Online Appendix for

"How Do Households Respond to Job Loss? Lessons from Multiple High-Frequency Data Sets"

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A Variable Definitions

Income variables

Disposable income: Sum of monthly incoming transactions to bank accounts owned by the affected person and/or the spouse. The following transaction types are included: Direct deposits, person-to-person transfers from outside the household, and cash deposits. We categorize these inflows into the following subcategories (see Appendix C for details):

Wage income, main person: Sum of monthly salary- and wage payments to bank accounts owned by the person affected by job loss. Payments to joint accounts are attributed to the spouse if they come from the spouse's employer, and otherwise to the affected person.

Wage income, spouse: Sum of monthly salary- and wage payments to bank accounts owned by the spouse. Payments to joint accounts are attributed to the spouse if they come from the spouse's employer, and otherwise to the affected person.

Government income transfers: Sum of monthly government income transfer inflows to bank accounts owned by the affected person and/or the spouse.

Private transfers and other income: The residual of disposable income minus wage income (main person and spouse) and government income transfers.

Spending

Total spending: The sum of outgoing transactions from the household's bank accounts using either of the payment methods card, mobile phone, and bill, plus cash withdrawals. Outflows categorized as tax or debt payments are excluded. We aggregate to the household level by summing spending for the person affected by job loss and the spouse, if any. Outflows from joint accounts are split evenly between the two account owners before summing to avoid double-counting. See Appendix B for further details.

Utilities: The value of the subset of transactions in total spending measure with MCC "4900", "4812", "4814", "4821", "4899", or bill payment label "utilities", "elec", "gas", "water", "heating", "internet", "cable TV", "telephone", or "TV license"

Restaurant and bar spending: The value of the subset of transactions in total spending measure with MCC "5813", 5462", "5811", "5812", or "5814".

Groceries: The value of the subset of transactions in total spending measure with MCC "5411", "5422", "5441", "5499", or "5921", or bill payment label "groceries".

Net saving and debt repayments

Net saving in liquid assets: The sum of (1) the change in end-of-month balances on deposit accounts at the bank owned by the affected person or the spouse, and (2) outflows minus inflows to all accounts from transactions with type code "securities trade".

Net repayments on non-mortgage loans: The change in end-of-month balances on loan accounts (with amounts owed coded as negative balances) owned by the affected person or the spouse.

Mortgage loan repayments: Average monthly mortgage payments with current mortgage loans. Calculated by determining the average monthly payment over a full calendar year for each loan, then summing across all mortgage loans that the household had at the end of the current month. See Appendix D for further details.

B Measuring Household Spending from Transaction Data

The basis for our measure of spending is raw transaction data from the bank's records. Each record holds information about the time and type of transaction and the amount transacted. For card transactions and bill payments, information about the type of recipient is provided in the form of Merchant Category Codes (MCCs). Before making it available to us, the bank aggregates the raw transaction to daily totals within each combination of customer account, transaction type and recipient category.

We include three types of outgoing transactions in our spending measure: Card payments (including payments initiated via mobile phone applications), bill payments and cash withdrawals. The remaining outflows include transactions that do not reflect consumption, for example fee payments to the bank and financial security purchases, and uncategorized bank transfers where the purpose is unobservable.

In a next step, we use recipient MCCs to exclude tax and debt repayments, which are not considered as spending. We then sum all the remaining outgoing transactions to construct a monthly spending measure for each individual person. For couples, household-level variables are constructed by aggregating spending for the two spouses. We split outgoing transactions from joint accounts evenly between the account owners to avoid double-counting.

Figure A1 shows the development in average quarterly spending per household for the gross sample of active bank customers, broken down by transaction type. The share of spending done by card or mobile phone transactions rises over the analysis period, from 43% in 2009Q1 to 57% in 2016Q4. Conversely, the share of cash spending gradually falls from 16% to 9% over the same years, while bills account for about 35-40% of total spending throughout the period. Cash payments account for 14% of total spending via cash or cards in 2016. In comparison, a 2017 household survey by the Danish central bank found a value-weighted cash payment share of 16% of total cash and card payments (Danmarks Nationalbank 2017).

Figure A2a compares the development in monthly card spending per person in our gross sample of active bank customers vs. the full population. For the latter, we use aggregate statistics on card transactions and the number of adults in the population published by Statistics Denmark. The two series follow each other extremely closely, suggesting that our spending measure is accurate in timing and that our sample of bank customers does well in terms of representing trends in the broader population. Figure A2b shows average levels of total annual household spending across income groups based on our transaction data and compares them to estimates from Statistics Denmark's consumer expenditure survey. When averaging over households in all income groups, we get very similar spending levels across the two data sources, suggesting a high degree of completeness in our transaction data measure. Looking across groups, we see a slightly steeper income gradient in our measure than in the survey-based one, perhaps because of disproportional under-reporting at the top of the income distribution in the latter (Sabelhaus et al. 2013). But, overall, there is a strong correspondence between the two data sources in this dimension, suggesting that our transaction data measure captures cross-sectional variation in spending well.

C Categorizing Inflows to Bank Accounts

We measure household disposable income as the sum of direct deposits, person-to-person transfers and cash deposits flowing into the household's bank accounts, excluding transactions between the household's own accounts. We break this measure down into wage payments for the person affected by job loss, wage payments for the spouse (if any), government income transfers, and other. There are two main steps in this process, which we describe in detail below: First, we construct a mapping from employer IDs to the IDs of the bank branches that they use to pay out wages, and similarly for the government agencies that pay out income transfers. Second, we look at each individual's incoming transactions and use this mapping to identify payments coming from employers and government agencies. For example, if person A works for company B, which uses bank branch C for its wage payments, then we interpret all payments from bank branch C going into person A's account as wage payments from company B.

We start by linking employers and government agencies to the registration number of the bank account(s) that they use to pay out wages and income transfers, respectively. A registration number is a four-digit Danish national bank code. Each number is associated with a unique bank *branch*, but branches may have more than one registration number (e.g., one for business customers' accounts and one for personal customers' accounts). There are more than 3,000 unique numbers across all banks. Some large customers have their own unique number. For example, all payments from the central government come from accounts with the same unique registration number, which is used solely for this purpose.

We link each employer and government agency to a registration number in the following way: First, for each employer/agency j and each month t, we use the payroll data from the Danish Tax Agency to identify all individuals in our sample of bank customers who appear on the employer's/agency's payroll. Second, for each bank registration number, we use the transaction data to compute the share of individuals in that group who received a payment from an account with that registration number in month t. We record the registration number with the highest share as the one associated with payments from employer/agency j in month t.[1]

In the transaction data, we code an incoming direct deposit as a wage payment if the sender's bank registration number is associated with an employer that the recipient works for according to the payroll data. That is, if person A appears on the payroll of employer B in month t and receives a payment from an account with a registration number that has been linked to employer B through the mapping procedure described above, then we conclude that this is a wage payment from employer B to person A. In addition, we also

[1]If the central government registration number is the top rank and j is not a central government agency, we use the second-ranked registration number

interpret transactions with certain type codes (e.g. “salary transfers”) as wage payments.

We code an incoming transaction as a government income transfer if either of the following conditions is satisfied: i) The sender’s bank registration number is linked to a government agency that the person received money from in that month according to the payroll data; ii) The bank registration number is the one used by the central government, and the person does not work for the central government (in which case we code it as a wage payment).

D Constructing Monthly Mortgage Data from Annual Snapshots

The mortgage data set provides an end-of-year snapshot of all active mortgage loans to private individuals in Denmark in each year from 2009 to 2015. We use this to construct monthly measures of the type of mortgage loans in the household’s portfolio and the average monthly payment on each of these loans.

We start by mapping the household’s portfolio of active loans in each month during the year by comparing the end-of-year snapshot with that of the previous year. Each loan has a unique ID that allows us to track it over time. If a loan appears in both snapshots, we conclude that it must have been part of the household’s portfolio all year. If it appears only in the most recent snapshot, we use information about the date of origination to infer when it entered the portfolio. For loans that disappear from the household’s portfolio during the year (e.g. because of refinancing), we assume that the date of termination coincides with the origination date for the household’s new loan. Cases where a loan disappears from the portfolio without being replaced by a new one are rare but do occur in our sample. In such cases, we use data on total interest payments on mortgage loans from annual tax returns to infer when the loan was terminated.[2]

[2]More precisely, we use the information about the loan’s interest rate and remaining balance to calculate how much interest would have been paid on the loan over the full year. We then compare that number to information from the tax return data on how much interest on mortgage loans the household actually paid. If the former number is twice as large as the latter, we conclude that the loan was terminated after the first six months of the year.

Once we have the full mapping of the household's loan portfolio in each month, we use the detailed information about each loan to characterize this portfolio. First, we use information about the loan type to infer whether the household holds any adjustable-rate loans or interest-only loans.[3] Second, we combine information about the loan's current remaining balance, time to maturity, interest rate and amortization profile (interest-only vs. amortizing) to impute the average monthly payment over the full calendar year.

E Mass Layoffs

We obtain information about mass layoff events from the Ministry of Employment. All firms with more than 20 employees are obliged to report to the Ministry if they plan to lay off workers on a large scale. The exact definition of "large scale" depends on firm size, ranging from 10 workers for firms with 20-100 employees to 30 workers for firms with more than 300 employees. The data contains information about the extent of the planned layoffs, the date of reporting, and firm IDs, which we use to link it to the payroll data from the Tax Agency. From this data, we construct a subsample of individuals who have been laid off shortly after their employer reported a planned mass layoff. The report must be submitted before workers are given notice of their impending layoff. Since we do not observe when this happens for the individual worker, we include all cases where the date of reporting is within months -7 to -1 relative to the observed month of layoff. This leaves us with a subsample of 1,156 individuals.

Figure A5 shows event graphs for income and spending for the mass layoff subsample vs. the full sample of active customers. The estimated development in wage income for the person affected by job loss – as well as the ensuing increase in government transfers – are nearly identical for the two samples, suggesting that there is no significant difference in the size and persistence of the shock. Spending responses also look highly similar across the two samples, although the small number of observations in the mass layoff sample

[3] A loan can change amortization profile during the year, i.e. from amortizing to interest-only, or vice versa. The end-of-year snapshots provide information about the date of the most recent such change, allowing us to infer the loan's profile in any given month during the year. A loan cannot change from fixed to adjustable rate, or vice versa. Households need to prepay their existing loan and take out a new one if they wish to switch between these loan types.

implies that confidence intervals are substantially wider. Combined, these results suggest that the total amount of self-insurance is about the same in the mass layoff subsample as in the full sample.

Columns (7) and (8) of Table A3 shows results for cumulated effects over the full observation window for the mass layoffs subsample. The estimated cumulative income loss is almost the same as in the main analysis. This suggests that the presence of voluntary resignations (e.g., individuals who deliberately take time off between jobs) in our baseline sample is no cause for concern, since the cumulative income loss would most likely be smaller in such cases. There are some differences when it comes to the relative importance of the behavioral responses to this income loss, especially for private transfers and other inflows where we find a negative but insignificant effect in the mass layoff sample. In general, the cumulative responses are imprecisely estimated in this sample due to the limited number of observations. But the point estimates suggest that our main findings are robust: First, household spending drops substantially, but much less than income, suggesting an important role for self-insurance. Second, the most important self-insurance response is reduced saving in liquid assets. Third, the compensating effects from spousal labor supply, borrowing and loan repayments are small and/or insignificant.

F Tables and Figures

Table A1: Sample selection and summary statistics, extended

	(1) Gross sample	(2) Active customers (baseline sample)	(3) Exclusive customers
No. of individuals	66,844	10,002	5,224
	------------------------ Sample means -------------------		
Female	0.43	0.47	0.48
Age	46.2	46.6	46.1
Couple	0.67	0.59	0.52
Capital region	0.33	0.44	0.42
Higher eduaction	0.23	0.28	0.27
Primary sector	0.01	0.01	0.01
Manufacturing	0.19	0.15	0.15
Construction	0.07	0.06	0.06
Trade & transport	0.26	0.26	0.26
Other services	0.20	0.22	0.20
Public Sector	0.23	0.28	0.28
Arts & entertainment	0.03	0.04	0.03
Homeowner	0.65	0.63	0.59
Spouse employed	0.79	0.84	0.85
Annual gross income for person who lost job (tax data)	371,621	394,499	375,019
Household bank deposits, all banks (tax data)	154,977	165,372	131,597
Household financial securities, all banks (tax data)	57,958	65,491	51,474
Household liquid assets, all banks (tax data)	212,936	230,863	183,071
Household loan balances, all banks (tax data)	234,496	225,325	177,228
Share of hsh. bank deposits held at other banks (tax data)	0.71	0.05	0.00
Share of hsh. retail bank loans held at other banks (tax data)	0.71	0.11	0.00
Household deposit balances at Danske Bank (bank data)	41,327	137,630	131,801
Household liquid assets at Danske Bank (bank data)	62,717	201,778	192,459
Household loan balances at Danske Bank (bank data)	49,590	174,754	165,132
Household inflows to Danske Bank accounts (bank data)	11,974	40,033	36,339
- salary, affected person	5,527	19,450	18,827
- salary, spouse	2,836	9,885	8,510
- government income transfers	859	2,630	2,431
- private transfers and other inflows	2,752	8,068	6,571
Household spending from Danske Bank accounts (bank data)	7,401	25,920	24,448
Household mortgage payments, all banks (mortgage data)	3,007	3,275	2,899
Household mortgage debt, all banks (mortgage data)	741,422	777,603	676,026

The table is an extended version of Table 1 in the main text. Column (1) shows statistics for the gross sample with no requirements on customer status at Danske Bank. Column (2) shows statistics for the baseline sample of active customers, i.e., individuals who have at least five outgoing spending transactions in each month of the event observation window and whose partner (if any) satisfies the same criterion. Column (3) is for the sample of exclusive customers, i.e., active customers who have no deposits or loans at other retail banks and whose partner (if any) satisfies the same criterion. All variables are measured in month -6 relative to the month of job loss, except the following: Annual gross income, measured over the calendar year in which month -6 occurs; shares of household loans and deposits held at other banks, household mortgage debt at all mortgage banks, all measured at the end of the calendar year before month -6.

Table A2: The dynamic effects of job loss on income, saving and spending

	Month 0	Month 6	Month 12	Month 24	Cumulative, months -5 to 24	Cumulative, months -5 to 24
	(1)	(2)	(3)	(4)	(5)	(6)
Effect on income, main person	--- Relative to monthly disposable income before job loss ---					Percent of income loss
[1] Wage income	-0.51	-0.31	-0.24	-0.21	-6.92	
	(0.00)	(0.00)	(0.01)	(0.01)	(0.14)	
[2] Government transfers	0.22	0.21	0.16	0.13	4.56	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	
[3] Income loss (= -[1] - [2])	**0.29**	**0.10**	**0.09**	**0.08**	**2.36**	**100.0%**
	(0.00)	**(0.00)**	**(0.01)**	**(0.01)**	**(0.14)**	**(0.0%)**
Compensating responses						
[4] Wage income, spouse	0.01	0.01	0.00	0.00	0.16	6.6%
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(2.9%)
[5] Private transfers and other income	0.04	0.02	0.01	0.00	0.23	9.8%
	(0.00)	(0.00)	(0.01)	(0.01)	(0.15)	(6.4%)
[6] Spending	-0.02	-0.03	-0.02	-0.03	-0.72	-30.3%
	(0.00)	(0.00)	(0.01)	(0.01)	(0.15)	(6.5%)
[7] Net saving in liquid assets	-0.19	-0.05	-0.06	-0.06	-1.16	-49.2%
	(0.01)	(0.01)	(0.01)	(0.02)	(0.29)	(12.0%)
[8] Non-mortgage loan net repayments	-0.03	0.00	0.00	0.00	-0.04	-1.9%
	(0.00)	(0.00)	(0.00)	(0.01)	(0.10)	(4.1%)
[9] Mortgage loan repayments	0.00	0.00	0.00	0.00	-0.06	-2.7%
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.6%)
[10] Total (= [5] + [6] - [7] - [8] - [9])	**0.26**	**0.10**	**0.09**	**0.10**	**2.38**	**100.7%**
	(0.01)	**(0.01)**	**(0.01)**	**(0.02)**	**(0.26)**	**(10.0%)**

All estimates are based on regression estimates from estimation of model (3). The reported outcomes are measured relative to the household's ex ante disposable income. Rows in normal font show coefficient estimates from single regressions with the indicated outcomes. Rows in bold font show combination of coefficients from multiple regressions, as indicated in parenthesis. Columns (1) to (4) report coefficients on the indicator variables representing months 0, 6, 12 and 24 after the unemployment event, respectively. Column (5) reports the sum of coefficient values for event months -5 to 24. Column (6) reports the ratio between the sum shown in the same row, column (5) and the corresponding sum shown in row [3], column (5). Standard errors (in parentheses) are estimated by bootstrapping with 300 replications. The bootstrapping procedure is carried out with resampling of individuals, rather than individual observations, to account for the panel nature of the data set.

Table A3: Cumulative effects of job loss: Robustness

	Baseline		No restriction on house trades		No restriction on same partner		Mass layoffs subsample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	------------------------------------ Cumulative effects, months -5 to 24 ------------------------------------							
	Rel. to disp. inc. before job loss	Percent of direct income loss	Rel. to disp. inc. before job loss	Percent of direct income loss	Rel. to disp. inc. before job loss	Percent of direct income loss	Rel. to disp. inc. before job loss	Percent of direct income loss
Effect on income, main person								
[1] Wage income	-6.92		-6.66		-6.97		-6.86	
	(0.14)		(0.13)		(0.13)		(0.39)	
[2] Government transfers	4.56		4.34		4.55		4.77	
	(0.08)		(0.08)		(0.07)		(0.24)	
[3] Income loss (= -[1] - [2])	**2.36**	**100.0%**	**2.31**	**100.0%**	**2.42**	**100.0%**	**2.10**	**100.0%**
	(0.14)	**(0.0%)**	**(0.13)**	**(0.0%)**	**(0.13)**	**(0.0%)**	**(0.37)**	**(0.0%)**
Compensating responses								
[4] Wage income, spouse	0.16	6.6%	0.12	5.3%	0.17	7.1%	0.07	3.4%
	(0.07)	(2.9%)	(0.06)	(2.8%)	(0.06)	(2.6%)	(0.20)	(10.0%)
[5] Private transfers and other income	0.23	9.8%	0.43	18.6%	0.40	16.6%	-0.39	-18.5%
	(0.15)	(6.4%)	(0.15)	(6.4%)	(0.14)	(5.8%)	(0.44)	(23.3%)
[6] Spending	-0.72	-30.3%	-0.71	-30.7%	-0.86	-35.4%	-0.92	-44.0%
	(0.15)	(6.5%)	(0.15)	(6.7%)	(0.13)	(5.6%)	(0.42)	(22.0%)
[7] Net saving in liquid assets	-1.16	-49.2%	-1.03	-44.6%	-1.12	-46.1%	-1.36	-65.0%
	(0.29)	(12.0%)	(0.30)	(12.6%)	(0.28)	(11.4%)	(0.94)	(46.6%)
[8] Non-mortgage loan net repayments	-0.04	-1.9%	-0.02	-0.9%	-0.07	-3.1%	0.06	3.0%
	(0.10)	(4.1%)	(0.09)	(4.1%)	(0.10)	(4.0%)	(0.28)	(14.2%)
[9] Mortgage loan repayments	-0.06	-2.7%	-0.08	-3.3%	-0.06	-2.4%	-0.01	-0.6%
	(0.01)	(0.6%)	(0.01)	(0.7%)	(0.01)	(0.5%)	(0.03)	(1.8%)
[10] Total (= [4] + [5] - [6] - [7] - [8] - [9])	**2.38**	**100.7%**	**2.39**	**103.4%**	**2.68**	**110.7%**	**1.92**	**91.7%**
	(0.26)	**(10.0%)**	**(0.27)**	**(10.5%)**	**(0.27)**	**(10.1%)**	**(0.86)**	**(40.3%)**
Number of individuals	10,002	10,002	11,096	11,096	11,798	11,798	1,156	1,156

The table reports summary measures of results from estimation of model (3) for various variations on our sample selection criteria. Columns (1)-(2) show baseline results, reproduced from columns (5)-(6) of Table A2. Columns (3)-(4) report parallel results when we relax the sample restriction that household members must not be involved in a real estate trade during the observation window. Columns (5) to (6) show results when we relax the restriction that the person experiencing job loss must have the same or no partner during the entire observation window. Columns (7) and (8) report results for the subsample of individuals who lose their job concurrently with mass layoffs at their employer. All estimates are based on regressions where the reported outcomes are measured relative to the household's average disposable income in the pre-event months. Odd-numbered columns report the sum of coefficients for event months -5 to 24 from such regressions. Even-numbered columns report the ratios between these sums and the corresponding sum for the direct income loss shown in row [3]. Standard errors (in parentheses) are estimated by bootstrapping with 300 replications. The bootstrapping procedure is carried out with resampling of individuals, rather than individual observations, to account for heteroskedasticity and autocorrelation within observations for the same individual.

Table A4: Descriptive statistics of subsamples used in heterogeneity analysis

	(1) Low liquid assets	(2) High liquid assets	(3) Low groceries spend. share	(4) High groceries spend. share	(5) Singles	(6) Married / co-habiting	(7) Young	(8) Old
Observations	196,961	154,339	210,198	209,416	171,535	248,079	203,043	216,571
Share old	0.46	0.61	0.51	0.52	0.51	0.52	0.00	1.00
Share married / co-habiting	0.55	0.64	0.47	0.71	0.00	1.00	0.59	0.60
Share high liquid assets	0.00	1.00	0.43	0.45	0.39	0.48	0.36	0.51
Share high grocery spending	0.50	0.51	0.00	1.00	0.35	0.60	0.50	0.50
Share homeowner	0.54	0.74	0.52	0.73	0.32	0.84	0.58	0.67
Share unempl. duration > 6 months	0.49	0.49	0.51	0.48	0.57	0.44	0.45	0.54
Mean age at job loss	45.98	48.97	46.94	47.16	46.93	47.13	40.21	53.46
Mean ex ante liquid-assets-to-income ratio	0.76	9.73	5.08	4.33	5.16	4.38	3.41	5.85
Mean ex ante grocery spend. share	0.17	0.17	0.10	0.23	0.14	0.19	0.17	0.17
Mean ex ante monthly income (main person), DKK	23,841	25,433	25,421	23,796	23,366	25,471	24,187	25,007
Mean unemployment duration, months	10.9	11.4	12.3	10.8	13.6	10.2	10.1	13.0

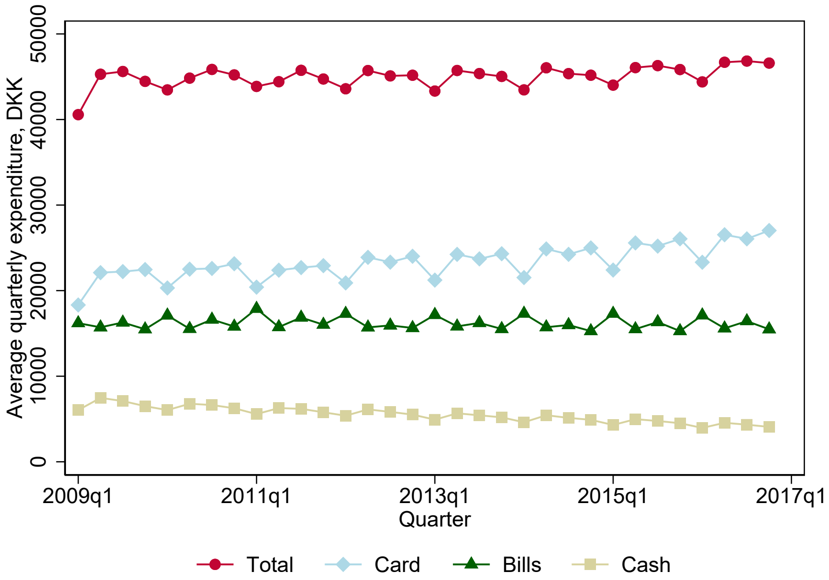
The table shows descriptive statistics for the subsamples shown in Table 3 in the main text. High liquid assets is defined as having liquid assets worth at least two months of ex ante household disposable income, measured 25 months earlier. High groceries spending is defined as having an ex ante groceries spending share above the sample median. Unemployment duration is defined as the number of consecutive months after job loss with wage income below 10,000 DKK (2010 price level). Old is defined as being at least 47 years of age at the time of job loss.

Table A5: Heterogeneity analysis: Full interaction of low liquid assets with high ex ante grocery spending

	Low groceries share, low liquid assets		Low groceries share, high liquid assets		High groceries share, low liquid assets		High groceries share, high liquid assets	
Observations	98,699		75,259		98,262		79,080	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cumulative effects, months -5 to 24							
Effect on income, main person	Rel. to hh disp. inc. before job loss	Percent of income loss	Rel. to hh disp. inc. before job loss	Percent of income loss	Rel. to hh disp. inc. before job loss	Percent of income loss	Rel. to hh disp. inc. before job loss	Percent of income loss
[1] Wage incme from lost job	-15.26		-14.64		-13.06		-13.12	
	(0.39)		(0.42)		(0.31)		(0.36)	
[2]Wage income from new jobs	7.35		6.82		7.19		6.34	
	(0.16)		(0.20)		(0.16)		(0.16)	
[3] Government transfers	5.42		4.51		3.96		4.20	
	(0.21)		(0.22)		(0.19)		(0.21)	
[4] Income loss (= -[1] - [2] -[3])	**2.49**	**100.0%**	**3.31**	**100.0%**	**1.91**	**100.0%**	**2.58**	**100.0%**
	(0.38)	**(0.0%)**	**(0.42)**	**(0.0%)**	**(0.31)**	**(0.0%)**	**(0.35)**	**(0.0%)**
Compensating responses								
[5] Wage income, spouse	-0.02	-0.9%	0.26	7.9%	0.28	14.9%	0.24	9.1%
	(0.15)	(6.1%)	(0.18)	(5.8%)	(0.19)	(10.5%)	(0.20)	(7.9%)
[6] Private transfers and other income	0.17	6.8%	-0.60	-18.1%	0.79	41.6%	0.46	17.7%
	(0.36)	(14.5%)	(0.42)	(13.4%)	(0.35)	(19.5%)	(0.38)	(15.0%)
[7] Spending	-1.46	-58.6%	-0.42	-12.6%	-0.35	-18.5%	-0.17	-6.8%
	(0.37)	(17.1%)	(0.45)	(14.0%)	(0.33)	(18.7%)	(0.38)	(14.8%)
[8] Net saving in liquid assets	-0.95	-37.9%	-2.79	-84.2%	-0.45	-23.5%	-1.12	-43.4%
	(0.64)	(25.6%)	(1.02)	(31.0%)	(0.60)	(33.0%)	(0.90)	(34.5%)
[9] Non-mortgage loan net repayments	-0.27	-10.8%	-0.22	-6.6%	0.16	8.6%	0.01	0.5%
	(0.23)	(9.3%)	(0.24)	(7.7%)	(0.25)	(14.5%)	(0.19)	(7.7%)
[10] Mortgage loan repayments	-0.06	-2.6%	-0.06	-1.8%	-0.05	-2.4%	-0.13	-5.1%
	(0.03)	(1.1%)	(0.03)	(1.1%)	(0.04)	(2.1%)	(0.04)	(1.8%)
[11] Total (= [5] + [6] - [7] - [8] - [9] - [10])	**2.89**	**115.9%**	**3.15**	**95.1%**	**1.76**	**92.2%**	**2.10**	**81.6%**
	(0.64)	**(23.3%)**	**(0.86)**	**(26.1%)**	**(0.56)**	**(27.3%)**	**(0.79)**	**(28.0%)**

The table shows cumulated effects of job loss for four subsamples, defined by i) whether or not the household held liquid assets worth at least two months of ex ante disposable income 25 months earlier, and ii) whether the share of the household's total spending in event months -18 to -3 that is spent on groceries is below or above the median value in the sample. All outcomes are measured relative to the household's ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month. Estimates of cumulated effects are obtained by estimating model (3) on each subsample and summing the $\beta_h$coefficients for event months -5 to 24. Odd-numbered columns report the value of the sums. Even-numbered columns report the ratios between the sums and the corresponding sum for the income loss shown in row [4]. Standard errors (in parentheses) are estimated by bootstrapping with 300 replications. The bootstrapping procedure is carried out with resampling of individuals, rather than individual observations, to account for heteroskedasticity and autocorrelation within observations for the same individual.

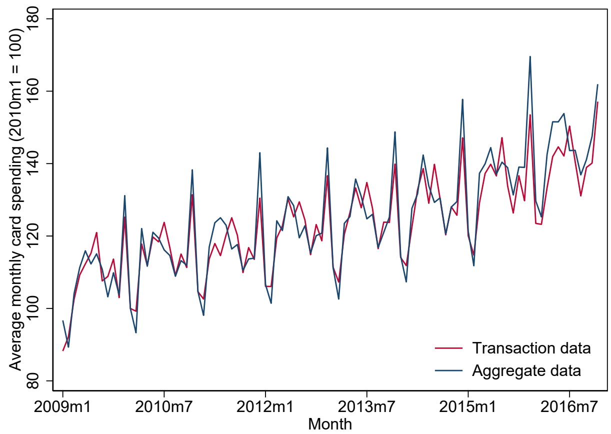
Figure A1: Average spending for active customers, by payment method and quarter



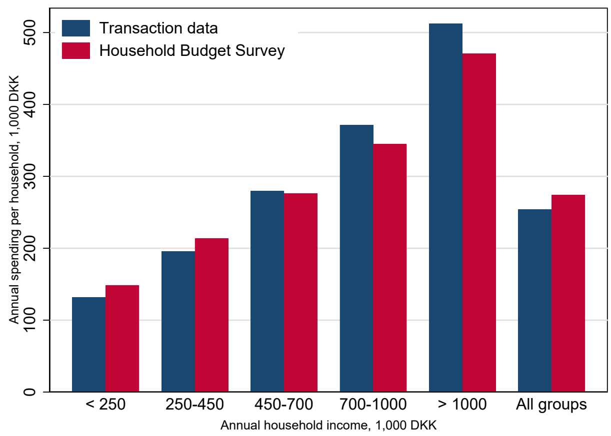
The figure shows the breakdown of the spending measure on categories of outflows for the complete sample of active customers. Card payments include payments via cellular phone.

Figure A2: Measuring household spending: Transaction data vs. other sources

(a) Card spending per person

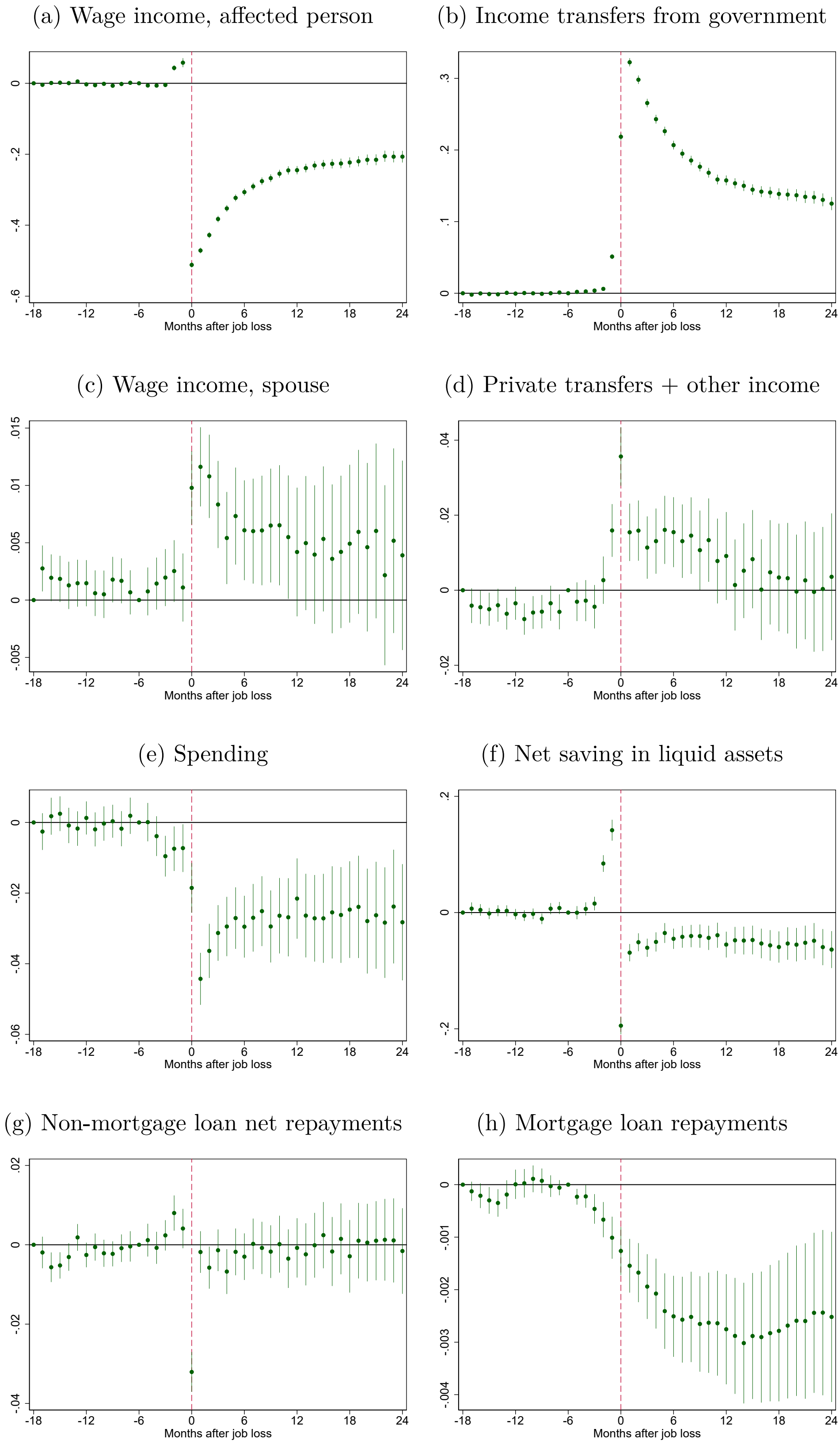


(b) Total annual spending per household, by income group



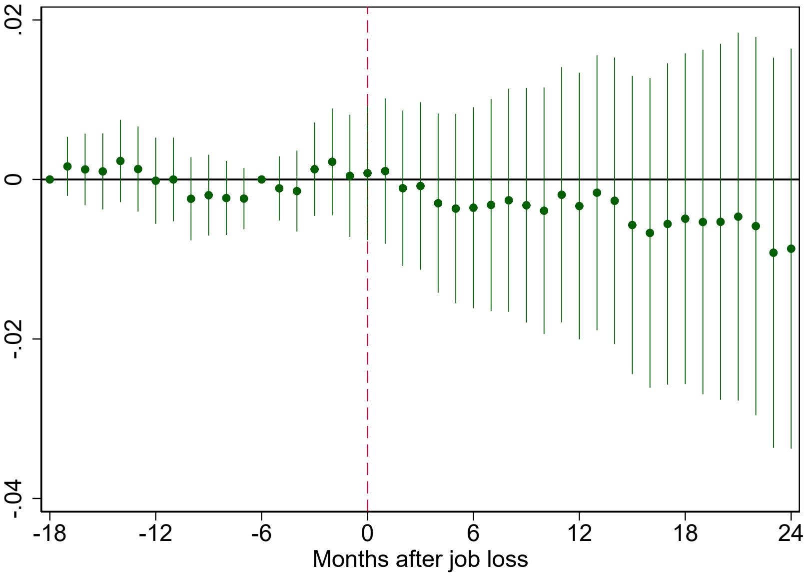
The figure compares aggregates of our measure of household spending based on transaction data to publicly available measures from existing sources. The transaction data measures are computed for our full sample of Danske Bank customers with at least five outgoing transactions per month for each adult person in the household. Panel (a) shows the development in average card spending per person in this sample (red line) vs. the full adult population (blue line), indexed relative to January 2010. The aggregate data for the full population are calculated from official statistics published by Statistics Denmark (Statistics Denmark, 2019b). To construct the series, we have divided total aggregate card spending in each month by the number of persons in the population above age 18. Panel (b) shows averages of total annual household spending across income groups. Income groups are defined by total annual household income in DKK. Average spending levels are computed within each group and each year and then averaged across the years 2009-16. Blue columns are based on the bank transaction data. Red columns are based on Statistics Denmark's Household Budget Survey (Statistics Denmark, 2019a) and show total annual spending excluding the imputed value of owner-occupied housing.

Figure A3: Dynamic responses to job loss, individual outcomes



The figure shows estimation results from the event study model (3) of the effects of job loss on various outcomes. All outcomes are measured relative to the household's ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month. Vertical lines represent 95% confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

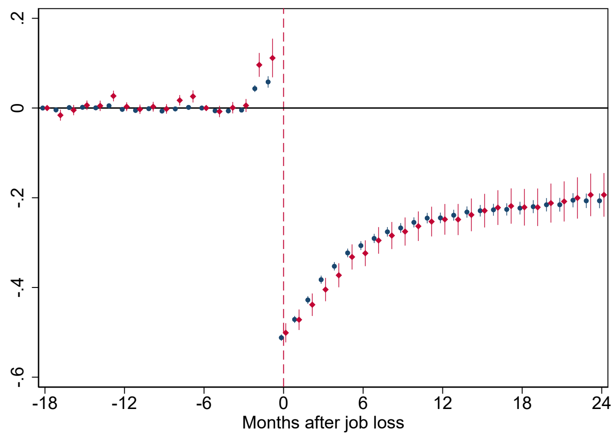
Figure A4: Spouse employment, extensive margin



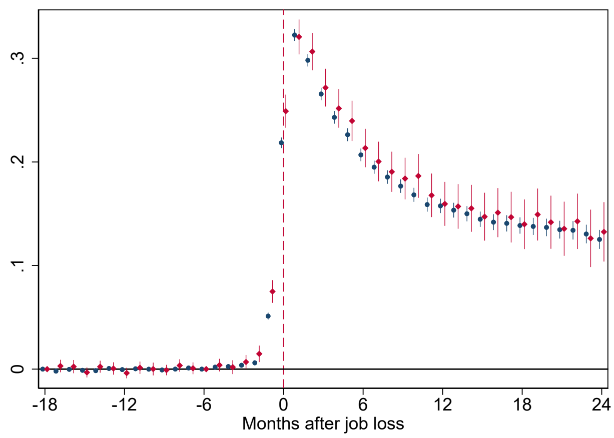
The figure shows estimation results from the event study model (3) of the effects of job loss on spouses' employment rates. The dependent variable is a dummy variable equal to 1 if the spouse of the person experiencing job loss appears on the payroll of at least one employer in the given month. Individuals with no spouse are excluded. Vertical lines represent 95% confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

Figure A5: Impact of job loss on income and spending: Baseline sample vs. mass layoff sample

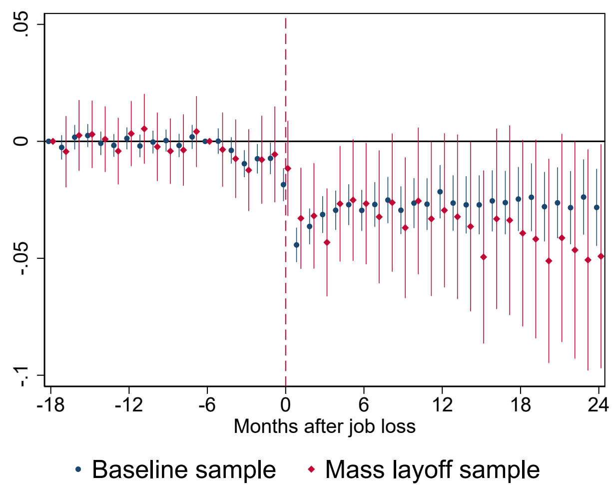
(a) Wage income, affected person



(b) Government transfers

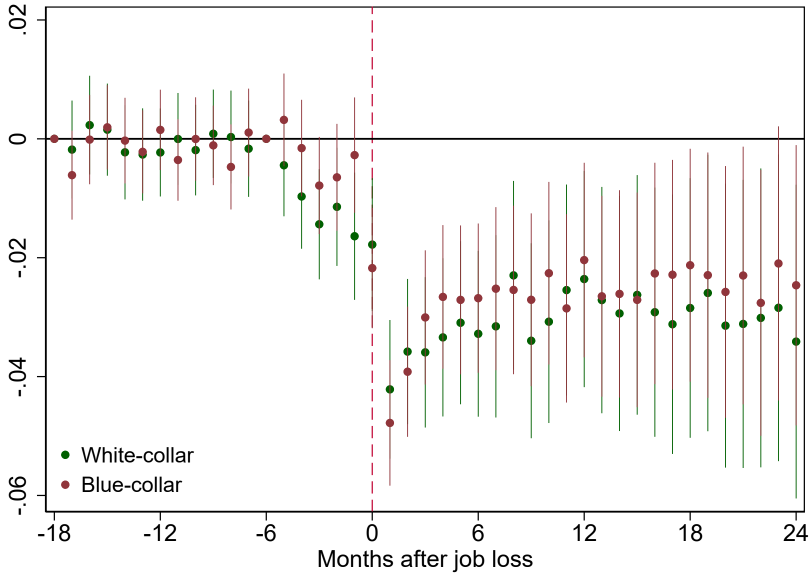


(c) Spending



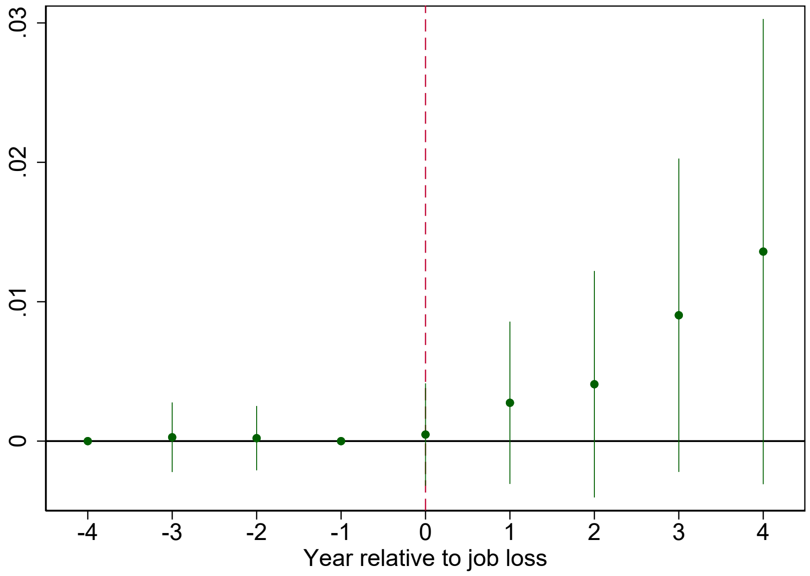
The figure shows estimation results from the event study model (3) of the effects of job loss on income and spending. Blue markers show estimates for the baseline sample of active customers. Red markers show estimates for the subsample of individuals who were laid off concurrently with a mass layoff at their employer. All outcomes are measured relative to the household's ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month. Vertical lines represent 95% confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

Figure A6: Spending responses to job loss: Blue collar vs. white collar



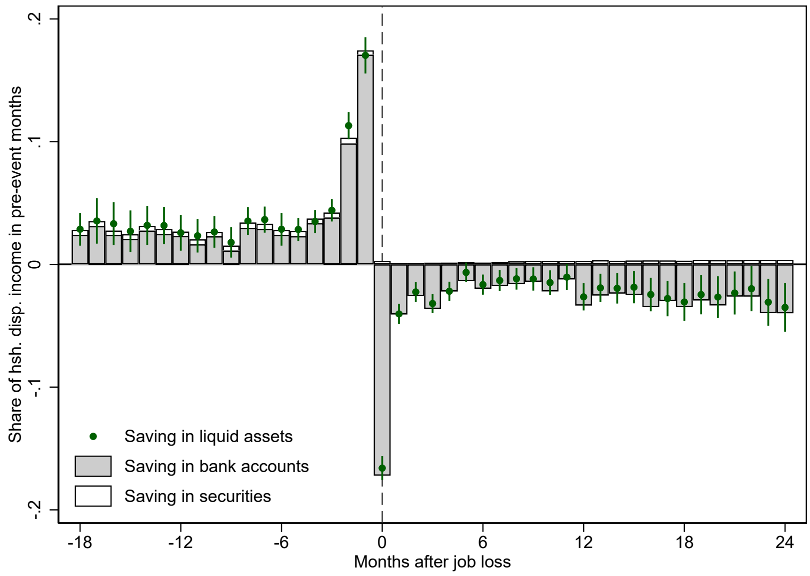
The figure shows estimation results from the event study model (3) with household spending (normalized by the household's ex ante disposable income) as the outcome for two subsamples: White-collar workers (green) are individuals who are covered by legislation guaranteeing a notice period of at least 3 months when laid off. Blue-collar workers (red) are not covered by such legislation and can have notice periods as short as one day. Data on blue- vs. white-collar status comes from the employment registry and are mainly based on information about employment contracts submitted by employers. The outcome variable is winsorized at the 2.5 and 97.5 percentiles within each event month. Vertical lines represent 95% confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

Figure A7: Loan arrears



The figure shows estimation results from an event study corresponding to model (3), but using annual data. The dependent variable is a dummy variable equal to 1 if the person experiencing job loss or his/her spouse is in arrears on any loan at the end of the year. Information on loan arrears comes from the tax data on bank relationships. Vertical lines represent 95% confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

Figure A8: Net saving in liquid assets around time of job loss, levels



The figure shows average predicted values from the event study model (3) with net saving in liquid assets and its two subcomponents as outcome variables. Each estimate is the average predicted value when the event time variable takes the value indicated on the horizontal axis and control variables are evaluated at their actual values. Green dots illustrate the total level of net saving in liquid assets, while the stacked bars show the predicted values of each of its subcomponents. The dependent variables are measured relative to the household's ex ante disposable income and winsorized at the 2.5 and 97.5 percentiles within each event month.Vertical lines represent 95% confidence intervals. Standard errors are estimated allowing for clustering at the level of the individual.

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