237	0.72
Medical Copay	36	80	0.46	177	0.21
Professional & Personal Services	78	183	0.42	921	0.08
Retail Nondurables	225	278	0.81	709	0.32
Telecom	113	112	1.01	193	0.59
Utilities	178	211	0.84	210	0.85
<u>Total</u>	1,328	1,671	0.79	3,490	0.38
Cash and Miscellaneous Nondurables ^a	989				
<u>Total (with Cash and Misc Nondurables)</u>	2,317	1,671	1.39	3,490	0.66
<u>Durable Expenditures</u>					
Auto Repair	45	230	0.20	168	0.27
Entertainment	35	149	0.24	334	0.11
Home Improvement	55	213	0.26	276	0.20
Hotels & Rental Cars	28	61	0.47	135	0.21
Insurance	148	276	0.54	233	0.64
Miscellaneous Durables	29	261	0.11	298	0.10
Retail Durables	55	90	0.61	199	0.27
<u>Total</u>	395	1,280	0.31	1,643	0.24
Not in JPMCI ^c		1,250	-	2,888	-
<u>Total (with Not in JPMCI)</u>	395	2,530	0.16	4,531	0.09
<u>Other Bank Account Outflows^d</u>	2,834				

Notes: n = 182,361. This table compares monthly spending by UI recipients that meet the sampling criteria described in Section 2.1 to the Consumer Expenditure (CE) Survey and the Bureau of Economic Analysis' Personal Consumption Expenditures (PCE) from 2015. See online Appendix B.2 for details.

a. Cash and miscellaneous nondurables are classified as nondurable on the basis of payment method. See Section 2.2 for details.

b. This nondurable spending estimate is the sum of the rows above. Because each spending category has been winsorized at the 95th percentile, this estimate is slightly smaller than the estimate when winsorization is applied after summing categories in Appendix Table 1.

c. JPMCI durables spending does not capture pensions and Social Security, health insurance, auto purchases, and shelter.

d. Other bank account outflows include transfers to external accounts (likely saving), debt payments, paper checks, and uncategorizable electronic transactions.

Table 3: Representativeness: Spending in JPMCI Data Compared to the Consumer Expenditure Survey

	External Benchmarks		
	JPMCI Mean (\$)	CE Survey Mean (\$)	Ratio to Benchmark
<u>Nondurable Expenditures</u>			
Alcoholic beverages	8	43	0.19
Apparel and services	59	154	0.38
Drugs	13	35	0.37
Food at home	181	335	0.54
Food away from home	139	251	0.55
Gasoline and motor oil	59	174	0.34
Household operations	14	109	0.13
Medical	26	78	0.33
Miscellaneous	34	73	0.47
Personal care products and services	44	57	0.77
Pets, toys, hobbies, and playground equipment	25	54	0.46
Public and other transportation	24	55	0.44
Reading	1	10	0.10
Tobacco products and smoking supplies	2	29	0.07
Utilities, fuels, and public services	138	324	0.43
<u>Total</u>	767	1,781	0.43
Cash and Miscellaneous Nondurables ^a	989		
<u>Total (with Cash and Miscellaneous Nondurables)</u>	1,756	1,781	0.99
<u>Durable Expenditures</u>			
Education	11	110	0.10
Fees and admissions	20	54	0.37
Household furnishings and equipment	59	152	0.39
Housekeeping supplies	98	55	1.78
Other entertainment supplies, equipment, and services	39	38	1.03
Other lodging	13	61	0.21
Other vehicle expenses	56	230	0.24
Vehicle rental, leases, licenses, and other charges	9	52	0.17
<u>Total Comparables</u>	305	752	0.41
Not in JPMCI ^b		2,186	--
<u>Total (with Not in JPMCI)</u>	305	2,938	0.10

Notes: This table compares monthly spending for a one percent sample of all JPMCI households (not just UI recipients) with at least five monthly bank account outflows to the Consumer Expenditure (CE) Survey from 2015. See online Appendix B.2.3 for details.

a. Cash and miscellaneous nondurables are classified as nondurable on the basis of payment method. See Section 2.2 for details.

b. JPMCI durables spending does not capture pensions and Social Security, health insurance, auto purchases, and shelter.

Table 4: Representativeness: Spending in JPMCI Data Using PCE Category

	External Benchmarks		
	JPMCI Mean (\$)	PCE Mean (\$)	Ratio to Benchmark
<u>Nondurable Expenditures</u>			
Alcoholic beverages purchased for off-premises consumption	8	89	0.09
Clothing and footwear	61	268	0.23
Food and nonalcoholic beverages purchased for off-premises consumption	181	510	0.35
Food services	139	460	0.30
Household maintenance	6	51	0.12
Household utilities	126	224	0.56
Medical	25	176	0.14
Motor vehicle fuels, lubricants, and fluids	59	189	0.31
Personal care products and services	45	172	0.26
Pharmaceutical products	14	44	0.32
Postal and delivery services	5	7	0.71
Professional and other services	17	124	0.14
Public transportation (air)	15	38	0.39
Public transportation (other)	9	33	0.27
Reading	3	75	0.04
Recreation - Other	46	221	0.21
Social services and religious activities	19	114	0.17
Sporting equipment, supplies, guns, and ammunities, and sports and recreational vehicles	9	80	0.11
Telecom	14	193	0.07
Tobacco	2	72	0.03
<u>Total</u>	803	3,140	0.26
Cash and Miscellaneous Nondurables ^a	989		
<u>Total (with Cash and Miscellaneous Nondurables)</u>	1,792	3,140	0.57
<u>Durable Expenditures</u>			
Education	10	206	0.05
Furnishings and durable household equipment	43	208	0.21
Hotels and motels	13	64	0.20
Housing supplies	89	84	1.06
museums	21	120	0.18
repair	52	168	0.31
Other durable goods	4	76	0.05
Other motor vehicle services	10	57	0.18
equipment, media, and services	55	220	0.25
<u>Total Comparables</u>	297	1,203	0.25
Not in JPMCI ^b	-	3,660	-
<u>Total (with Not in JPMCI)</u>	297	4,863	0.06

^aNotes: This table compares monthly spending for a one percent sample of all JPMCI households (not just UI recipients) with at least five monthly bank account outflows to the Bureau of Economic Analysis' Personal Consumption Expenditures (PCE) from 2015. See online Appendix B.2.3 for details.

a. Cash and miscellaneous nondurables are classified as nondurable on the basis of payment method. See Section 2.2 for details.

b. Spending not in JPMCI includes pensions and Social Security, health insurance, auto purchases, and shelter.

Table 5: Representativeness: Income in JPMCI Data Compared to External Benchmarks

Dataset	Sample	Share < Age 21 (1)	Household Income (Median) (2)	Household Income (Mean) (3)	Share in Poverty (4)	Household Earnings (Mean) (5)	Person Earn (Mean) (6)	Share Other Earn > 0 (7)	Others' Earnings (Mean) (8)
SIPP	Employed	0.06	6,019	7,333	0.07	6,800	3,723	0.61	3,077
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		5,142	6,334		5,002			
JPMCI	Exhaust UI		5,392	6,558		5,138			

Notes: All income statistics are monthly, for the 12-month period prior to the onset of unemployment. All variables are in dollars, other than variables explicitly labeled "share."

The first three rows are from the Survey of Income and Program Participation panel (SIPP) and are inflated to 2015 \$ using CPI-U. This survey covered years 2004-2007. "Unemployed" are people with a reported job separation followed by unemployment in the subsequent month. "Receive UI" are people who report positive UI income.

JPMCI data are for September 2013 through June 2016 for UI recipients that meet the sampling criteria described in Section 2.1. 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 percent below \$6,671, 13 percent below \$11,048, 14 percent below \$15,316, 15 percent below \$19,484, 17 percent below \$23,588, 18 percent below \$29,592, 20 percent below \$37,428, 23 percent below \$50,798, 25 percent below \$69,933, 28 percent below \$117,368, 36 percent below \$257,355, 47 percent below \$510,789, 52 percent below \$824,902 and 53 percent above. We calculate in the Survey of Consumer Finances that 15 percent 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 percent.

Table 6: 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	50	1,250	9,450	4,738

Notes: This table compares liquid assets in the 2013 Survey of Consumer Finances (SCF) to UI recipients that meet the sampling criteria described in Section 2.1. 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 7: Sensitivity of Spending Drop to Sample and Winsorization

Sample	Winsorization	Pre-onset mean	Two-Month Spending Change at Exhaustion	
			Drop	% of Pre-onset mean
Analysis Sample ^a	95th percentile	\$2,459	-\$263	-10.7%
All Valid UI Spells ^b	95th percentile	\$2,487	-\$265	-10.7%
All Valid UI Spells	99th percentile	\$2,650	-\$277	-10.5%
All Valid UI Spells	99.99th percentile	\$2,776	-\$332	-11.9%
All Valid UI Spells	None	\$2,778	-\$335	-12.1%
Labor Income Prior to UI Receipt ^c	95th percentile	\$2,629	-\$253	-9.6%

Notes: This table shows the spending drop at exhaustion under alternative sampling assumptions and winsorization procedures.

a. UI recipients that meet the sampling criteria described in Section 2.1. This includes restricting the sample to households with at least five bank account outflows each month.

b. UI recipients with a single contiguous spell as defined in Section 2.1. This sample includes UI recipients with five or fewer bank account outflows each month.

c. UI recipients with a single contiguous UI spell as defined in Section 2.1 and receive labor income by direct deposit in at least one of the six months prior to UI receipt.

Table 8: Income, Spending, and Borrowing 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)
Spending Measures				
Nondurable (% ^d)	2,459	-0.064 (0.001)	-0.0081 (0.0007)	-0.107 (0.003)
Nondurable (\$)	2,459	-158 (3)	-20 (2)	-263 (8)
Strict Nondurable (\$)	1,106	-67 (1)	-6 (0)	-113 (3)
Total Outflows (\$)	5,546	-199 (8)	-97 (3)	-456 (19)
Food (\$)	522	-32.6 (0.7)	1.3 (0.2)	-69.2 (1.7)
Income Measures				
Direct Deposit Labor + UI ^e (\$)	3,265	-470 (6)	-73 (2)	-1,300 (11)
Total Inflows (\$)	5,544	-164 (9)	-169 (3)	-618 (23)
N Checking Account Outcomes		182,361	538,287	27,740
Chase Credit Cards^f				
New Charges (\$)	263	-14 (1)	1 (0.4)	-2 (3)
Revolving Balance (\$)	2,447	23 (6)	21 (3)	54 (16)
Credit Limit (\$)	12,899	110 (9)	44 (4)	42 (20)
N Credit Card Outcomes		77,057	231,689	12,851

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

Sample is households that receive UI and meet the sampling criteria described in Section 2.1.

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. The sample is exhausters eligible for 26 weeks of benefits. Exhaustion is defined as the difference from one month before the last UI payment to one month after the last UI payment for benefit exhausters.

This two-month time horizon differs from the one-month time horizon that is used in Section 3.1.2 and Figures 2 and 3. Using that one-month time horizon, we estimate a 12 percent drop in spending at exhaustion.

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

e. 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.

f. 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 9: Spending Drop at Onset By Pre-Onset Characteristics

	Spending Change in \$ (1)	Ratio of Spending Drop to Income Drop (2)	p-val vs baseline (3)
Baseline	-158	0.352 (0.011)	--
<u>Demographics and Economic Characteristics</u>			
Annual Income < Median	-149	0.422 (0.017)	< 0.001
One Name on Account	-184	0.404 (0.013)	< 0.001
Shared Account, Other HH Member Employed	-94	0.381 (0.037)	0.155
Shared Account, Other HH Member Not Employed	-192	0.566 (0.033)	< 0.001
Age < Median	-186	0.409 (0.014)	< 0.001
Makes ACH Mortgage Payments	-142	0.283 (0.026)	0.001
UI Benefits / Income in Bottom Tercile	-164	0.320 (0.018)	0.035
UI Benefits / Income in Top Tercile	-149	0.366 (0.019)	0.3
<u>Assets and Liabilities</u>			
Total Assets in Bottom Tercile	-202	0.461 (0.018)	< 0.001
Total Assets in Top Tercile	-110	0.236 (0.019)	< 0.001
Chase Assets in Bottom Tercile	-209	0.489 (0.017)	< 0.001
Chase Assets in Top Tercile	-101	0.210 (0.019)	< 0.001
<u>Other Heterogeneity</u>			
Has Chase Credit Card	-148	0.301 (0.016)	< 0.001
Exhaust in 2015 or Later	-162	0.341 (0.013)	0.179

Notes: This table examines heterogeneity in the spending response to the onset of unemployment by pre-onset characteristics. Onset is defined as the period from three months before the first UI check ($t=-3$) to one month before the first UI check ($t=-1$). 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 in the MPC subsample. Sample is households that receive UI and meeting the sampling criteria described in Section 2.1.

Table 10: 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	-259	0.200 (0.009)	--
<u>Demographics and Economic Characteristics</u>			
Annual Income < Median	-298	0.247 (0.012)	< 0.001
One Name on Account	-277	0.223 (0.012)	0.015
Shared Account, Other HH Member Employed	-188	0.145 (0.027)	0.016
Shared Account, Other HH Member Not Employed	-271	0.222 (0.012)	0.019
Age < Median	-310	0.259 (0.014)	< 0.001
Makes ACH Mortgage Payments	-142	0.104 (0.024)	< 0.001
UI Benefits / Income in Bottom Tercile	-188	0.165 (0.022)	0.031
UI Benefits / Income in Top Tercile	-336	0.241 (0.013)	< 0.001
<u>Assets and Liabilities</u>			
Total Assets in Bottom Tercile	-329	0.268 (0.017)	< 0.001
Total Assets in Top Tercile	-186	0.137 (0.015)	< 0.001
Chase Assets in Bottom Tercile	-373	0.304 (0.016)	< 0.001
Chase Assets in Top Tercile	-166	0.122 (0.016)	< 0.001
<u>Other Heterogeneity</u>			
Has Chase Credit Card	-170	0.127 (0.014)	< 0.001
Exhaust in 2015 or Later	-242	0.183 (0.012)	0.020

Notes: This table examines heterogeneity in the spending response to exhaustion by pre-onset characteristics. Exhaustion is defined using one month before the last UI check and one month after the last UI check among UI exhaustees. 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 in the MPC subsample. Sample is households that exhaust UI benefits and meet the sampling criteria described in Section 2.1.

Table 11: Robustness Checks to Alternative Payment Channels at Onset

	Spending Drop at Onset					
			Dollars		Percent	
	% with channel	Pre-onset Spending	Families with this channel	Estimate for all families	Families with this channel	Estimate for all families
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Have Chase Checking Account	100%	2,459	-158	-158	-6.4%	-6.4%
(B) Have Outside Checking Account	28%	1,592	-35	-10	-2.2%	-0.6%
(C) Have Outside Credit Card	64%	989	-14	-9	-1.5%	-0.9%
Sum Over All Bank Accounts (A)+(B)		2,900		-167		-5.8%
Sum Over All Payment Channels (A)+(B)+(C)		3,533		-176		-5.0%

Notes: This table quantifies how nondurable spending changes on outside credit cards and outside checking accounts affect the estimated drop in spending at the onset of unemployment. To approximate outside checking accounts, we examine unlinked checking accounts within Chase for customers that Chase infers are members of the same household. Onset is defined as the period from three months before the first UI check ($t=-3$) to one month before the first UI check ($t=-1$). See Section 3.1.3 for details.

Column 1 estimates the share of UI recipients with each channel. Row B: The McKinsey Consumer Financial Life Survey reports that 28 percent of households had checking accounts at multiple banks. Row C: We estimate using the SCF that 64 percent of UI recipients with a bank account have an outside credit card.

Column 2 shows our estimate of spending within this payment channel among households that have this payment channel. Row A is households that receive UI and meet the sampling criteria described in Section 2.1. Row B is households in row A that have an unlinked checking account with Chase. Row C is households in row A that have a Chase credit card. In row C, we estimate spending on non-Chase credit cards as spending on Chase credit cards times the ratio of electronic payments on non-Chase credit cards to payments on Chase cards.

Column 3 shows the change in spending. For outside checking accounts we use Appendix Figure 5 and for credit cards we use Appendix Table 7.

Column 4 multiplies the drop for families with the channel (column 3) by the percent of families with each channel (column 1). Column 5 recomputes the drop in spending relative to onset using the denominator in column 2. Column 6 multiplies the drop in column 5 by column 1.

Table 12: Robustness Checks to Alternative Payment Channels at Exhaustion

	Spending Drop at Exhaustion					
			Dollars		Percent	
	% with channel	Pre-onset Spending	Families with this channel	Estimate for all families	Families with this channel	Estimate for all families
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Have Chase Checking Account	100%	2,459	-263	-263	-10.7%	-10.7%
(B) Have Outside Checking Account	28%	1,559	40	11	2.6%	0.7%
(C) Have Outside Credit Card	64%	989	-2	-1	-0.2%	-0.1%
Sum Over All Bank Accounts (A)+(B)		2,891		-252		-8.7%
Sum Over All Payment Channels (A)+(B)+(C)		3,523		-253		-7.2%

Notes: This table quantifies how nondurables spending changes on outside credit cards and outside checking accounts affect the estimated drop in spending at UI benefit exhaustion. To approximate outside checking accounts, we examine unlinked checking accounts within Chase for customers that Chase infers are members of the same 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. See Section 3.1.3 for details.

Column 1 estimates the share of UI recipients with each channel. Row B: The McKinsey Consumer Financial Life Survey reports that 28 percent of households had checking accounts at multiple banks. Row C: We estimate using the SCF that 64 percent of UI recipients with a bank account have an outside credit card.

Column 2 shows our best estimate of spending within this payment channel among households that have this payment channel. Row A is households that exhaust UI and meet the sampling criteria described in Section 2.1. Row B is households in row A that have an unlinked checking account with Chase. Row C is households in row A that have a Chase credit card. In row C, we estimate spending on non-Chase credit cards as spending on Chase credit cards times the ratio of electronic payments on non-Chase credit cards to payments on Chase cards.

Column 3 shows the change in spending. For outside checking accounts we use Appendix Figure 5 and for credit cards we use Appendix Table 7.

Column 4 multiplies the drop for families with the channel (column 3) by the percent of families with each channel (column 1). Column 5 recomputes the drop in spending relative to onset using the denominator in column 2. Column 6 multiplies the drop in column 5 by column 1.

Table 13: Spending Drop Using Alternative Time Horizons

	Spending Drop Compared to Three Months Before UI Onset			
	Pre-Onset Mean	Onset (t=-1) ^a	While Receiving UI ^b	Annual (t=-1,0,...10) ^c
	(\$)	(2)	(3)	(4)
(a) Nondurables	2,459	-6.4%	-7.8%	-6.9%
(b) Food ^d	522	-6.3%	-4.9%	-4.3%

Notes: This table computes the spending drop for various time horizons and various spending concepts. In each column, we compute the percent change in spending from three months before UI onset to the given reference period, i.e. $(\text{Spend}_{\text{reference}} - \text{Spend}_{t=-3}) / \text{Spend}_{t=-3}$. Time subscripts are relative to the first month of UI receipt. The reference period for each column is specified in the column-specific notes below. Sample is households that receive UI and meet the sampling criteria described in Section 2.1.

a. $\text{Spend}_{\text{reference}} = \text{Spend}_{t=-1}$. This column reports the average spending drop in the first month of unemployment relative to three months prior to UI receipt.

b. $\text{Spend}_{\text{reference}} = \text{Mean}(\text{Spend}_{t=0}, \text{Spend}_{t=-1}, \dots, \text{Spend}_{t=T})$. T is the last month of UI receipt for a given household in our sample. This column reports the average spending drop while households are receiving UI relative to three months prior to UI receipt.

c. $\text{Spend}_{\text{reference}} = \text{Mean}(\text{Spend}_{t=-1}, \text{Spend}_{t=0}, \dots, \text{Spend}_{t=10})$. This column reports the average spending drop in the year after job loss relative to three months prior to UI receipt.

d. Gruber (1997) estimates a drop in food spending of 6.8 percent. The reference period in the PSID for food spending is ambiguous. If the reference period is unemployment onset, the comparable estimate is 6.3 percent, while if the reference period is an annual time horizon after job loss, then the comparable estimate is 4.3 percent.

Table 14: Spending Decomposition at Unemployment Onset

Spending		Pre Onset	Post Onset	Change in \$	Change in %
Type ^a	Category ^b	(\$)	(\$)	(2) - (1)	(3) / (1)
		(1)	(2)	(3)	(4)
Other ND	Department Stores	20.7	17.8	-2.8	-13.7%
Other ND	Other Retail	156.8	140.3	-16.5	-10.5%
Durable	Hotels & Rental Cars	28.3	25.3	-3	-10.5%
Strict ND	Flights	32.4	29.3	-3.2	-9.8%
Strict ND	Food Away From Home	215.5	194.7	-20.8	-9.6%
Strict ND	Transportation	169.5	154.1	-15.5	-9.1%
Nondurable	Cash	664.5	613.3	-51.1	-7.7%
Other ND	Online	44.0	41.6	-2.4	-5.4%
Other ND	Drug Stores	37.0	35.1	-2.0	-5.3%
Durable	Entertainment	33.5	31.7	-1.8	-5.3%
Other ND	Discount Stores	59.5	56.9	-2.7	-4.5%
Durable	Retail Durables	54.8	52.3	-2.5	-4.5%
Durable	Home Improvement	47.7	45.8	-1.9	-4.0%
Strict ND	Professional & Personal Services	58.0	55.7	-2.3	-4.0%
Durable	Auto Repair	45.1	43.3	-1.8	-3.9%
Strict ND	Groceries	320.8	309.0	-11.9	-3.7%
Strict ND	Telecom	113.3	111.1	-2.2	-1.9%
Strict ND	Utilities	177.5	175.5	-2.0	-1.1%
Nondurable	Miscellaneous Nondurables	280.5	277.8	-2.7	-1.0%
Durable	Insurance	148.4	147.2	-1.3	-0.9%
Durable	Miscellaneous Durables	29.2	29.4	0.2	0.5%
Other ND	Medical Copay	35.0	36.6	1.6	4.4%
Other Bank Account Outflows					
	Non-Chase Credit Card Bill	382.8	364.9	-18.0	-4.7%
	Uncategorizable Electronic	589.1	571.2	-17.9	-3.0%
	Installment Debt	379.4	374.5	-4.9	-1.3%
	Paper Checks	985.6	987.1	1.4	0.1%
	Transfer to External Account	353.8	366.0	12.2	3.4%

Notes: n=182,361 households. This table decomposes the drop in spending at the onset of unemployment into 27 categories. Column 1 is three months prior to the first UI payment and column 2 is one month prior to the first UI payment. Sample is households that receive UI and meet the sampling criteria described in Section 2.1.

a. Spending categories of strict nondurable, other nondurable, and durable from Lusardi (1996). Cash withdrawals and miscellaneous nondurables are included in the headline nondurables series.

b. See online Appendix B for additional details.

Table 15: Model Environment Parameters

Parameter	Value	Data Source
Employed Income	1	JPMCI
Unemployed (1-6 months) Income	0.83	JPMCI
Unemployed (>6 months) Income	0.54	JPMCI
Initial Assets a_0	0.66	JPMCI with SCF ^a
Monthly Interest Rate R	1.0025	Cagetti (2003) ^b
Separation Rate	0.0325	BLS (2014) ^c
Number of Periods ^d	240	

Notes: This table shows the assumptions about the economic environment for the model in Section 4.

a. We estimate total liquid assets at onset by multiplying median checking account balances in JPMCI by the ratio of total liquid assets to checking account balances in the SCF.

b. Following Cagetti (2003), we choose a monthly real interest rate of 0.25 percent, which translates to an annual interest rate of 3 percent.

c. We choose an exogenous separation rate to UI of 2.5 percent in order to match the 11.5 percent of households with an unemployed member during 2014 (Bureau of Labor Statistics, 2014).

d. We consider a time horizon of 240 months, corresponding to a middle-aged worker with 20 years left in her career.

Table 16: Model Target Moments

Months Since First UI Check	Nondurable Consumption		Job-Finding Rate	
	Estimate	Standard Error	Estimate	Standard Error
-5	1.000	--	--	--
-4	1.007	0.001	--	--
-3	1.009	0.001	--	--
-2	0.997	0.001	--	--
-1	0.939	0.001	--	--
0	0.928	0.001	0.199	0.006
1	0.933	0.002	0.238	0.010
2	0.918	0.002	0.223	0.012
3	0.909	0.003	0.200	0.016
4	0.901	0.004	0.207	0.021
5	0.895	0.006	0.282	0.025
6	0.777	0.006	0.273	0.033
7	0.783	0.007	0.260	0.045
8	0.770	0.007	0.197	0.058
9	0.755	0.008	0.210	0.070
10	0.744	0.008	0.131	0.075

Notes: This table reports the moments for the "stay-unemployed" used in equation (8) to fit the models in Section 4. The nondurable consumption moments are depicted in Figure 3 and the job search moments are depicted in Figure 7. For the weight matrix W in equation (8), we use the inverse of the variances implied by the standard errors above.

Table 17: Model-Implied Search Responses to Changes in UI Generosity

	Cost of Extensions			ξ	Search Goodness Of Fit
	BCMC - Benefit Increase	BCMC - Benefit Extension	Relative to Increases (col 2) / (col 1) - 1		
	(1)	(2)	(3)	(4)	(5)
Data: Schmieder and von Wachter (2017) Literature Review					
25th Percentile	1.15	1.14	-1%		
Median	1.32	1.52	15%		
75th Percentile	1.39	1.94	40%		
Model					
Standard Model	1.21	1.45	20%	1.4	81
Heterogeneity in β	1.31	1.57	20%	1.1	86
Heterogeneity in β , $\xi=1.0$	1.32	1.51	14%	1.0	77

Notes: Schmieder and von Wachter (2017) propose a metric which is the ratio of behavioral cost (BC)—the total cost to the government of increasing UI generosity, including the extra spending induced because UI recipients will respond by taking longer to find a job— to the mechanical cost (MC) of increasing generosity absent any change in behavior. They call this statistic the “BCMC” ratio. In this table we present the BCMC ratios from the Schmieder and von Wachter (2017) literature review and those implied by various models we consider for one-month benefit extensions and for increases in the benefit level of the same fiscal cost.

Table 18: Model Robustness

	No heterogeneity in k	Heterogeneity in β	Estimate one β	Heterogeneity in β , fixed ξ
	(1)	(2)	(3)	(4)
Number of Types	1	4	4	4
Calibrated Consumption Parameters				
Risk Aversion γ^a	2	2	2	2
Naive Hyperbolic Discount Factor β	1	--	{--, 1.000}	--
Estimated Consumption Parameters				
Exponential Discount Factor δ	0.9907 (0.0003)	0.9951 (0.0001)	0.9940 (0.0001)	0.9899 (0.0005)
Naive Hyperbolic Discount Factor β	--	{0.522, 0.899} (0.025, 0.026)	{0.551, --} (0.008, --)	{0.450, 1.000} (0.015, 0.025)
Borrowing Limit \underline{a}	4.4 (0.3)	6.1 (0.6)	5.9 (0.3)	7.3 (0.4)
Impatient/Myopic Population Share	--	0.25 (0.01)	0.25 (0.01)	0.19 (0.01)
Calibrated Search Parameters				
Convexity of Job Search Cost ξ	--	--	--	1.0
Estimated Search Parameters				
Cost of Job Search k	30.0 (4.0)	{4.7, 53.6} (1.0, 20.3)	{4.5, 50.0} (0.9, 18.9)	{3.4, 33.5} (0.3, 4.4)
Convexity of Job Search Cost ξ	1.6 (0.1)	1.1 (0.1)	1.1 (0.1)	--
Share	--	0.79 (0.03)	0.70 (0.03)	0.65 (0.04)
Goodness of Fit				
N Moments	27	27	27	27
N Estimated Parameters	4	9	8	8
Consumption Goodness of Fit	458	99	139	117
Search Goodness of Fit	205	86	79	77
Total Goodness of Fit	663	186	218	194

^aNotes: This table presents parameter estimates of models of consumption and job search during unemployment. The model is described in Section 4.1 and is fit using equation (8) to the data on spending and job search during an unemployment spell from Figures 3 and 7, respectively. Standard errors of estimated parameters in parentheses.

Column 1 examines a representative agent model with no heterogeneity in job search costs.

Column 2 reproduces our preferred β -heterogeneity model from Table 3, column 3.

Column 3 re-estimates the β -heterogeneity model, restricting the β parameter to 1 for the high- β types.

Column 4 re-estimates the β -heterogeneity model, restricting the job search cost parameter ξ to 1

In columns 2, 3 and 4, β is constrained to be between 0 and 1.

a. Calibrated from Carroll (1997).

Table 19: Welfare Impact of Changes in UI Generosity with Low and High Risk Aversion

Welfare Change as an Equivalent Increase in Lifetime Income

	Consumption-Smoothing Gains Only		Consumption-Smoothing Gains and Moral Hazard Loss		Ratio (col 2 / col 1)
	UI Benefits ↑ 1.8% (1)	UI Duration ↑ 1 Month (2)	UI Benefits ↑ 2.0 or 1.9% (3)	UI Duration ↑ 1 Month (4)	
Baily-Chetty Approximation					
JPMCI Nondurables, $\gamma=0.999$	0.010%	0.036%	-0.005%	0.024%	3.59
Gruber (1997) Food, $\gamma=0.999$	0.009%		--	--	
Baily-Chetty Approximation					
JPMCI Nondurables, $\gamma=4.0$	0.046%	0.219%	0.023%	0.081%	4.80
Gruber (1997) Food, $\gamma=4.0$	0.042%		--	--	

Notes: We evaluate the welfare impact of budget-neutral tax-financed changes in the generosity of UI benefits as a percentage of lifetime income for CRRA utility for risk aversion parameter values of $\gamma=0.999$ and $\gamma=4.0$. See Section 5 for further details.

Column 1 considers a policy that raises monthly benefits by 1.77 percent and raises taxes during employment by 0.14 percent; this tax revenue is sufficient to finance the increase in benefits if there is no job search distortion from increased UI benefits.

Column 2 considers a policy that extends potential UI benefit durations by one month and raises taxes during employment by 0.14 percent; this tax revenue is sufficient to finance the extension in benefits if there is no job search distortion from UI extensions.

Column 3 considers a policy that raises monthly benefits by 2.00 percent (1.85 percent), and raises taxes during employment by 0.19 percent (0.17 percent) in the models with $\gamma=0.999$ (4.0) respectively; this tax revenue is sufficient to finance the increase in benefits when increased UI levels reduce job search.

Column 4 considers a policy that extends potential UI benefit durations by one month and raises taxes during employment by 0.19 (0.17 percent) in the models with $\gamma=0.999$ (4.0) respectively; this tax revenue is sufficient to finance the extension in benefits when extended UI durations reduce job search.

Table 20: Welfare Impact of Changes in UI Generosity in Structural Models

<i>Welfare Change as an Equivalent Increase in Lifetime Income</i>				
	Δ Welfare - UI Benefit Increase (1)	Δ Welfare - UI Duration Extension (2)	Difference (col 2 - col 1) (3)	Ratio (col 2 / col 1) (4)
Consumption-Smoothing Gains Only [Baily-Chetty]				
JPMCI Nondurables	0.021%	0.082%	0.061%	3.94
Gruber (1997) Food	0.019%	--		
Consumption-Smoothing Gains and Moral Hazard Loss [Baily-Chetty]				
JPMCI Nondurables	-0.023%	0.016%	0.039%	--
Gruber (1997) Food	-0.025%	--		
Structural Model Simulation				
Heterogeneity in β , Consumption Gains Only	0.024%	0.059%	0.035%	2.45
Heterogeneity in β	-0.033%	-0.031%	0.003%	--
Heterogeneity in β , fixed $\xi = 1.0$	-0.022%	0.003%	0.025%	--

Notes: We evaluate the welfare impact of budget-neutral tax-financed changes in the generosity of UI benefits as a percentage of lifetime income for CRRA utility with risk aversion of 2 using the Baily-Chetty approximation, and using a structural model with endogenous job search. Rows 1-4 repeat the results in Table 4 and present the Baily-Chetty results without and with moral hazard. Rows 5-7 present the simulation results from our estimated structural models in Appendix Table 18.

In rows 1, 2 and 5, a one-month benefit extension has the same fiscal cost as a 1.77 percent increase in benefits, and requires a tax increase of 0.14 percent to fund.

In rows 3 and 4, a one-month benefit extension has the same fiscal cost as a 2.03 percent increase in benefits, and requires a tax increase of 0.21 percent to fund.

In row 6, a one-month benefit extension has the same fiscal cost as a 1.75 percent increase in benefits, and requires a tax increase of 0.18 percent to fund.

In row 7, a one-month benefit extension has the same fiscal cost as a 1.78 percent increase in benefits, and requires a tax increase of 0.18 percent to fund.

Table 21: Share of Spending Type by Payment Method in DCPC

Payment	Share by Durability			
	Nondurable Share	Durable Share	Consumption Share ^a	Other Share ^b
Cash	75%	17%	92%	8%
Check	32%	62%	94%	6%
Credit Card	83%	16%	99%	1%
Debit Card	79%	19%	98%	2%
Electronic Transfer	34%	59%	93%	7%
Online Pay	38%	54%	92%	8%
Other	54%	40%	93%	7%
Total	58%	37%	95%	5%

Notes: Federal Reserve's 2012 Diary of Consumer Payment Choice (DCPC). We classify payment recipients in the DCPC using the Lusardi (1996) taxonomy.

Note that nondurable and durable shares include some miscellaneous consumption and transactions where some detail is missing. Exact method of allocation is outlined in Appendix B.1.2.

a. This is the sum of nondurable and durable shares.

b. This includes taxes and inter-household transfers.

B Measuring UI Reciprocity and Exhaustion

This section describes how we clean the JPMCI data to classify UI benefit recipients and exhaustees. Within the JPMCI data one can observe direct deposit of UI benefits. 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.

To measure UI duration, we use the difference between the date of the first UI check and the last UI check. In principle, a worker who receives the maximum benefit duration of 26 weeks of checks should have 25 weeks elapse between the date on her first UI check and the date on her last UI check. There are several reasons why this assumption may fail to hold in bank account data. A worker could exhaust her UI benefits with fewer than 25 weeks between the first and last check if the state pays benefits biweekly, or if she forgets to pick up her last check as in Meyer (1990a). A household might also have more than 25 weeks between the first and last check because of part-time work while receiving UI, payment errors by the UI agency, multiple household members getting UI, or workers pausing UI benefits.

We use a data-driven approach to find *exhaustees*. First, the modal number of checks received by exhaustees varies by state. For example, among states where benefits last 26 weeks, the modal number of weeks of benefits received is 23 weeks in Texas, 24 weeks in New Jersey and 26 weeks in Illinois. For the three states in our sample where benefits last less than 26 weeks, the mode is 14 weeks in Florida during the time period that benefits last 16 weeks, 17 weeks in Michigan during the time period that benefits last 20 weeks and 13 weeks in Georgia in the the time period that benefits last 18 weeks.

Second, we use a four-week window around the modal UI duration. We plotted a histogram of the number of weeks between first and last UI check and found significant excess mass in numbers of weeks close to the state-level modal number weeks. We analyzed the evolution of labor income around the last UI check to determine that a four-week window is appropriate. For example, if a state’s modal number of weeks was 24, we use a window of 22 weeks through 25 weeks. Below 22 weeks, we saw an uptick in labor income at the end of UI receipt similar to what we observe for much shorter durations (e.g. 10 weeks). Above 25 weeks, there were very few UI recipients.

C Spending Estimates

We measure spending on nondurables and durables in order to link empirical results in our data to consumption models. In this appendix, we describe how we categorize bank account outflows (debits from a checking account) by whether they qualify as spending for consumption and if so, how we categorize that spending.⁴²

The motivation for this categorization exercise is best illustrated using an example based on Browning and Crossley’s (2009) model of spending during unemployment. Their model says that when a member of a household becomes unemployed, the household will cut its investment in durables and may not cut its spending on nondurables. In this scenario, the household continues to receive service flows from its existing durable stock. The drop in household consumption is proportional to the depreciation rate on the durables stock. If

⁴²For example, a transfer of funds to another bank account is an outflow that we do not count as spending.

the depreciation rate is low, it is possible for an unemployment spell to occur with little change in the utility flows from consumption.

For example, a household might choose not to buy a new car during unemployment. So long as the old car does not break down, the household will consume the same transportation services as prior to unemployment. In contrast, if a household were to cut its *nondurable* consumption during unemployment, the Browning and Crossley model would conclude that the household received substantially less utility flows from consumption during this period.

We classify outflows as “strict nondurables,” “other nondurables,” and “durables” using the taxonomy in Lusardi (1996). Her taxonomy has become the standard in the literature for classifying spending in survey data in the context of testing excess sensitivity models.⁴³ In Section C.1, we use her taxonomy to construct the first exhaustive categorization of spending in bank account data. We have made the details of this categorization algorithm public and it may be useful to other researchers working with administrative spending data. In addition to the three spending categories in Lusardi, we also classify the residual outflows as either debt payments, transfers to external accounts, or outflows with insufficient information to be categorized. In Section C.2, we compare categorized spending in the JPMCI data to external benchmarks. We discuss how we use bank account *inflows* (credits to a checking account) in Appendix D.

C.1 Classifying Spending

C.1.1 Classifying Spending with Payment Recipient

Nearly all outflows can be categorized into four payment methods: payments on a debit card, electronic transfers (also known as Automated Clearing House transfers), cash withdrawals at an Automated Teller Machine, and paper checks.⁴⁴ Debit card payments have structured information on the recipient and electronic transfers carry some unstructured information on the recipient. Cash withdrawals and paper checks contain no information on payment recipient in our data. Table 2 presents an exhaustive decomposition of bank account outflows for UI exhaustees and Appendix Table 14 presents the same information for all UI recipients in the analysis sample.

When information is available on a payment recipient, we use it to classify outflows. For debit and credit card purchases, payment recipient is always available through a Merchant Category Code (MCC). Any merchant with a terminal to accept card payments is required to report revenues captured by the terminal to the Internal Revenue Service. The merchant reports this MCC on their tax form. There are about 600 MCCs in JPMCI’s underlying transaction-level data. To construct our primary data file—which is a monthly profile of spending by UI recipients—JPMCI collapsed these MCCs into 19 groups. In section C.2.3, we show that we obtain similar estimates of nondurable and durable spending using a supplementary data file with transaction-level data that includes the exact MCC code for the transaction rather than the broader MCC group.

We classify these 19 groups of debit and credit card purchases using the Lusardi taxonomy into “strict nondurables,” “other nondurables,” and “durables.” Strict nondurables are food away from home, groceries, ground transportation, flights, and professional & personal services. Other nondurables are retail nondurables, discount stores, drug stores,

⁴³Examples of papers which use the Lusardi taxonomy include Souleles (1999), Stephens Jr. (2003), and Johnson et al. (2006). We use the Lusardi taxonomy, subject to the modifications introduced by Parker et al. (2013), such as classifying education expenditures as a durable.

⁴⁴Five percent of outflows do not fit into any of these four groups. We classify these as nondurable consumption and explain the reasoning for this decision later in this section.

medical copayments and online.⁴⁵ Durables are retail durables, auto repair, entertainment, hotels & rental cars, home improvement, and miscellaneous durables.⁴⁶ The exhaustive decomposition of spending in Table 2 indicates the durability of each spending category.

Beyond debit cards, we also measure spending on consumption goods and services from electronic transfers and credit cards. Following Lusardi, we classify telecom and utilities as strict nondurables and insurance as durable.⁴⁷ For Chase credit cards, we define spending using the MCC for each card transaction and the date when the goods are purchased, rather than when the credit card bill is paid, which may be months later. Mean monthly Chase credit card spend in our sample is \$263, which is equal to five percent of monthly outflows. Using payment recipient information from debit cards, credit cards, and electronic transactions, we estimate that 21 percent of outflows are for strict nondurables, six percent are for other nondurables, and seven percent are for durables. Altogether, this categorized spending accounts for 34 percent of outflows.

Some electronic transfers reflect debt payments for items purchased at an earlier date, and we do not include these outflows in our definition of spending. For example, we observe payments on student loans, mortgages, and auto loans, which are seven percent of outflows. We similarly observe payments on non-Chase credit cards (also seven percent of outflows). Because we are unable to characterize the timing of consumption, we exclude these debt payments from our definition of spending.

Finally, some electronic transfers likely reflect saving or cannot be categorized. Transfers to other checking accounts, savings accounts, money market accounts, and investment accounts likely reflect saving behavior and account for six percent of outflows. In some cases, the electronic transfer cannot be categorized due to insufficient information about recipient and these account for 10 percent of outflows. Altogether across spending for consumption, debt payments, and transfers to other accounts, 54 percent of outflows can be categorized using recipient information.

C.1.2 Classifying Spending with Payment Method When Payment Recipient is Unavailable

When information on the payment recipient is not available, we use payment method to classify outflows. We motivate our classification decisions by relying on a supplementary data source: the Federal Reserve’s 2012 Diary of Consumer Payment Choice (DCPC). The DCPC is a three-day diary survey where respondents record every expenditure, including the amount, the payment method, and the payment recipient. This is helpful because—unlike the JPMCI data—it contains information on what types of items are typically purchased using paper checks and cash.

We measure spending shares by payment method in the DCPC using the Lusardi taxonomy. Appendix Table 21 shows that among purchases made using cash, 75 percent are for nondurables and 17 percent are for durables or debt payments.⁴⁸ Among purchases made

⁴⁵“Retail Nondurables” combines several types of retailers. The three largest subcategories are clothing stores, bookstores, and discount stores. “Online” combines various online purchases and purchases from direct marketing companies.

⁴⁶“Retail Durables” combines several types of retailers. The three largest subcategories are electronics stores, jewelry stores, and sporting goods stores. “Miscellaneous Durables” reflects education spending, organizational dues, and charitable contributions.

⁴⁷These three categories are usually paid using electronic transfers, but are occasionally paid using a debit card. The estimates for these categories reported in Table 2 and Appendix Table 14 are the sums across these two payment methods.

⁴⁸The remaining eight percent of purchases are taxes and inter-household transfers.

with checks, 32 percent are nondurable and 62 percent are durable. Among purchases made with online bill pay, 38 percent are for nondurables, and 54 percent are for durables.

We classify outflows from two payment methods as nondurable consumption. First, motivated by the fact that 75 percent of all cash purchases are for nondurables, we include cash withdrawals in nondurable consumption. Second, the JPMCI data contains a variable with the internal label “miscellaneous consumption.” It accounts for five percent of monthly outflows and captures outflows from cashing a check and online bill pay where the recipient is unknown. Although we are unable to disaggregate these two types of outflows for UI recipients, analysis of a transaction-level JPMCI dataset with other households indicates that the composition of outflows is roughly split equally between these two types of payment methods. Using the DCPC, we estimate that a payment method which is half cash and half online bill pay will have 57 percent of its expenditures going to nondurables.

Motivated by this analysis, we assign the “miscellaneous consumption” variable to nondurable consumption and label it “miscellaneous nondurables.” This category has the smallest drop of any spending category at UI benefit exhaustion. As a result, assigning this type of spending to nondurables is a conservative choice that may lead us to understate the actual drop in spending on nondurables. We also report a robustness check in Section 3.1.3 where we assume that the fraction of cash and online bill pay spent on nondurables mirrors the fraction spent on nondurables in the DCPC.

There are two types of bank account outflows which jointly account for 29 percent of outflows that cannot be assigned to any category. Nineteen percent of outflows are paper checks, where no further information is available, and 10 percent are electronic transfers that cannot be categorized.

To summarize, we exhaustively categorize bank account outflows in the JPMCI data. Our baseline definition of nondurable consumption—which uses nondurable spending measured using payment recipient, cash withdrawals, and miscellaneous nondurables—includes 44 percent of total outflows. We also estimate that seven percent of outflows are for spending on durable consumption, 14 percent are for debt payments, six percent are for transfers to external accounts, and 29 percent cannot be categorized. These five summary categories sum to 100 percent of the outflows in the JPMCI data.

C.2 Comparison to External Benchmarks

Having explained how we categorize spending in our data, we next compare spending on nondurables and durables in the JPMCI to external benchmarks. Our main results in Section C.2.1 compare the spending categories we analyze for UI recipients to the Consumer Expenditure (CE) Survey from the Bureau of Labor Statistics and Personal Consumer Expenditures (PCE) from the Bureau of Economic Analysis. Because JPMCI captures spending by merchant, while the external benchmarks capture spending by product, we construct a crosswalk between the two ways of organizing spending in Section C.2.2. Finally, in a supplementary analysis in Section C.2.3, we compare spending in the JPMCI data to 34 categories in the CE Survey and 44 categories in the PCE. This analysis provides a more fine-grained comparison to external benchmarks, but we are unable to implement it for the UI recipient sample due to data constraints.

C.2.1 Comparison Using Data Aggregated to Monthly Level

We compare the spending of UI recipients in the JPMCI sample to external benchmarks for all U.S. households in Appendix Table 2. Although it would be ideal to compare our spending estimates to an external benchmark of spending for UI recipients prior to the

onset of unemployment, we are not aware of any data source that has this information. In addition, the income of UI recipients is similar to the income of all U.S. households that experience unemployment, as shown in Appendix Table 5, and nearly every U.S. household experiences unemployment at some point in their lives, so the UI screen is unlikely to be an important source of bias.

The first column in Appendix Table 2 is average monthly spending for three months prior to receipt of the first UI check.⁴⁹ This column uses the analysis sample described in Section 2.1, which requires at least five monthly outflows from three months before receipt of the first UI check to three months after receipt of the last UI check.

We crosswalk each JPMCI outflow category to the associated CE Survey and PCE spending categories. Each JPMCI spending category is composed of between one and eight types of spending in the external benchmark. Appendix Table 22 shows a crosswalk between these three data sources. Three challenges emerge when constructing a crosswalk between JPMCI and the external spending benchmarks: benchmark spending with no JPMCI counterpart, JPMCI outflows with no benchmark counterpart, and the fact that JPMCI captures spending by merchants while the benchmarks captures spending by product.

The first challenge is that some durable spending in external benchmarks is not well captured in bank account data for three reasons. First, many households have paycheck deductions to pay for pension funding, Social Security deductions, health insurance, life insurance, and personal insurance.⁵⁰ Second, we are unable to capture durables purchases of cars or homes with bank account data. Third, most households pay rent using paper checks, where we do not observe the identity of the payment recipient.⁵¹ Altogether, these categories—all of which are classified as durables in Lusardi (1996)—account for monthly spending of \$1,250 in the CE Survey and \$2,888 in the PCE, as shown in Appendix Table 2.

A second, related challenge is that sometimes it is impossible to crosswalk the JPMCI categories to the benchmarks. Three of the five summary bank account outflow categories—debt payments, transfers to external accounts, and uncategorized outflows such as paper checks—do not have a clear counterpart in the benchmark data. These “Other Bank Account Outflows” are \$2,834 each month, as shown in online Appendix Table 2. This estimate is quite similar to the \$2,888 in PCE spending with no JPMCI counterpart. However, these two totals reflect different concepts. For example, JPMCI outflows includes transfers to other bank accounts and PCE spending includes pre-tax health expenditures. Consequently, it is not appropriate to assume that “Other Bank Account Outflows” reflects the same spending as what is counted in “Not in JPMCI.”

The third challenge is that the CE Survey and PCE are designed to capture product types, while bank account data capture the merchant who received the payment. Online Appendix Table 2 reports spending by product type. This requires converting our spending estimates in the JPMCI data from spending by merchant to spending by product.

One example of a merchant category with multiple product categories is the “department

⁴⁹Most of these numbers are exactly the same as what is reported in Appendix Table 14. However, there are a few exceptions where we adjust our estimates to reflect spending by product type rather than by merchant. These adjustments are described in detail below.

⁵⁰These four examples are categories in the CE Survey. The PCE does not measure these categories because it focuses on services delivered rather than household expenditures. For example, while the CE Survey measures health insurance payments, the PCE measures spending on health services.

⁵¹In addition to the aforementioned categories, we also omit the following smaller categories: foreign spending and miscellaneous financial services such as portfolio management fees.

stores” spending variable in JPMCI. Using the public 10-K filings of large department stores (described in detail in Section C.2.2), we estimate that 80 percent of department store expenditures are for clothing (which falls under retail nondurables in the table), 10 percent are for home products (which falls under home improvement) and 10 percent are for personal care (which falls under professional & personal services). Therefore, of \$20.70 spent each month at department stores prior to the onset of unemployment, we allocate 80 percent to the retail nondurables category, 10 percent to the home improvement category, and 10 percent to the professional & personal services category.

We identified five other merchant categories which sell goods across multiple product types. They are: the “discount stores” spending variable (which includes both the MCC group for discount stores and the MCC groups for wholesale clubs), hotel-casinos, drug stores, grocery stores, and online. For the first four groups, we implement the same procedure described above for department stores: we estimate adjustment factors from merchant to product using 10-K filings described below in Section C.2.2 and we use these factors to allocate spending by product category. We assign purchases in the “online” category (less than one percent of monthly spending) to miscellaneous nondurables.

There are also two places where we modify estimated spending in the benchmark data to better reflect what is captured in the JPMCI data. First, CE Survey published tables⁵² do not separate air travel from other modes of transportation. In order to separate spending on air travel from total spending on transportation, we refer to Transportation Economic Trends⁵³ that uses 2016 CE Survey microdata. The document reports that 64 percent of public transportation expenditure was spent on air travel. We, therefore, reallocate 64 percent of the CE Survey spending on public transportation to air travel.

Second, PCE captures all medical spending, while JPMCI and the CE Survey document out-of-pocket spending. Because we are interested in understanding what fraction of out-of-pocket spending is captured by the JPMCI data, we draw on National Health Expenditure Accounts (NHEA)⁵⁴ Table 6: Personal Health Care Expenditures. It reports that about 12.5 percent of health expenditures in 2015 were out-of-pocket. We therefore multiply PCE medical spending by a factor of 12.4 percent.

The crosswalk and the adjustment for product versus merchant data yield estimates of comparable spending between JPMCI and the benchmarks in the second and fourth columns. These columns show that spending in the CE Survey is below the PCE in nearly every category. This finding is consistent with Wilson (2017), who reports that the ratio of CEX to PCE is 0.59 overall and 0.74 for comparable categories. This gap likely arises from differences in how each series is constructed: the CE Survey asks households what they bought, while the PCE asks manufacturers and service providers what they sold. Although manufacturers keep detailed records of their sales, most households do not keep detailed records of their purchases and so the CE Survey estimates are likely to be lower because of recall bias.

Comparing spending levels between JPMCI and the benchmarks, we find that the JPMCI data do a much better job of capturing spending on nondurables than spending on durables. Columns 3 and 5 report the ratio of each JPMCI measure to each benchmark. JPMCI nondurables spending by UI recipients is 139 percent of the CE Survey benchmark (79 percent excluding cash and miscellaneous nondurables) and 66 percent of the

⁵²<https://www.bls.gov/cex/2015/combined/age.pdf>

⁵³https://www.bts.gov/sites/bts.dot.gov/files/docs/Transportation_Economic_Trends_2016.pdf

⁵⁴<https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html>

PCE benchmark (38 percent excluding cash and miscellaneous nondurables). In contrast, durables spending on comparable categories by UI recipients is only 31 percent of the CE Survey benchmark and 24 percent of the PCE benchmark. If we expand the denominator to include all durables spending in the benchmark datasets, then the coverage rate is even lower.

The key reason why the JPMCI data are better at capturing nondurables spending is because people usually use debit cards, credit cards, and cash to buy nondurables. By analyzing the DCPC, we find that 69 percent of all household spending on nondurables is paid for with debit cards, credit cards, or cash. In contrast, many durables and debt payments rely on paper checks, where the JPMCI data do not contain data on payment recipient.

C.2.2 Reallocating Spending by Merchant to Products

Department Stores (MCC 5311) Three large department stores by sales according to this page⁵⁵ are:

1. Kohl's⁵⁶: 82 percent on clothing (including accessories and footwear), 18 percent on home products in 2015
2. Dillard's⁵⁷: 79 percent on clothing (including accessories and shoes), 4 percent on home and furniture, 14 percent on cosmetics, 3 percent on construction segment in 2015
3. Macy's⁵⁸: 84 percent on clothing (including accessories, footwear, and cosmetics), 16 percent on home and miscellaneous goods in 2015

Based on these three stores, we allocate the spending of MCC 5311 (Department Stores) to: 80 percent on clothing (retail nondurables in JPMCI), 10 percent on home products (home improvement in JPMCI), and 10 percent on personal care (professional & personal services in JPMCI).

Hotel and Casino (MCCs 3662, 3730, 3731, 3774) Some hotels also run casinos: MCC 3662 (Circus Circus Hotel and Casino), 3730 (MGM Grand Hotel)⁵⁹, 3731 (Harrah's Hotels and Casinos), and 3774 (New York-New York Hotel and Casino). We look at the 10-K reports of the operators of these hotels and casinos.

1. MGM Resorts International (owner of 3730, 3774)⁶⁰: 49 percent on casino, 19 percent on rooms, 16 percent on food and beverage, 16 percent on entertainment, retail, and other
2. Caesars Entertainment Corp (owner of 3731)⁶¹: 43 percent on casino, 17 percent on rooms, 16 percent on food and beverage, 15 percent on entertainment, 9 percent on other

⁵⁵<https://risnews.com/top-10-department-stores-who-made-cut>

⁵⁶https://www.sec.gov/Archives/edgar/data/885639/000088563916000033/kohls_10kx2015.htm

⁵⁷<http://files.shareholder.com/downloads/DDS/5039604361x0xS28917-16-262/28917/filing.pdf>

⁵⁸<https://www.sec.gov/Archives/edgar/data/794367/000079436716000221/m-0130201610k.htm>

⁵⁹Circus Circus Hotel and Casino and New York-New York Hotel and Casino are owned and operated by MGM Resorts International, which also owns and operates MGM Grand Hotel.

⁶⁰<http://app.quotemedia.com/data/downloadFiling?webmasterId=101533&ref=10778591&type=HTML&symbol=MGM&companyName=MGM+Resorts+International&formType=10-K&dateFiled=2016-02-29>

⁶¹http://files.shareholder.com/downloads/ABEA-5FED0N/5044522270x0x885604/EE83369E-1BAF-4610-A74F-FD018DC07086/CZR_2015_Form_10-K.pdf

Based on these operators, we allocate the spending of the above MCCs to: 40 percent on casino (entertainment in JPMCI), 25 percent on accommodation (hotels & rental cars in JPMCI), 20 percent on food away from home (food away from home in JPMCI), and 15 percent on non-casino entertainment (also entertainment in JPMCI).

Drug Stores (MCC 5122, 5912) Again, the difference in the data collection method raises problem in most health care spending, including spending on drugs. While JPMCI and CE Survey report out-of-pocket spending, PCE reports all co-pay too, and so does not accurately capture an individual's out-of-pocket spending. We look at the 10-K reports of CVS, Walgreens, and Walmart, which are the three largest drug sellers by sales according to this page⁶².

1. CVS⁶³: 73 percent on prescription drugs, 11 percent on over-the-counter and personal care, 5 percent on beauty and cosmetics, 12 percent on general merchandise and other
2. Walgreens⁶⁴: 66 percent on pharmacy, 34 percent on retail

The 10-K reports do not separate out-of-pocket spending from insurance reimbursement. The National Health Expenditure Accounts (NHEA)⁶⁵ Table 16: Retail Prescription Drugs Expenditures reports that 14 percent of total spending on drugs were out-of-pocket. This roughly matches what we get when we divide CE Survey drug spending by PCE drug spending (13 percent), where PCE drug spending captures those from product-line sales. Using the NHEA rescaling factor, of 14 percent we estimate that about 10 percent (14 percent * 70 percent) of drug store revenue is out-of-pocket spending for drugs.

Combining the two merchant groups, we reallocate the spending of MCC 5122 (drugs, drug proprietors, and druggist's sundries) and 5912 (drug stores and pharmacies) to: 30 percent on drugs (drug stores in JPMCI), 40 percent on personal care (professional & personal services in JPMCI), and 30 percent on retail (retail nondurables in JPMCI). We also scale the PCE spending on drugs by the factor of 14 percent, following the NHEA Table.

Discount Stores (MCC 5310) We look at the 10-K reports of Walmart and Target, which are the largest retail chains in the United States.

1. Walmart⁶⁶: 56 percent on groceries, 11 percent on health and wellness (drugs), nine percent on entertainment, nine percent on hardlines (including appliances, electronics, and personal care), eight percent on apparel, seven percent on home products
2. Target⁶⁷: 26 percent on household essentials, 17 percent on hardlines (including appliances, electronics, and personal care), 19 percent on apparel and accessories, 21 percent on food and pet supplies, 17 percent on home furnishings and decor

We therefore reallocate the spending of MCC 5310 to: 50 percent on groceries (groceries in JPMCI), 10 percent on drugs (drug stores in JPMCI), 15 percent on home products (home

⁶²https://en.wikipedia.org/wiki/Pharmacies_in_the_United_States

⁶³http://otp.investis.com/clients/us/cvs_caremark1/SEC/sec-show.aspx?FilingId=11159630&Cik=0000064803&Type=PDF&hasPdf=1

⁶⁴<http://files.shareholder.com/downloads/WAG/5039680083x0xS1140361-15-38791/1618921/filing.pdf>

⁶⁵<https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html>

⁶⁶<http://d1lge852tjjqow.cloudfront.net/CIK-0000104169/46c5c2e3-666c-4865-b437-eb351ae5dbfe.pdf>

⁶⁷https://corporate.target.com/_media/TargetCorp/annualreports/2015/pdfs/Target-2015-Annual-Report.pdf

improvement in JPMCI), 10 percent on entertainment (entertainment in JPMCI), and 15 percent on nondurable retail (including apparel) (retail nondurables in JPMCI).

Grocery Stores (MCC 5411, 5422, 5441, 5499, 5921) We look at the 10-K reports of Publix and Whole Foods, which are among the largest grocery stores in the United States. Other large grocery stores (e.g., Kroger, Safeway, Albertson’s, and H-E-B) either do not report share of revenue on groceries or are private companies.

1. Publix⁶⁸: 85 percent on groceries, 15 percent on other
2. Whole Foods⁶⁹: 67 percent on groceries (perishables), 34 percent on others (non-perishables)

We assume “other” reflects spending on household supplies (e.g., paper towels). We, therefore, reallocate the spending of MCC 5411, 5422, 5441, 5499, and 5921 to: 75 percent on groceries (groceries in JPMCI) and 25 percent on household supplies (retail nondurables in JPMCI).

Wholesale Clubs (MCC 5300) We look at the 10-K reports of Costco, BJ’s, and Sam’s Club, which are considered as the largest wholesale clubs in the United States.

1. Costco⁷⁰: 57 percent on foods (including foods, fresh foods, and sundries), 16 percent on hardlines (including appliances, electronics, and personal care), 11 percent on softlines (including apparel and small appliances), 16 percent on ancillary and other (including gas station, pharmacy, food court, optical)
2. BJ’s Wholesale Club⁷¹: 66 percent on groceries, 34 percent on other
3. Sam’s Club⁷²: 59 percent on grocery and consumables; 20 percent on fuel and other categories; 9 percent on home and apparel; 7 percent on technology, office, and entertainment; and 5 percent on health and wellness

We therefore reallocate the spending of MCC 5300 to: 60 percent on groceries (groceries in JPMCI), 5 percent on health care (medical copay in JPMCI), 15 percent on electronics (retail nondurables in JPMCI), 10 percent on personal care (professional & personal services in JPMCI), and 10 percent on home appliances (home improvement in JPMCI).

C.2.3 Comparison Using Transaction Data

One limitation of the analysis above is that it compares spending levels between JPMCI and the external benchmarks using product types that follow the 19 groups of MCC codes constructed by JPMCI. In this section, we present alternative results which compare JPMCI spending to two more natural benchmarks: 34 CE Survey categories and 44 PCE categories.⁷³ To build this crosswalk, we rely on transaction-level bank account data which

⁶⁸<http://www.publixstockholder.com/stockholders/financial-information-and-filings/sec-filings/sec-document/d85b55e1d9dd43b6a67c9f1b92cbce3b/html>

⁶⁹http://s21.q4cdn.com/118642233/files/doc_financials/2015/Annual/2015-WFM-10K.pdf

⁷⁰<https://www.sec.gov/Archives/edgar/data/909832/000090983215000014/cost10k83015.htm>

⁷¹<https://www.sec.gov/Archives/edgar/data/1037461/000119312511079572/d10k.htm>

BJ’s 10-K was filed for the fiscal year 2011. BJ’s was acquired by two private equity firms, Leonard Green & Partners and CVC Capital Partners, in 2011.

⁷²<http://d1lge852tjjqow.cloudfront.net/CIK-0000104169/46c5c2e3-666c-4865-b437-eb351ae5dbfe.pdf>

⁷³We do not have sufficient information to crosswalk spending to the categories used in the concordance table (Wilson 2017).

includes detail on about 600 individual MCC categories.⁷⁴ We again follow the Lusardi spending definitions for nondurable and durable spending.⁷⁵

The transaction data are available for a one percent random sample of all JPMCI households and are not available for the UI analysis sample. We sample households with at least five monthly outflows in calendar year 2015, which is similar to the screen for inclusion in the UI recipient analysis sample. However, the accounts in the transaction sample may include a smaller share of households' primary accounts if the UI receipt screen itself is an indicator of primacy.

Using these richer data and more detailed crosswalk, we continue to find that the JPMCI data do a much better job of covering nondurables. JPMCI nondurables spending in the transaction file is 99 percent of the CE Survey benchmark and 57 percent of the PCE benchmark. In contrast, durables spending on comparable categories in the transaction file is only 41 percent of the CE Survey benchmark and 25 percent of the PCE benchmark. All the ratios of JPMCI to benchmark spending are lower than for the UI receipt sample, likely because the absence of a UI receipt sample screen reduces the share of households' primary accounts in the transaction sample.

⁷⁴Our crosswalk between MCC codes, CE survey categories and PCE categories is posted here: <https://bit.ly/2qoDqoM>

⁷⁵There are two types of CE Survey spending which both Lusardi (1996) and Parker et al. (2013) do not discuss how to categorize: "Housekeeping supplies" and "Pets, toys, hobbies, and playground equipment". We categorize the former as durable because it pertains to shelter and Lusardi categorizes shelter as a durable expense. We categorize the latter as "other nondurable" because of the similarity to other types of retail spending in this category.

D Job-Finding Estimates

D.1 Validating Paycheck-Inferred Job Transitions

We use a novel JPMCI dataset on paychecks to identify labor market transitions. In this section, we validate the use of paychecks in two settings where we know that labor market transitions occurred—UI onset and UI exit before benefit exhaustion. We find that paycheck data are informative about transitions, but have three shortcomings relative to administrative data: false positives, false negatives, and excess job starts after UI exit. In Section D.2, we describe a method for overcoming these three challenges to construct a job-finding hazard. Although in principle any administrative bank dataset or financial app data could be used to construct such a measure, to the best of our knowledge our paper is the first to use paycheck data in this way. Our methodology may be useful to other researchers interested in measuring job transitions using bank account data.

The paycheck dataset is constructed based on categorization logic that captures the subset of direct deposit payments to households in the JPMCI sample which appear to represent labor income. One limitation of paycheck data from bank accounts is that they understate household employment for two reasons. First, some workers are paid by paper check (not direct deposit). Second, the JPMCI categorization logic will omit some direct deposits that actually are paychecks. An additional limitation of the data available to us at the time of writing this paper is that the paycheck data are monthly, so we do not observe the exact start and end dates of jobs.⁷⁶

We validate the use of paycheck data to infer labor market transitions in a setting where we know that a transition occurred – UI onset. We use an anonymized identifier associated with the *employer* named on each direct deposit paycheck and define paycheck-inferred *jobs* as the number of unique employers making direct deposit payments to the household in one month.⁷⁷ The number of jobs falls markedly around a household’s first UI check. The top panel of Appendix Figure 24 plots the mean number of jobs for people with UI durations of at least five calendar months. Consistent with incomplete coverage of employment, the mean number of paycheck-inferred jobs drops by 0.66 around UI onset. The mean number of jobs stabilizes by two months after UI onset and is greater than zero during UI receipt presumably because of spousal employment.

Paycheck-inferred job separations spike around a household’s first UI check. We infer a *separation* if a household receives their final paycheck from an employer.⁷⁸ The bottom panel of Appendix Figure 24 plots the separation rate around first UI check. Prior to receipt of the first UI check, the separation rate rises sharply. In most states, it takes a few weeks for the first benefit check to be deposited in the UI claimant’s account and so it is not surprising that the modal separation date is one month prior to receipt of the first UI check. A small share of separations are more than one month before the UI claim, indicating that some workers wait to file a UI claim.

We use Appendix Figure 24 to estimate the rate of false positives (paycheck changes without a job separation) and false negatives (job separations without a paycheck change). To quantify the false positive rate, we examine the household separation rate in month two of UI receipt, when the UI recipient cannot possibly separate from a job, and estimate a

⁷⁶In principle, JPMCI or other researchers using bank account data could construct a dataset which measured employment transitions using paychecks at a higher frequency.

⁷⁷For confidentiality reasons, the JPMCI paycheck dataset does not contain the employer’s name.

⁷⁸A recall to a prior employer with an employment gap of longer than one month is defined as a new employment spell.

rate of 3.2 percent per month.⁷⁹ (We would obtain a very similar false positive rate if we used month three instead.)

To quantify the false negative rate, we integrate the difference between the monthly separation rate and the monthly false positive rate. We estimate that the paycheck data capture a separation for 62.3 percent of UI recipients, which is quite similar to the decline of 0.66 in the mean number of jobs. Put otherwise, we estimate that the paycheck file misses 37.7 percent of job separations.

Having shown that paycheck data provide an informative (albeit incomplete) description of separations at UI onset, we next validate the use of paycheck data to infer job starts. We define *paycheck-inferred job starts* analogously to separations: a first paycheck from an employer. Appendix Figure 25 plots job starts by UI duration and shows visual evidence that job starts coincide with UI exit. Households that receive UI for between two and four calendar months—and therefore exit UI before exhausting their potential benefits—show a sharp increase in the job start rate around UI exit, followed by a sharp drop.⁸⁰ Households that receive UI for seven calendar months—nearly all of whom are exhaustees—show a small and sustained increase in job starts around UI exit. Like Appendix Figure 24, Appendix Figure 25 suggests the presence of false positives (the job start rate is greater than zero during UI receipt) and false negatives (the integral under job starts is less than one).

Appendix Figure 25 also reveals an additional challenge for estimating a monthly job-finding hazard from paycheck data—job starts remain elevated after UI exit. They are highly elevated in the month after UI exit, likely reflecting a delay between when work starts and when the first paycheck arrives. They remain persistently elevated for several months after UI exit, perhaps reflecting employees for whom it takes a few months to set up direct deposit or high turnover among the recently unemployed (Hall and Schulhofer-Wohl 2015). In the next section, we develop a methodology to calculate the job-finding hazard in the presence of false positives, false negatives and elevated job starts after UI exit.

We also use job starts to infer nonemployment duration. We define *nonemployment duration* as the number of months from the first UI check until the first paycheck-inferred job start. If a household never has another paycheck-inferred job start, their nonemployment duration is coded as their final month in the panel. We use nonemployment durations to calculate the path of consumption during unemployment after UI benefit exhaustion.

Incomplete coverage of employment poses a problem for reliably calculating nonemployment durations. About half our sample has a paycheck-inferred nonemployment duration greater than 12 months. Nevertheless, two pieces of evidence show that paycheck-inferred job starts are informative about nonemployment duration. First, Appendix Figure 25 plots the bivariate distribution of nonemployment durations and UI durations using a heat map and most of the mass is on the diagonal. Second, Appendix Figure 25 plots the share with any UI payment by nonemployment duration. UI payments stop within one calendar month of the first paycheck-inferred job start for at least 75 percent of households.⁸¹ The

⁷⁹Spousal transitions cannot be the only source of false positives. Assuming that the average of 0.30 jobs during UI receipts reflects spousal employment and that the false positives are due to spousal transitions implies a monthly separation rate for spouses of UI recipients of $(0.028/0.30=)$ 10 percent, which is about twice the monthly separation rate in the CPS (Chodorow-Reich and Karabarbounis 2016).

⁸⁰For Appendix Figure 25 and all subsequent analysis in this section, we drop households who receive only one calendar month of UI. Because of the way payments from state UI agencies are recorded, we can only reliably identify UI recipients if they receive at least two payments from the state agency. This creates an imbalance between one-month and multiple-month UI recipients in the share of their last month of UI during which they are non-employed, and hence in the pattern of paycheck-inferred job starts.

⁸¹For households with a nonemployment duration of two calendar months, 76 percent have UI payments

fact that some households continue to receive UI after a job start could reflect the false positives discussed above, allowed part-time work by UI recipients, or UI claims by ineligible recipients.

D.2 Hazard Construction

We use the JPMCI paycheck data to construct a job-finding hazard for UI recipients. In European administrative datasets, nonemployment durations are constructed using time from first UI check until first paycheck. Replicating this methodology is difficult in the JPMCI data because of three problems: false negatives, false positives, and a delay between job start and first paycheck. False negatives in particular are a problem; it is unclear how many UI recipients without a paycheck-inferred job start are actually long-term unemployed and how many found a job not recorded in the paycheck data. This can arise if someone is paid by paper check or paid by direct deposit, but the transaction was not categorized as labor income.

Instead of exactly replicating methodology implemented in European datasets, we conduct a two-step analysis. In the first step, we develop a methodology to go from a paycheck-inferred job start rate to an *actual job start rate*, which is the fraction of all unemployed starting a job for the first time in a given month. This methodology addresses the aforementioned three problems. Then, we use the actual job start rate to construct a *job-finding hazard*, which is the fraction of those remaining unemployed who find a job each month.

We develop a methodology to calculate the actual job start rate that uses paycheck-inferred job start patterns among UI recipients who did find a job to infer the actual job start rate for all UI recipients. Our approach relies on the observation that a jobseeker who finds a job at date t may get her first direct deposit paycheck in date t , $t + 1$, or even months later, as documented in Appendix Figure 25. Our approach is attractive because it does not require us to take a stance on the level of the false negative rate for job-finding. The intuition for our approach is that we learn about the job-finding hazard by UI exhaustees, for example, by comparing the paycheck-inferred job start rate of UI exhaustees to the paycheck-inferred job start rate of UI recipients that we know found a job.

Our methodology relies on three assumptions. The first assumption is on the level of the false positive rate of paycheck-inferred job starts (the share of paycheck-inferred job starts that do not actually represent re-employment for the UI recipient). To measure this, we take the share of paycheck-inferred job starts in the first month of UI receipt for households that receive four calendar months of UI. Our assumption is that the UI recipient in these households is not actually starting a new job this month since they receive UI benefits for three subsequent months. This delivers a false positive rate for job starts of 3.1 percent. This is very similar to the false positive rate for separations of 3.2 percent that we calculated for a larger sample in Section D.1. In Section D.3 we explore the sensitivity of our results to this assumption.

Our second assumption is that 91 percent of households who exit UI after two, three, or four calendar months are exiting to re-employment, whereas only nine percent of these households exit to non-employment. A jobseeker exiting UI in 2–4 calendar months will not have exhausted their benefits.⁸² Appendix Figure 25 shows that the pattern of paycheck-

stopping within one month. The rate at which UI payments stop after reemployment is even higher for longer durations.

⁸²People who receive five calendar months of benefits are a mix of exhaustees and non-exhaustees. In states where the maximum potential duration is six months, a small share of UI recipients are eligible for a shorter duration because of insufficient earnings history. According to the Department of Labor Benefit

inferred job starts is very similar across these three UI duration groups. Furthermore, Rothstein and Valletta (2017, henceforth RV) report that 81.2 percent of UI recipient spells end with an exit to work. Because the remaining 18.8 percent of exits combines exits due to exhaustion and exits before exhaustion to non-employment, and because exhaustion is very unlikely among our sample, we view the 81.2% rate as a lower bound and take the mid-point of this number and 100 percent to arrive at our 91 percent assumption. In Section D.3 we also explore the sensitivity of our results to this assumption.

Our third assumption is that the pattern of paycheck-inferred job starts for households exiting nonemployment to employment after two to four calendar months of UI is representative of the pattern for any household exiting to employment. Hence we assume that for households gaining employment in month t , 27.8 percent receive a paycheck from a new employer in month t (the average paycheck-inferred job start rate in the last month of UI receipt for households receiving two to four calendar months of UI (25.3 percent divided by 91 percent), 24.7 percent receive a paycheck from a new employer in month $t + 1$ (the average for the same group), 9.1 percent in month $t + 2$, and so on.

To explain how we use these assumptions to calculate the actual job start rate, we provide a worked example for the first month after benefits begin and then provide a general formula. Our first step calculates the actual job start rate. In the first month after benefits begin, 7.9 percent of all UI recipients have a paycheck-inferred job start. If every person had exited UI benefit receipt in this month (with 91 percent exiting to employment), according to our assumptions we would have observed a paycheck-inferred job-start rate of 25.3 percent. This is the average paycheck-inferred job start rate in the last month of UI receipt for households receiving two to four calendar months of UI. Using our two assumptions from above – a false positive rate of 3.1 percent and that 91 percent of UI exits are to employment – we estimate an actual job start rate of

$$\text{Actual Job Start Rate} = \frac{\text{paycheck-inferred job start rate in month 1} - \text{false positive rate}}{\left(\frac{\text{job-start rate if everyone exited UI}}{\text{job-start rate if everyone exited UI}} - \frac{\text{false positive rate}}{\text{false positive rate}} \right) / 91\%} = 19.6\%$$

in the first month after UI benefits begin.

Our second step constructs an adjusted paycheck-inferred job start rate in subsequent months removing the apparent job starts in subsequent months which are actually attributable to job starts in the first month. For example, in month 2 after UI payments begin, we observe a paycheck-inferred job start rate of 11.3 percent. However, we know that a job start in month t can generate a paycheck-inferred job start in month $t + 1$ (and later). If 19.6 percent of UI recipients already found a job in month t and UI exit at month t generates a paycheck-inferred job start rate of 22.5 percent in $t + 1$, that alone will generate excess paycheck-inferred job starts. The adjusted paycheck-inferred job start rate is then

$$\tilde{s} = \frac{\text{paycheck-inferred rate in } t=2}{\text{paycheck-inferred rate in } t=2} - \frac{\text{actual rate in } t=1}{\text{actual rate in } t=1} \times \left(\frac{\text{inferred rate in } t=2 \text{ if for } t=1 \text{ exits}}{\text{inferred rate in } t=2 \text{ if for } t=1 \text{ exits}} - \frac{\text{false positive rate}}{\text{false positive rate}} \right) = 7.3\%$$

We similarly subtract 19.6 percent times the paycheck-inferred job start rate for months $t + 2$, $t + 3$, and so on.

Accuracy Measurement system, in states where the maximum potential duration of UI benefits is six months, about 15 percent of UI recipients are eligible for five months of benefits.

These two steps of calculating an actual job start rate and then adjusting the paycheck-inferred job start rate in subsequent months suggest a general procedure. Define s_t as the observed paycheck-inferred job-start rate in calendar month t for all UI recipients, \tilde{s}_t as the paycheck-inferred job start rate adjusted for job starts in prior months, f_t as the paycheck-inferred job-start rate that would have been observed if all UI recipients had exited UI at date 0, and fp as the false positive rate. We compute the share of UI recipients starting a job as

$$start_t = \frac{\tilde{s}_t - fp}{f_0} \quad (11)$$

and we adjust the unconditional paycheck-inferred job start rate using the formula

$$\tilde{s}_t = s_t - \sum_{r=1}^{t-1} start_r f_{r-t}. \quad (12)$$

Iterating between equations 11 and 12, our approach calculates the actual job start rate in every month since UI onset.

We construct a job-finding hazard using the hazard formula to convert the actual job start rates \tilde{s}_t in each period:

$$hazard_T = \frac{\tilde{s}_t}{1 - \sum_{t=1}^{T-1} hazard_t}.$$

A final challenge to calculating a job-finding hazard around benefit exhaustion arises because of the monthly time aggregation of the JPMCI paycheck data. Among households eligible for 26 weeks of benefits, some households will receive benefit payments in up to six calendar months before exhaustion, while others will receive benefit payments in up to seven calendar months. This poses a problem for calculating the spike in the job-finding hazard at benefit exhaustion because after five calendar months of UI receipt, some households are one month away from benefit exhaustion, while others are two months away.

To address this time aggregation issue, we construct a household-specific measure of months until last potential UI check.⁸³ This measure uses the day of the month on which the household received their first UI check and the state in which they are receiving UI benefits. For example, in New Jersey, we categorize a UI recipient whose first check arrived on the 10th of the month or earlier as likely to receive six months of benefits and anyone whose first check arrived later as likely to receive benefits in seven calendar months. We validate our predictions using UI exhaustees and find that our household-specific estimates of the number of calendar months in which UI payments are received is accurate for 84 percent of exhaustees.

The estimated spike in job-finding coincides with the predicted number of calendar months of UI receipt. Appendix Figure 26 shows in the top-left panel that households who we guess will receive benefits for six calendar months show a sharp spike in job-finding in the sixth calendar month of UI receipt, with a declining job-finding hazard thereafter. In contrast, households who we guess will receive benefits for seven calendar months have a job-finding hazard that rises gradually in the sixth and seventh calendar month of UI receipt before declining. This analysis is useful for two reasons. First, it provides additional

⁸³In Section 3.1.1, we address the time aggregation issue in the spending data by limiting the sample to households that exhausted UI benefits on a “seam” such that they experienced an income drop between one calendar month and the next calendar month. That approach is not useful here because we are interested in job-finding behavior for both exhaustees and non-exhaustees.

empirical evidence that job-finding spikes when UI benefits run out. Second, it motivates a re-organization of the job-finding hazard estimates by months until last potential UI check instead of months since first UI check.

The steps described above yield Figure 6 in the text of the main paper. Figure 6 shows that we estimate a hazard rate around 20 percent until UI exhaustion. The best benchmark we could find for the U.S. comes from the labor force status flows data in the CPS. Using this data, we calculate that the average monthly transition rate from unemployed to employed was 23 percent during our sample period. One limitation of this comparison is that the unemployed sample in CPS data combines both UI recipients and non-UI recipients. Nevertheless, we find the consistency of these estimates reassuring.

D.3 Hazard Robustness

In this section, we describe two types of additional evidence which suggest that our estimate above of a modest surge in job-finding at benefit exhaustion is reliable and robust to alternative assumptions. We compare our evidence to UI exit hazards and to alternative assumptions about the data-generating process for paycheck-inferred job starts.

First, we compare our estimated job-finding hazards to UI exit hazards. The top-right panel of Appendix Figure 26 plots UI exit hazards compared to the job-finding hazards reported above. Two aspects of Appendix Figure 26 suggest that our job-finding hazards are reliable. First, for months $t = -5$ to $t = -2$, the UI exit hazard rate is approximately constant, just as the estimated job-finding hazard is approximately constant.⁸⁴ Second, the level of the rate of UI exits is similar to the level of the estimated job-finding hazard. This second fact suggests that the assumptions underlying our construction of job-finding hazards are reasonable.

Next, we explore the robustness of our methodology by varying two assumptions described in Section D.2. The results are shown in the bottom panels of Appendix Figure 26. First, we compute hazards under alternative false positive (type I) error rates. We consider rates of 2.3 percent, which corresponds to the job-finding hazard during the first month of UI receipt in Florida, and 3.7 percent, which corresponds to the false positive rate for the first month of UI receipt for people who receive two calendar months of benefits. Although changing the false positive rate changes the level of the job-finding hazard, the conclusions that job-finding rises modestly around UI benefit exhaustion before falling off after exhaustion remains the same.

Second, we compute hazards under alternative assumptions about what share of UI exits are to employment. We consider an assumption that 100 percent of UI exits are to employment and that 82 percent of UI exits are to employment. The latter estimate is the share of UI exits to employment estimated by RV, which is a lower bound because some of the UI exits in RV reflect benefit exhaustion. Again, changing the UI exit hazard to employment does not change the overall shape of the job-finding hazards.

We conclude that the share of jobseekers finding a job and the path of hazards after UI exhaustion is sensitive to the assumptions we make about the data-generating process (the false positive and false negative rate). Nevertheless, under a wide variety of parameterizations, the JPMCI data show a modest spike in job-finding at UI benefit exhaustion.

⁸⁴Meyer (1990b) and Card and Levine (2000) report similar results using U.S. administrative data.

E Empirical Results

E.1 Robustness Checks on Spending Drop at UI Benefit Exhaustion

One potential concern about our finding that spending drops at UI benefit exhaustion is that a portion of checking account outflows are uncategorized in our baseline specification, as noted in Section 2.2. To address this concern, we report two supplemental analyses. First, we analyze all outflows by payment method. Spending drops sharply at UI benefit exhaustion for every payment method except paper checks and electronic transfers, as shown in online Appendix Figure 6. Second, we use the Federal Reserve’s Diary of Consumer Payment Choice (DCPC) to infer spending categories for otherwise uncategorized spending based on the payment method. The DCPC is a three-day diary survey where respondents record every expenditure, including the amount, the payment method and the merchant type. The DCPC is helpful because—unlike the JPMCI data—it contains information on what types of items are typically purchased using paper checks and cash.

Our finding that spending falls at exhaustion is robust to alternative assumptions about the composition of uncategorized outflows that leverage evidence from the DCPC. Our baseline specification described in Section 2 focuses on expenditures that we can directly categorize as nondurable with high confidence. In addition to credit and debit card spending, which can be categorized based on the merchant, and electronic transactions, which can be categorized in some cases, our baseline definition also includes all cash withdrawals as miscellaneous nondurables because a majority of spending in the DCPC using these payment methods is for nondurables. By the same logic, we exclude all paper checks and electronic transfers from our definition of nondurable spending, even though a portion of the spending from these channels surely reflects purchases of nondurables. In an alternative specification, we construct nondurable spending by allocating uncategorized dollars using the nondurables expenditure share by channel from the DCPC. We estimate that 75 percent of cash spending, 83 percent of credit card spending, 32 percent of paper checks, and 34 percent of electronic transfers are spent on nondurables using the DCPC. Applying these expenditure shares to uncategorized expenditures in the Chase data yields very similar conclusions about the drop in spending at exhaustion, as shown in online Appendix Figure 6.

Another potential concern is that our findings about people who receive direct deposit of UI benefits might not generalize to other UI recipients. However, a cross-state comparison of the drop at exhaustion suggests that the direct deposit screen is not an important source of bias. Online Appendix Figure 7 compares the state-level size of the spending drop at exhaustion (normalized by the income loss at exhaustion) to the share of UI recipients that receive their benefit payments via direct deposit. The share of UI recipients paid by direct deposit varies widely, from 15 percent to 70 percent 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.

E.2 Durables Spending

Spending on the subset of durables that we observe falls less during unemployment than nondurables.⁸⁵ Finding a smaller drop in durables is surprising in light of the Browning and Crossley (2009, henceforth BC) model. Since the unemployed continue to enjoy utility flows from previously-purchased durables, their model predicts that households will cut new

⁸⁵See online Appendix Figure 10.

durable expenditures by *more* than nondurables because this is associated with less of an immediate consumption drop.

Our results may differ from the BC model because we use the Lusardi (1996) definition of durables, which in some cases does not correspond well with the definition in the BC model. The five categories where we observe the most durable spending in dollar terms are insurance, home improvement, auto repairs, hotels & rental cars, and retail durables (sporting goods, jewelry, and electronics stores). The service flows from an insurance product lapse if payment stops, so it does not fit the BC definition. Empirically, we find that insurance payments are relatively stable during unemployment. In comparison, we find much steeper drops in types of durables that fit the BC conception. For example, spending on home improvement drops by 20 percent at exhaustion, and spending on retail durables drops by 15 percent at exhaustion. A second reason our results differ from BC is that we do not observe vehicle purchases, which make up a large share of total durable spending and are likely more responsive than the categories we do observe.

E.3 Work-Related Spending

The cross-state variation is also useful for understanding the role of home production in explaining the spending drop at onset. A substantial literature has focused on households substituting time for money to explain lifecycle expenditure patterns (Aguiar and Hurst 2013) and business cycle fluctuations (Nevo and Wong 2015). In our context, five of the six expenditure categories with the largest spending drops at unemployment onset are department stores (clothing), hotels & rental cars, flights, food away from home, and transportation, all of which seem to be plausibly work-related (Appendix Table 14). Building on Aguiar and Hurst’s methodology, we analyze a subset of work-related expenditure categories in the JPMCI data. We define a spending category as work-related if it exhibits a larger-than-median drop at retirement (Aguiar and Hurst 2013). We define retirement as the first receipt of a Social Security check. In order to focus on households that face relatively little financial constraints around retirement, we limit the sample to households that are estimated to have at least \$100,000 in total liquid assets by JPMCI. The top panel of Appendix Figure 27 illustrates this methodology and shows which spending categories are defined as work-related.

We find that spending drops by nine percent for the work-related categories compared to around six percent for the rest of spending. This is shown in the bottom panel of Appendix Figure 27. Put otherwise, spending drops 1.5 times as much on work-related categories as it does on non-work-related categories. This implies a modest role for home production in explaining the decline in spending on work-related categories during unemployment.

F Positive Implications

F.1 Labor Market Explanations for Drop at Exhaustion

Two potential labor-market focused explanations, permanent income loss and optimism about one’s job search prospects, are also unable to account for the sharp drop in spending at exhaustion. To explore the impact of more pessimistic scenarios for income risk, 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 percent *permanent* income loss, which is at the upper end of estimates in the literature.⁸⁶ We also consider an alternative scenario

⁸⁶Abraham et al. (2016) report that medium-term re-employment earnings in the U.S., including zeros, are 10 percent lower for someone unemployed three quarters relative to someone unemployed for one quarter.

where after exhaustion agents have a 50 percent chance of getting a job at their old wage and a 50 percent chance of getting a job where permanent income is 10 percent lower. At exhaustion, the agent learns which state of the world she is in. The model’s predictions are essentially unchanged under these two alternative parameterizations, as shown in online Appendix Figure 16. The reason that these changes do not affect the path of spending at exhaustion is that these changes affect permanent income but not immediate income, and buffer stock agents with few liquid assets are unresponsive to news about permanent income that does not affect their immediate resources (Ganong and Noel 2017). A household with substantial wealth would respond to news about permanent income, but such a household would also have much smoother consumption throughout the spell than what we observe.

Although it is theoretically possible that spending drops suddenly at benefit exhaustion because job seekers have optimistic beliefs about their chance of finding a job, the beliefs necessary to explain the drops we observe are quantitatively inconsistent with prior data. We conduct two exercises to evaluate this theory. First, we calibrate our model to match the optimism in surveys documented in Spinnewijn (2015), as shown in online Appendix Figure 16. In Spinnewijn’s (2015) sample, jobseekers report their mean expected time to find a job is seven weeks, while the mean 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 percent + 21 percent =) 46 percent chance of finding a job each month. (A model where the perceived job-finding hazard is (2.75 * 25 percent =) 69 percent yields even more extreme results.) Relative to the baseline model, persistent 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, we estimate the subjective job-finding probabilities implied by the spending behavior in the data. We find that to rationalize the observed path of spending, households would have to believe they have a 62 percent chance of finding a job exactly in the month of exhaustion, which is far greater than the 26 percent chance of finding a job observed in the data. Online Appendix Figure 16 compares the implied beliefs to the job-finding hazard in the data. However, these implied beliefs are inconsistent with the optimism at onset documented by Spinnewijn (2015).

F.2 Sparsity Model (Gabaix 2016)

F.2.1 Explanation

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:

$$\max_{c_t, s_t} u(c_t) - \psi(s_t) + \delta EV_j(a_{t+1}; \tilde{z}_{exhaust, j}) \quad (13)$$

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

When conditioning on positive earnings, the decline is only 1.6 percent. Schmieder et al. (2016) show that re-employment wages in Germany fall by about 10 percent 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.

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 (13). 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.

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 (13) using a different value for perceived income at benefit exhaustion:

$$\tilde{z}_{exhaust,j} = 0.54m_j(\bar{\kappa}) + 0.83(1 - m_j(\bar{\kappa})). \quad (14)$$

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:

$$m_j(\bar{\kappa}) = \mathcal{A} \left(\left(\frac{dc_j}{dm_j} c_j \right)^2 \frac{1}{\bar{\kappa}^2} \right). \quad (15)$$

Appendix Figure 22 shows the path of spending predicted by the inattention model where $\bar{\kappa}$ is chosen to match the drop at exhaustion in the data. The sparse model is able to generate a larger drop at UI benefit exhaustion than we find in the representative agent model. However, relative to the data, the model predicts too small of a drop in spending at the start of unemployment, too much of a drop in spending during UI receipt, and too small of a drop at UI exhaustion. We estimate that the cognitive cost $\bar{\kappa}$ which generates the best fit to the data is 0.04. A cost of this size means that an inattentive agent would completely ignore an income shock of 4 percent or smaller until it arrived.

F.2.2 Estimation Procedure

This appendix describes the estimation method used for the analysis in Appendix Figure 22. 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:

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

Once benefit exhaustion has occurred, the agent correctly perceives her income. Let \mathcal{A} be the attention function, $\frac{d\tilde{c}_t}{dm_t}$ be 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:

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

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. For a grid of values $\bar{\kappa}$:
 - (a) Use a seed value of \tilde{z} to compute $\tilde{c}_t(\tilde{z})$. We use $\tilde{z} = z_{ui}$ as our initial seed value; i.e., complete inattention.
 - (b) For each date t , compute optimal attention $m_t^* \left(\frac{d\tilde{c}_t}{dm} \tilde{c}_t, \bar{\kappa} \right)$ using equation (17).
 - (c) For each date t , calculate perceived income at exhaustion $\tilde{z}_t(m_t^*)$ using equation (16). Perceived income \tilde{z}_t falls as t gets larger and exhaustion approaches.
 - (d) For each date t , the agent forms a consumption plan c_t^* using the perceived \tilde{z}_t .
 - (e) Check if this combination of $\tilde{z}, m^*, \tilde{c}$ are consistent. I.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} .
2. Evaluate distance from generated sequences $\{c_t^*(\bar{\kappa})\}$ to the data. We weight our data using the inverse of the variance-covariance matrix (as in equation 8) and choose the $\bar{\kappa}$ which minimizes distance to the data.

G Normative Implications

We compare the welfare gains from raising UI benefits to extending their duration in the context of the structural model from Section 4.2. Although the sufficient statistic formula has the advantage of being highly transparent, it has three shortcomings. First, it uses average consumption rather than individual consumption. Second, the formula is exactly correct only when evaluating infinitesimally small changes to UI policy. Finally, it assumes rational behavior which we reject in Section 4.1. We next show that our conclusions are unchanged using a structural alternative to the sufficient statistic analysis that avoids these three shortcomings. In this exercise, we consider the consumption-smoothing gains of level increases and duration extensions inside the structural model we analyze in Section 4.2.

This approach includes four steps. First, we simulate employment histories for 1,500 households indexed by i . To mirror the sufficient statistic analysis above, which focused on evaluating the consumption smoothing gains from UI reforms and ignored the moral hazard costs from distorting job search decisions, we specify an employment transition matrix that matches the job-finding hazards in Figure 6 and set $\psi(s) = 0$. (We also evaluate a version of the model that incorporates moral hazard with endogenous job search, whose results are shown in online Appendix Table 20 and discussed at the end of this appendix.) Second, for this set of employment histories, we construct three income histories: the baseline z from Section 4, an alternative z^{level} with an increase in monthly benefit levels db of 1.8 percent 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. We use the consumption policy functions for a representative agent, which is the natural structural counterpart of the Baily-Chetty formula for a household with consumption preference parameters described in Table 15 and column 1 of Table 3. Fourth, we evaluate the change in date-0 welfare (average discounted lifetime utility of consumption) from the consumption paths generated by the 1.8 percent benefit level increase or the one-month benefit duration extension relative to a money metric of a one percent increase in

lifetime income. For the level increase in the representative agent model, this formula is given by

$$\Delta Welfare = \frac{1}{n_{agent}} \frac{\sum_{t=0}^T \sum_i \delta^t (u(c(z_{it}^{level})) - u(c(z_{it})))}{\sum_{t=0}^T \sum_i \delta^t (u(c(z_{it} + 0.01)) - u(c(z_{it})))}. \quad (18)$$

We use the same formula to evaluate the gains from extending durations, substituting $z^{duration}$ for z^{level} . We make the paternalistic assumption that $\beta < 1$ reflects the agent's self-control problems (following O'Donoghue and Rabin 2006) and therefore do not include β in our welfare calculation.⁸⁷

Implementing this structural approach, we find that the consumption-smoothing gains from a duration extension are 2.5 times greater than from a level increase in the structural model, as shown in row 5 of online Appendix Table 20. Three forces can lead the structural analysis to have different conclusions from the sufficient statistic analysis. First, equation (18) uses simulated individual consumption histories, whereas equations (9) and (10) use the average consumption level. Because of the concavity of utility and Jensen's inequality, the gains from increased UI generosity may be larger in the structural model. Second, the sufficient statistic formula is correct only for infinitesimally small changes to UI policy, while the structural model captures the endogenous decrease in private saving associated with, for example, a one-month extension of UI benefits (Hubbard et al. 1995). Third, the structural model features heterogeneity in the quasi-hyperbolic β parameter as well as the job search cost parameter. In spite of these three differences, it is reassuring that we get relatively similar estimates of the consumption-smoothing gain from this model.

We also analyze the total welfare change (including the fiscal externality) from raising the level of UI benefits and extending the duration of UI benefits in the structural model. We show results in online Appendix Table 20, but the estimates are difficult to compare to the Baily-Chetty framework for two reasons. First, in the structural model UI benefits affect welfare for two reasons: they function as social insurance (as in the representative agent Baily-Chetty framework) and they redistribute from low search cost types to high search cost types and from high β types to low β types. This redistribution complicates the welfare analysis in ways that are interesting to understand for future research but outside of the Baily-Chetty framework. Second, even in the absence of the redistribution issue, we find that these estimates are sensitive to small changes in the convexity of job search costs. Evaluated at our parameter estimates from Table 3 column 3, we find a similar change in welfare from benefit increases and extensions. These parameter estimates include an estimated convexity ξ of 1.1 (standard error: 0.1). If we re-estimate the model holding ξ fixed to 1.0, we obtain similar implied BCMC ratios (shown in online Appendix Table 17) and similar goodness of fit (shown in online Appendix Figure 23). However, under this slightly tweaked parameterization, we find larger welfare gains from extensions than from benefit increases, consistent with the results using the generalized Baily-Chetty formula reported in Table 4.

⁸⁷Formally, the change in welfare is now given by

$$\Delta Welfare = \frac{1}{n_{agent}} \frac{\sum_{t=0}^T \sum_j w_j \sum_i \delta^t (u(c_j(z_{it}^{level})) - u(c_j(z_{it})))}{\sum_{t=0}^T \sum_j w_j \sum_i \delta^t (u(c_j(z_{it} + 0.01)) - u(c_j(z_{it})))},$$

where j indexes types and w_j corresponds to the weight on each type.

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